Modelling and Forecasting Exchange Rate Volatility in Nigeria: Does One Model Fit All?

Afees A. Salisu, Ph.D*

Abstract

This study analyses the extent of volatility in exchange rate in Nigeria covering the sustainable democratic transitions between 1999 and 2011 using daily returns. The main innovation of this paper is that it evaluates the volatility under each democratic regime of four years namely 05/29/ 1999 – 05/28/2003; 05/29/2003 – 05/28/2007; and 05/29/2007 – 05/28/2011. The empirical evidence indicates that the behaviour of exchange rate tends to change over short periods of time with inconsistent leverage effects and persistence of shocks. Thus, applying a one-model-fits-all approach for exchange rate volatility in Nigeria will yield misleading and invalid policy prescriptions.

Key Words: Exchange rate, volatility modelling, volatility forecasting, monetary policy

JEL Classification: C22, C51, C53, E52, G10

Author's E-mail: aa.salisu@cear.org.ng; aa.salisu@mail.ui.edu.ng

I. Introduction

The Central of Bank of Nigeria (CBN), just like any other Central Bank, is charged, among other functions, with the responsibility of ensuring and maintaining exchange rate stability. This is underscored by the fact that incessant exchange rate fluctuations may: (i) lead to huge losses or gains for traders in the foreign exchange market; (ii) deteriorate or improve balance of payments; (iii) cause significant losses or gains to both foreign and local investors; and (iv) distort international comparisons (see for example, Arize, 1995, 1997, 1998; Esquivel and Larraín, 2002; and Schnabl, 2007 for recent empirical evidence)[1]. Thus, both the government and profit-maximizing investors are keenly interested in the extent of volatility in exchange rate to make policy/investment decisions. Therefore, a measure of volatility in exchange rate provides useful information both to the investors in terms of how to make investment decisions and relevant monetary authorities in the formulation of appropriate liquidity supply policies to protect and strengthen the domestic currency. A more serious

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* *Afees A. Salisu is of the Centre for Econometrics and Allied Research (CEAR), Department of Economics, University of Ibadan, Nigeria.* *This work was substantially supported by a research fellowship granted by CEAR. The author would also like to thank Prof. S.O. Olofin for his useful comments. The usual disclaimer applies.*

[1]*See for example, Clark (1973), Baron (1976a&b), Hooper and Kohlhagen (1978), Broll (1994) and Wolf (1995) for early contributions to the evidence.*

concern however, centres on how to model exchange rate when confronted with such volatility.

The concept of exchange rate volatility has been extensively dealt with in the literature.[2]However, different dimensions witnessed in the various analyses have continued to create vacuum for further studies. Summarily, two concerns can be raised on the modelling of exchange rate volatility: (i) Is exchange rate volatility regime neutral?[3] and (ii) Does a one-model-fits-all syndrome automatic in intra-regime analyses of exchange rate volatility? The former concern has been extensively dealt with in the literature (see Kočenda and Valachy, 2006 and Chipili, 2009 for a survey of literature). Majority of these studies find that exchange rate is more volatile in flexible exchange rate than in fixed exchange rate regime. Of course, a fixed exchange rate regime does not usually respond systematically to market forces and, therefore, one can easily pre-empt the results of these studies of larger variations in a flexible regime than in fixed.

The latter question, to the best of the knowledge of the author, does not seem to have received any notable attention in the literature.[4] This is the contribution of the present study. It can be argued that a flexible exchange rate regime under different democratic periods may give substantially different volatility trends depending upon the interest and effectiveness of monetary policy authorities in maintaining exchange rate stability. For example, different democratic periods in Nigeria (through the monetary policy institutions) have implemented several strategies to strengthen the value of the naira under a flexible exchange rateregime and, therefore, the extent of exchange rate volatility may differ significantly across different periods. Thus, if this was true, it becomes imperative to understand the peculiarities of the modelling framework for accounting for such significant differences. Generalizing the model of exchange rate volatility, notwithstanding the significant peculiarities, may lead to invalid and misleading policy prescriptions. Essentially, the study considers sub-samples determined by the different democratic periods in Nigeria which practiced flexible exchange rate regime to provide answers to the latter question. With these sub-samples, this study is able to evaluate the effectiveness of monetary policy authorities under each democratic period in maintaining exchange rate stability and assess the robustness of the empirical results.

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[2] *A brief review of some of these papers is provided in section 3.*

[3] *That is, can modeling of exchange rate be generalized for both fixed and flexible regimes?*

[4] *The only but unrelated paper is Narayan and Narayan (2007) that examined the modeling of oil price volatility. They considered various subsamples between 1991 and 2006 in order to judge the robustness of their results although the choice of the subsamples was not justified. In relation to exchange rate volatility however, studies in this regard are non-existent.*

In Nigeria, research in the area of modelling exchange rate is gradually emerging. The available studies are Olowe (2009) and Dallah (2011). These studies however, did not allow for probable significant variations in the modelling structure of exchange rate volatility in Nigeria. In addition, the use of high frequency daily returns on Nigeria'sexchange rate in the present study further provides reasonable basis for probable existence of autoregressive time varying heteroscedaticity in the series.

The full sample (FS) of the study is the period of sustainable democratic transitions in Nigeria- 05/29/1999 – 05/28/2011. Essentially, the period – 05/29/1999 marked the beginning of sustainable democratic era in Nigeria and subsequently followed by four successful democratic transitions each with four-year period. Thus, the sub-samples are 05/29/1999 – 05/28/2003 (SUB1); 05/29/2003 – 05/28/2007 (SUB2); and 05/29/2007 – 05/28/2011 (SUB3).[5] The current administration is barely five (5) months old and, therefore, is not included in the estimation sample.

In addition, in the course of empirical analysis, attention is paid to: (i) the use of appropriate model selection criteria including pre-tests as suggested by Engle (1982) to determine the choice of volatility model; and (ii) the application of appropriate forecast measures to evaluate the forecast performance of the preferred models

The findings from the empirical analysis appear mixed and in particular, there is evidence of inconsistent leverage effects and persistence of shocks.[6]Large depreciations were recorded during SUB1 and SUB3 compared to SUB2. Thus, monetary policy strategies seem more effective in the latter period than the two former periods. Comparatively, the TGARCH (1,1) model gives the best fit under SUB2 and SUB3 while the GARCH (1,1) is preferred under SUB1. The results obtained from the TGARCH (1,1) model reveals evidence of strong leverage effects. These effects indicate that positive shocks increased the volatility of exchange rate more than negative shocks of the same magnitude. Thus, good news in the foreign exchange market has the potential of increasing volatility in the exchange rate than bad news. In addition, the shocks leading to a change in volatility seem permanent during SUB3. This evidence further reinforces the need to restructure the current design of exchange rate management in Nigeria. The incessant reliance on monetary policy rate to influence the level of exchange

[5]FS and SUB1-3 denote full sample period-05/29/1999 – 05/28/2011 and sub-sample periods 05/29/1999 –05/28/2003; 05/29/2003 - 05/29/2007 and 05/29/2007 – 05/28/2011 respectively.
[6] This evidence is consistent with Narayan and Narayan (2007).

rate, among others, may not completely produce the desired results. Overall, applying one-model-fits-all approach for exchange rate volatility in Nigeria will yield misleading and invalid policy prescriptions.

Some stylized facts about the exchange rate management in Nigeria are provided in section 2. Relevant theoretical and applied research studies on volatility modelling of exchange rate are reviewed in section 3. While section 4 describes the structure of the volatility models considered in this paper, section 5 presents the empirical applications including forecasting. Section 6 concludes the paper.

II. Stylized Facts about Exchange Rate Management in Nigeria

Exchange rate management in Nigeria is motivated by the need to ensure and maintain exchange rate stability.[7] The actualization of this important objective is anchored on the ability of the monetary authorities to (i) prevent distortions in the foreign exchange (FOREX) market by at least narrowing the gap between the official and parallel markets; (ii) maintain a favourable external reserve position;(iii) promote healthy external balances; (Iv) diversify the export base and reduce incessant dependence on imports; and (v) curtail the incidence of capital flight. Table 1 presents some selected indicators of exchange rate management in Nigeria. The statistics provided cover the period 1999 to 2010 in line with the study period and structured along the democratic periods. The demand for FOREX has increased drastically during the three democratic transitions. The total FOREX utilization in Nigeria grew rapidly by 63.89% (from US$35,265.58 million to US$57,797.96 million) during 2003-2006 and subsequently by a significantly higher rate of 109.40% (from US$57,797.96 million to US$121,030.37) in 2007-2010.

The trends further reveal that the ever-increasing demand for FOREX in Nigeria was majorly driven by the need to settle high import bills. The ratio of FOREX utilization on imports to total shows that about 77.29% (equivalent to US$27,257.93 million) of the total FOREX utilization was used on imports during 1999-2002; a slightly higher magnitude of 81.71% (equivalent to US$47,224.08 million) during 2003-2006 and somewhat lower degree of 64.17% during 2007-2010 compared to the previous periods.The FOREX utilization on imports, just as the overall, grew rapidly by 73.24% (from US$27,257.93 million to US$47,224.08 million) during 2003-2006 period and subsequently by a somewhat lower rate of 64.46% (from US$47,224.08 million to US$ 77,664.05) in 2007-2010. The BOP values also support evidence of higher FOREX payments than receipts as huge deficits were

[7] The reasons for maintaining exchange rate stability have been discussed under section 1.

recorded for all the periods under consideration. Thus, the incessant high demands for FOREX may also account for the persistent depreciation in the domestic currency (naira) as presented in table 1.

Overall, the management of exchange rate in Nigeria has been rather challenging to the monetary authorities particularly on how to address the attendant consequences of increasing demands for huge FOREX in the country.

Table 1: Selected indicators of exchange rate management in Nigeria

Indicator	1999-2002	2003-2006	2007-2010
FOREX utilization on Imports (US$' Million)	27,257.93	47,224.08	77,664.05
Percentage change of Import FOREX	-	73.24	64.46
Total Utilization of FOREX(US$' Million)	35,265.58	57,797.96	121,030.37
Percentage change of Total FOREX	-	63.89	109.40
(a)Percentage of FOREX utilization on Imports to Total (%)	77.29	81.71	64.17
Balance of Payments (BOP) (US$' Million)	(4,624.85)	(28,250.40)	(68,909.52)
Official Exchange Rate (Naira/US$1.00): End-Period	126.8833	128.2919	150.4799
Average Official Exchange Rate (₦/US$1.00)	106.928	130.9139	135.8999

Source: Central Bank of Nigeria (CBN) Statistical Bulletin, 2010.

NB: Figures in (a) were computed by the author from the CBN Statistical Bulletin. The BOP values are cumulative and the parentheses imply deficits. Also, BOP values were provided in US$ million only for the period 2005 to 2010 and therefore, values for the preceding period 1999-2004 were computed by dividing the BOP in the local currency unit (Naira) by the official exchange rate (N/US$). Also note that BOP surpluses were recorded in between the periods.

III. Literature Review

The issue of volatility in financial time series including exchange rate has received considerable attention from both researchers and relevant practitioners and policy makers alike. Despite this phenomenal growth in research efforts, the choice of a modelling framework has remained inconclusive both theoretically and empirically. The Engle (1982) paper is the first notable work on volatility modelling of financial time series. The paper develops an Autoregressive Conditional Heteroscedasticity (ARCH) model to capture probable statistically significant correlations between observations that are large distance apart and time varying. After the seminal paper of Engle (1982), several extensions have emerged to improve on the latter. Among these extensions are the ARCH in Mean (ARCH-M) by Engle, et al (1987), the Generalized ARCH (GARCH) developed by Bollerslev (1986) and the GARCH family. The latter includes the integrated GARCH (IGARCH) model by Engle and Bollerslev (1986), the multivariate GARCH models (MGARCH) developed by Baba, et al (1990) and extended by Engle and Kroner (1995) and asymmetric GARCH models [exponential GARCH (EGARCH) proposed by Nelson (1991), GJR-GARCH by Glosten, et al(1993), and asymmetric power GARCH ((APGARCH) model by Ding, et al (1993)].[8]

Several extensive applications of these dimensions of volatility models in relation to modelling of exchange rate volatility exist in the literature. A survey of the existing literature can be found in Chipili (2009). A number of studies have evaluated exchange rate volatility under two prominent policy regimes namely fixed and floating regimes (see for example, Stockman, 1983; Mussa, 1986; Savvides, 1990; Papell, 1992; Lothian and Taylor,1996; Hasan and Wallace, 1996; Flood and Rose, 1998; Canales-Kriljenko and Habermeier, 2004; Kočenda and Valachy, 2006; and Stancik, 2006 and Olowe, 2009). The dominant consensus in the literature is that exchange rate volatility is greater under a flexible regime than under a fixed arrangement.

Some of these studies have also focused on country-specific analysis (see Singh, 2002, for India; Yoon and Lee, 2008, for South Korea; Chipili, 2009, for Zambia; Olowe, 2009, and Dalla, 2011, for Nigeria), while some others have evaluated comparatively for a panel of countries (e.g. Savvides, 1990, for developing countries; Papell, 1992, for European Monetary System; Bangake, 2006, for Africa; and Kočenda and Valachy, 2006, for Visegrad four countries); and the use of both asymmetric and symmetric volatility models has remained dominant. The significance of modelling exchange rate has also been reflected in a number of empirical studies capturing macroeconomic effects of exchange rate volatility (see Esquivel and Larrain, 2002, on linking exchange rate volatility with foreign direct investment and trade and Chowdhury, 1993; Arize, 1995, 1997, 1998; Dell'Ariccia, 1999; Arize, et al ,2000; Esquivel and Larraín, 2002; and Schnabl, 2007; examining exchange rate volatility on trade). The dominant empirical evidence

[8] See Engle (2002) for a comprehensive review of volatility models and recent extensions.

indicates that an increase in exchange rate volatility is associated with a decrease in the volume of international trade.

By and large, issues dwelling on exchange rate volatility have been extensively debated in the literature. As earlier emphasized, the issue of whether or not we can generalize the modelling of exchange rate volatility under different democratic transitions of the same policy regime (flexible regime) appears not to have received any attention in the literature. This is the contribution of this study. The section that follows describes the structure of the volatility models used.

IV. The Models

This paper begins with the following AR (*k*) process for financial time series $\left(z_t\right)$:

$$z_t = \eta + \sum_{i=1}^{k} \delta_i z_{t-i} + \varepsilon_t ; i = 1, \ldots, k; t = 1, \ldots, T; \varepsilon_t \sim \mathrm{IID}\left(0, \sigma^2\right); \left|\delta_i\right| < 1 \tag{1}$$

z_t the return from holding the financial securities/assets, η is the risk premium for investing in the long-term securities/assets or for obtaining financial assets, z_{t-i} captures the autoregressive components of the financial series, δ_i represent the autoregressive parameters and ε_t is the error term and it measures the difference between the *ex-ante* and *ex-post* rate of returns. In equation (1), z_t is assumed conditional on immediate past information set $\left(\Omega_{t-1}\right)$ and, therefore, its conditional mean can be expressed as:

$$E\left(z_t \middle| \Omega_{t-1}\right) = \eta + \sum_{i=1}^{k} \delta_i z_{t-i} \tag{2}$$

Equation (2) shows that the conditional mean of z_t is time-varying which is a peculiar feature of financial time series. Assuming the error term $\left(\varepsilon_t\right)$ follows Engle (2002):

$$\varepsilon_t = \mu_t \left(\beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \right)^{1/2}; \quad j = 1, \ldots, q \tag{3}$$

where $\mu_t \sim \mathrm{IID}(0,1)$ and it is also assumed that $\beta_0 > 0$ and $0 < \beta_1 < 1$.[9] Equation (3) defines ARCH (q) model as proposed by Engle (2002). Equivalently, equation (3) can be expressed as:

$$\varepsilon_t^2 = \mu_t^2 \left(\beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \right) \tag{4}$$

Taking expectation of equation (4) given relevant information set (π_{t-1}) the conditional variance is derived as:

$$\mathrm{var}\left(\varepsilon_t | \pi_{t-1}\right) = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \text{ since } \mathrm{E}\left(\mu_t^2 | \pi_{t-1}\right) = 1 \tag{5}$$

In the case of unconditional variance, however, using the lag operator (L), equation (5) becomes:

$$\sigma_t^2 = E\left(\varepsilon_t^2\right) = \frac{\beta_0}{1-\beta(L)} \tag{6}$$

where $\sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 = \beta(L)\varepsilon_t^2$ and $\beta(L)$ is the polynomial lag operator $\beta_1 L + \beta_2 L^2 + \ldots + \beta_q L^q$ Equation (4) defines ARCH (q) model where the value of the conditional variance $\left[\mathrm{var}\left(\varepsilon_t | \pi_{t-1}\right)\right]$ is a function of squared error term from past periods $\left(\varepsilon_{t-j}^2\right)$. The null hypothesis is given as: $H_0 : \beta_1 = \beta_2 = \cdots = \beta_J = 0$ and the hypothesis is tested using either the *F-test* or nR^2 that follows chi-square distribution proposed by Engle (1982). If the null hypothesis is (not) rejected, then there is (no) ARCH effect in the model. Equation (6) shows that the variance is larger when there is evidence of volatility in the time series.

Also considered is the model developed by Bollerslev (1986) which extends Engle (1982) ARCH model by incorporating lags of the conditional variance. Based on the latter, equation (5) becomes:

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[9] This is a non-negativity constraint imposed on the ARCH model as proposed by Engle (1982) to ensure that the conditional variance is positive.

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 + \sum_{\gamma=1}^{p} \gamma_i \sigma_{t-i}^2 \qquad (7)$$

Where $p \geq 0$, $q > 0$, $\beta_0 > 0$, $\beta_j \geq 0$, $\gamma_i \geq 0$, $j = 1, \ldots, q$ and $i = 1, \ldots, p$.
Equation (7) is the GARCH (*p,q*) model where p and q denote the lagged terms of the conditional variance and the squared error term respectively. The ARCH effect is denoted by $\sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2$ and the GARCH effect $\sum_{\gamma=1}^{p} \gamma_i \sigma_{t-i}^2$. Using the lag operator, equation (7) is expressed equivalently as:

$$\sigma_t^2 = \beta_0 + \beta(L)\varepsilon_t^2 + \gamma(L)\sigma_t^2 \qquad (8)$$

Similarly, $\gamma(L)\sigma_t^2 = \sum_{\gamma=1}^{p} \gamma_i \sigma_{t-i}^2$ and $\gamma(L)$ is the polynomial lag operator $\gamma_1 L + \gamma_2 L^2 + \ldots + \gamma_p L^p$. By further simplification, equation (8) can be expressed as:

$$\sigma_t^2 = \beta_0 \left[1 - \gamma(L)\right]^{-1} + \beta(L)\left[1 - \gamma(L)\right]^{-1} \varepsilon_t^2 \qquad (9)$$

The unconditional variance, however, is smaller when there is no evidence of volatility:

$$\sigma_t^2 = \left[1 - \beta(L) - \gamma(L)\right]^{-1} \beta_0 \qquad (10)$$

Another important extensions also considered in the modelling of volatility in exchange rate are the ARCH in mean (ARCH-M) and the GARCH-M models that capture the effect of the conditional variance (or conditional standard deviation) in explaining the behaviour of stock returns. For example, when modelling the returns from investing in a risky asset, one might expect that the variance of those returns would add significantly to the explanation of the behaviour of the conditional mean, since risk-averse investors require higher returns to invest in riskier assets (see Harris and Sollis, 2005). For the ARCH-M, equation (1) is modified as:

$$z_t = \theta + \lambda \sigma_t^2 + \sum_{\gamma=1}^{p} \gamma_i \delta_i z_{t-i} + \varepsilon_t; \qquad i = 1, \ldots, k \qquad (11)$$

Thus; $\eta_t = \theta + \lambda \sigma_t^2$ (12)

Where σ_t^2 is as defined in equation (5). The standard deviation of the conditional variance can also be used in lieu. For the GARCH-M, the only difference is that conditional variance (σ_t^2) follows equation (7) instead.

Also of relevance to the study are the volatility models that capture the asymmetric effects or leverage effects not accounted for in the ARCH and GARCH models. Nelson (1991) proposed an exponential GARCH (EGARCH) model to capture the leverage effect. The EGARCH(p,q) is given as:

$$\text{Log}\left(\sigma_t^2\right) = \varnothing + \left[1-\gamma\left(L\right)\right]^{-1}\left[1+\beta\left(L\right)\right] f\left({\varepsilon_{t-1}}/{\sigma_{t-1}}\right) \quad (13)$$

and

$$f\left({\varepsilon_{t-1}}/{\sigma_{t-1}}\right) = \alpha\varepsilon_{t-1} + \vartheta\left(\left|{\varepsilon_{t-1}}/{\sigma_{t-1}}\right| - E\left|{\varepsilon_{t-1}}/{\sigma_{t-1}}\right|\right) \quad (14)$$

Unlike the ARCH and GARCH models, equation (13) shows that, in the EGARCH model, the log of the conditional variance is a function of the lagged error terms. The asymmetric effect is captured by the parameter α in equation (14) (i.e. the function $f\left(\varepsilon_{t-1}/\sigma_{t-1}\right)$). There is evidence of the asymmetric effect if $\alpha < 0$ and there is no asymmetric effect if $\alpha = 0$. Essentially, the null hypothesis is $\alpha = 0$ (i.e. there is no asymmetric effect and the testing is based on the t-statistic.[10] The conditional variance in the EGARCH model is always positive with taking the natural log of the former. Thus, the non-negativity constraint imposed in the case of ARCH and GARCH models is not necessary.

The asymmetric effect can also be captured using the GJR-GARCH[11] model which modifies equation (7) to include a dummy variable I_{t-j}.

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^{q}\beta_j\varepsilon_{t-j}^2\varepsilon_{t-j}^2 + \sum_{\gamma=1}^{p}\gamma_i\sigma_{t-i}^2 + \sum_{j=1}^{q}\varphi_j\varepsilon_{t-j}^2 I_{t-j} \quad (15)$$

[10] Conversely, a symmetric GARCH model can be estimated and consequently, the tests proposed by Engle and Ng (1993) namely the sign bias test (SBT), the negative sign bias test (NSBT) and the positive sign bias test (PSBT) can be used to see whether an asymmetric dummy variable is significant in predicting the squared residuals (see also Harris and Sollis, 2005).
[11] This was developed by Glosen, et al (1993)

where $I_{t-j} = 1$ if $\varepsilon_{t-j} > 0$ (positive shocks) and $I_{t-j} = 0$ otherwise. Therefore, there is evidence of asymmetric effect if $\varphi_j < 0$ which implies that positive shocks reduce the volatility of z_t more than negative shocks of the same magnitude. However, in some standard econometric packages like *G@RCH* programme and E-views, the reverse is the case for the definition of I_{t-j}. That is, $I_{t-j} = 1$ if $\varepsilon_{t-j} < 0$ (negative shocks) and $I_{t-j} = 0$ otherwise. Thus, there is evidence of asymmetric effect if $\varphi_j > 0$ which implies that negative shocks increase the volatility of z_t more than positive shocks of the same magnitude.[12]

V. Empirical Analysis

The empirical applications consider different plausible models for measuring volatility in the Nigerian exchange rate returns as previously discussed and consequently compare the forecasting strengths of these models for policy prescriptions. The analyses are carried out in four phases.[13] The first phase deals with some pre-tests to ascertain the existence of volatility in the Nigerian exchange rate returns. The ARCH Lagrangian Multiplier (LM) test proposed by Engle (1982) is used in this regard. The second phase proceeds to the estimation of different volatility models involving $\mathrm{ARCH}\ (p)$ to $\mathrm{GARCH}\ (p, q)$ type of models including their extensions. Model selection criteria such as Schwartz Information Criterion (SIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQC) are used to determine the model with the best fit. The third phase provides some post-estimation analyses using the same ARCH LM test to validate the selected volatility models. The fourth, which is the last phase, assesses the forecasting power of the model using forecasting measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Theil's Inequality Coefficient (TIC) and Mean Absolute Percent Error (MAPE). Daily exchange rate (exr) data utilized in this study are collected from the Statistical bulletin of the Central Bank of Nigeria (CBN) over the period 05/29/1999 –05/28/2011.[14] All the analyses are carried out for the full sample and sub-samples as earlier emphasized. The exchange rate used in this paper is measured by the units of Nigerian domestic currency (*Naira*) to one unit of US dollar. The choice of exchange rate is underscored by the fact that the US dollar (USD) has remained dominant in the

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[12] *A comprehensive exposition of volatility models is provided by Harris and Sollis (2005)*

[13] *Engle (2001) and Kočenda and Valachy (2006) adopted a similar approach.*

[14] *Find the data at http://www.cenbank.org/rates/ExchRateByCurrency.asp. Accessible data for the period 05/29/1999 – 05/28/2003 from the official source- Central Bank of Nigeria (CBN) began on 12/10/2001.*

Nigerian foreign exchange market and, therefore, trading on USD may exert more impact on the *Naira* than all other foreign currencies combined.

V.1 Pre-Estimation Analysis

The pre-estimation analysis is done in two-folds: the first provides descriptive statistics for exchange rate and its returns and the second involves performing ARCH LM test on model (1) above which can now be re-specified as:

$$r_t = \eta + \sum_{i=1}^{k} \delta_i r_{t-i} + \varepsilon_t; \quad i = 1,\ldots,k; \quad t = 1,\ldots,T; \;\; \varepsilon_t \sim \mathrm{IID}\left(0,\sigma^2\right); \quad \left|\delta_i\right| < 1 \tag{16}$$

Where r_t denotes the exchange rate returns and is measured in this paper as:

$$r_t = 100*[\Delta \log\left(asi_t\right)] \tag{17}$$

Essentially, Engle (1982) proposes three steps for the ARCH LM test to detect the existence of volatility in a series: (i) the first step is to estimate equation (16) by OLS and obtain the fitted residuals; (ii) the second step is to regress the square of the fitted residuals on a constant and lags of the squared residuals, i.e. estimate equation (18) below;

$$\varepsilon_t^2 = \rho_0 + \rho_1 \varepsilon_{t-1}^2 + \rho_2 \varepsilon_{t-2}^2 + \ldots + \rho_p \varepsilon_{t-p}^2 + u_t \tag{18}$$

(iii) the third step involves employing the LM test that tests for the joint null hypothesis that there is no ARCH effect in the model, i.e.: $H_0 : \rho_1 = \rho_2 = \ldots = \rho_P = 0$. In empirical analyses, the usual *F* test (or the statistic computed by multiplying the number of observations (n) by the coefficient of determination $\left(R^2\right)$ obtained from regression of equation (18)) is used. The latter statistic $\left(nR^2\right)$ is chi-squared distributed $\left(\chi_p\right)$ with p degrees of freedom which equal the number of autoregressive terms in equation (18).

Table 2 shows the descriptive statistics for exr_t and r_t covering both the full sample and sub-samples. The highest mean of exr_t was recorded during SUB3 followed by the mean values in SUB2 and SUB1, respectively. The exr_t reached its peak also during SUB3 while its least value was recorded during SUB1. Likewise, the highest standard deviation was recorded during SUB3 followed by SUB1, while the least standard deviation was recorded during SUB2.

There was evidence of negative skewness for exr_t during SUB1 and SUB3 implying the left tail was particularly extreme. However, positive skewness was evident during SUB2 suggesting that the right tail was particularly extreme in this instance. In relation to kurtosis, the exr_t was platykurtic for all the sub-samples indicating thinner tails than the normal distribution. Similarly, based on the Jarque Bera (JB) statistic that uses the information from skewness and kurtosis to test for normality, it was found that exr_t was not normally distributed.

Similarly in relation to exchange rate returns (r_t), the largest depreciation of exr_t (i.e. the largest positive r_t) as well as the highest standard deviation was recorded during SUB3. However, minimal appreciation of exr_t was experienced with the highest appreciation (i.e. highest negative r_t) recorded during SUB1. On the average, taking the full sample into consideration, the movements in exr_t have witnessed large depreciations. The r_t was positively skewed (i.e. the right tail is to the extreme) for SUB3 and negatively skewed over the periods SUB1 and SUB2. However, all the sub-samples were leptokurtic (i.e. evidence of fat tail). In addition, the JB test shows that r_t is not normally distributed for all the sub samples and, therefore, the alternative inferential statistics that follow non-normal distributions are appropriate in this case (see for example, Wilhelmsson, 2006). The available alternatives include the Student-*t* distribution, the generalized error distribution (GED), Student-*t* distribution with fixed degrees of freedom and GED with fixed parameter. All these alternatives are considered in the estimation of each volatility model and the Schwartz Information Criterion (SIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQC) are used to determine the one with the best fit. Based on the empirical analysis, the skewed Student-*t* distribution performed well than any other skewed and leptokurtic error distribution and are consequently reported.

Table 2: Descriptive Statistics

Statistics	Full sample		Sub-samples					
			SUB1		SUB2		SUB3	
	exr_t	r_t	exr_t	r_t	exr_t	r_t	exr_t	r_t
Mean	131.50	0.01	121.97	0.02	129.92	-0.00	136.57	0.01
Median	128.50	0.00	125.51	0.00	129.03	0.00	146.10	0.00
Maximum	153.09	6.39	130.51	2.01	137.70	2.03	153.09	6.39
Minimum	112.35	-3.91	112.35	-3.91	125.73	-2.65	116.05	-3.10
Std. Dev.	11.14	0.25	5.54	0.28	3.13	0.11	14.53	0.32
Skewness	0.37	9.29	-0.50	-3.63	0.37	-4.14	-0.47	11.01
Kurtosis	2.09	295.80	1.46	92.58	1.93	306.79	1.37	220.79
Jarque Bera	196.15	$1.24*10^7$	75.12	$1.78*10^5$	103.16	$5.62*10^5$	241.87	$2.92*10^6$
Obs	3457	3456	535	534	1462	1461	1462	1461

Source: Computed by the Author

Figure 1 below shows the trend in exr_t over the full sample (FS). The exr_t relatively increased incessantly over SUB1. During SUB2, it hovered around 125 and 135 before it declined persistently at the later part of the period. The FS period witnessed unprecedented sharp movements in exr_t as it rose significantly at the early part of the period before it eventually maintained a fairly steady pattern for the rest of the period. Overall, the pattern depicted in the graph adjudges the unsteady behaviour of exr_t over the period under consideration, although the variability seems to differ over the sub-sample periods.

Figure 1: Trends in Nigerian exchange rate- exr_t **(Naira/USD),12/10/2001-05/28/2011**

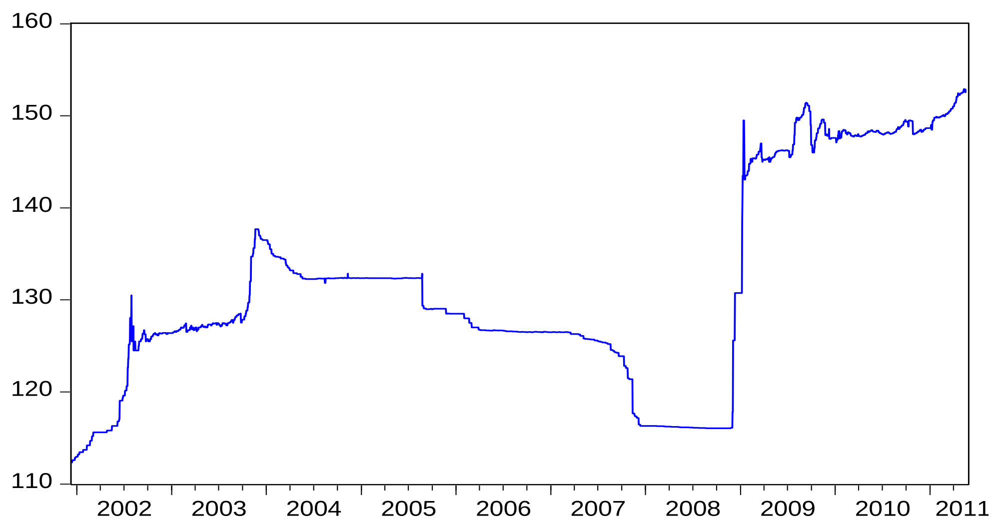

Figure 2: Trends in Nigerian exchange rate returns – r_t (%), 1999:06-2011:05

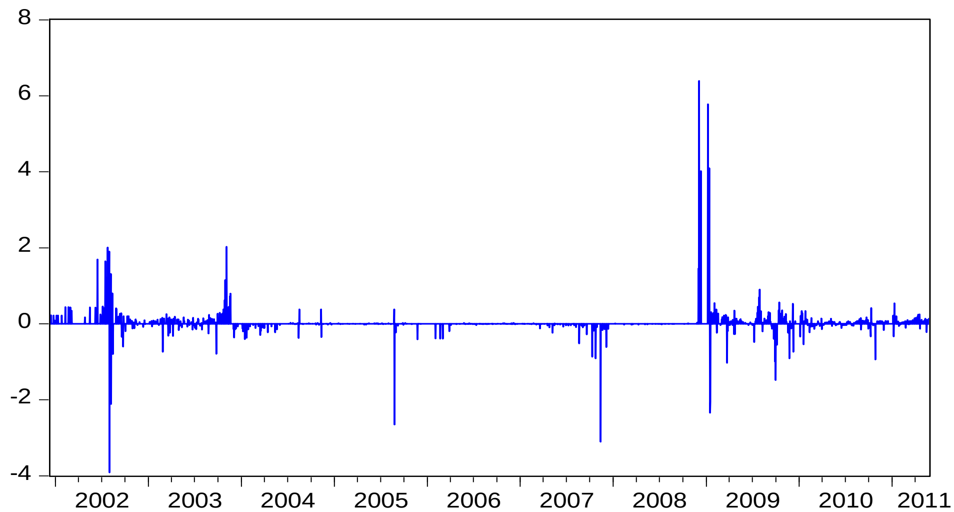

Figure 2 depicts the behaviour of r_t over FS. The notable spikes are evidences of significant unsteady patterns of exchange rate returns and the highest spike is recorded during SUB3 which also coincided with the period of global financial crisis. This observation also confirms the evidence in table 2, indicating that the period, SUB3 suggests the highest points of volatility in exr_t followed by SUB1. Thus, large depreciations in exr_t were observed during these periods. The exr_t was however, relatively steady over the period, SUB2. The graph also clearly shows evidence of volatility clustering where periods of high volatility are followed by periods of tranquillity. Overall, very few points in the graph hover around zero and, therefore, there are frequent instances of depreciation and appreciation although the former appears dominant.

Figure 3 shows a combined graph for exr_t and r_t over the same period. It further reinforces the observations in table 2 and figures 1 and 2 with the trends in r_t showing some evidences of variability in exr_t. It is easier to trace these spikes in r_t to the periods they represent.

Table 3 shows the test statistics for the existence of ARCH effects in the variables. The r_t shows evidence of ARCH effects as judged by the results of the *F-test* and nR^2 up to 10 lags for FS sample as well as SUB1-3. The test statistics at all the chosen lags are statistically significant at 1 percent and thus resoundingly rejecting the "no ARCH" hypothesis. However, the result is mixed for SUB2 as it shows evidence of ARCH effects only for first order autoregressive process with conditional variance of lag 5. This is consistent with the results described under the summary statistics in table 2 and figures 1 – 3 depicting the existence of large movements in exchange rate during SUB1 and SUB3, while fairly stable movements characterized SUB2.

Figure 3: A combined graph for exr_t and r_t , 1999:06-2011:05

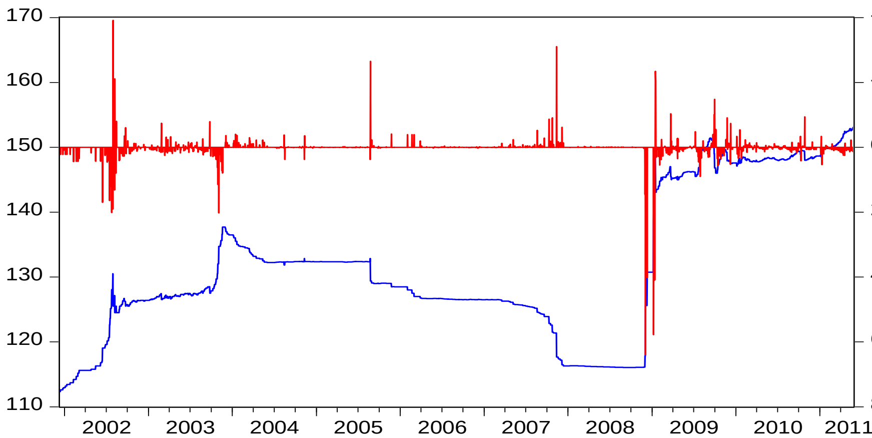

Table 3: ARCH TEST							
Dependent Variable: Exchange rate returns (r_t)							
Sample Period: 12/10/2001-05/28/2011							
Model	**Period**	$p=1$		$p=5$		$p=10$	
		F-test	nR^2	*F-test*	nR^2	*F-test*	nR^2
$k=1$	FS	4.352**	4.249**	18.00*	87.86*	24.97*	233.49*
	SUB1	46.173*	42.633*	9.74*	45.09*	22.85*	161.38*
	SUB2	0.348	0.348	2.25**	11.21**	1.27	12.72
	SUB3	0.356	0.356	8.51*	41.50*	9.66*	91.19*
$k=2$	FS	4.943**	4.939**	19.99*	97.30*	26.81*	249.45*
	SUB1	45.591*	42.132*	9.61*	44.49*	22.78*	160.94*
	SUB2	0.377	0.377	1.96	9.76	1.11	11.11
	SUB3	0.433	0.433	9.96*	48.33*	10.73*	100.65*
$k=3$	FS	4.733**	4.730**	20.44*	99.44*	26.88*	250.11*
	SUB1	45.462*	42.017*	9.58*	44.37*	22.73*	160.61*
	SUB2	0.378	0.378	1.96	9.76	1.11	11.11
	SUB3	0.342	0.342	10.71*	51.85*	10.95*	102.53*

Source: Computed by the Author

Note: Model follows the autoregressive process in equation (16) of order $k=1,2,3$ respectively and p is the lag length for the test statistics based on equation (18). *= 1% level of significance; **= 5% level of significance.

V.2 Estimation and Interpretation of Results

Given the evidence of ARCH effects in r_t, the paper begins the volatility modelling by first estimating equation (16) with GARCH(p,q) effects where $p,q=1$, followed by the various extensions. The ARCH(q) is not estimated based on the theoretical assumption that GARCH(p,q) model with lower values of p and q provide a better fit than an ARCH(q) with a high value of q (see Harris and Sollis, 2005). The model selection criteria – SIC, AIC and HQC are used to choose the model with the best fit among the competing models. Other model selection criteria such as R^2 and $\bar{R}^2$ (adjusted R^2) are not used due to their inherent limitations. For example, R^2, given as $\left(1-\hat{\varepsilon}'\hat{\varepsilon}/r'r-n\bar{r}^2\right)$, is non-decreasing of the number of regressors and, therefore, there is a built-in tendency to over-fit the model. Although the $\bar{R}^2$ is an improvement on R^2 as it penalizes the loss of degrees of freedom that occurs when a model is expanded, it is, however, difficult to ascertain whether the penalty is sufficiently large to guarantee that the criterion will necessarily produce the best fit among the competing alternatives. Hence, the AIC, SIC and HQC have been suggested as alternative fit measures. These criteria are given as:[15]

$$\text{AIC}(g)=\text{Log}\left(\hat{\varepsilon}'\hat{\varepsilon}/n\right)+2g/n \tag{19}$$

$$\text{SIC}(g)=\text{Log}\left(\hat{\varepsilon}'\hat{\varepsilon}/n\right)+g\log n/n \tag{20}$$

$$\text{HQC}(g)=\text{Log}\left(\hat{\varepsilon}'\hat{\varepsilon}/n\right)+2g\log\log n/n \tag{21}$$

Among these criteria shown by equations (19), (20) and (21), the SIC is often preferred as it gives the heaviest penalties for loss of degrees of freedom. Thus, the model with the least value of SIC is assumed to give the best fit among the competing alternatives.

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[15] Equations (19), (20) and (21) are derived from taking the natural logarithm of $\text{AIC}(g)=s_r^2\left(1-R^2\right)e^{2g/n}$ $\text{SIC}(g)=s_r^2\left(1-R^2\right)n^{g/n}$ and $\text{HQC}(g)=s_{(r)}^2(1-R^2)n^{e^{2g/n}}$. g denotes the number of parameters in the model. For example, if only the AR model (equation 16) is estimated, $g=k+1$ However, if equation (16) is estimated with ARCH (*q*) effects (i.e. a combination of equations (16) and (5)), $g=k+q+2$ On the other hand, if equation (16) is estimated with GARCH (*p,q*) effects (i.e. a combination of equations (16) and (7)), $g=k+p+q+2$.

Table 4: AR(1)-GARCH(1,1) model estimation

Dependent Variable: Exchange rate returns (r_t)

Variable	Coefficient			
	FS	**SUB1**	**SUB2**	**SUB3**
constant (M)	$-1.07*10^{-4}$ (-0.820)	0.004 (1.474)	$-9.02*10^{-5}$ (-0.545)	$-8.20*10^{-5}$ (-0.285)
AR(1) (M)	-0.002 (-0.037)	-0.016 (-0.133)	-0.006 (-0.069)	0.030 (0.507)
constant (V)	$4.76*10^{-7}$ (22.205)*	$3.13*10^{-5}$ (7.271)*	$1.31*10^{-6}$ (23.545)*	$7.63*10^{-8}$ (7.661)*
ARCH1 (V)	0.059 (37.392)*	0.016 (10.637)*	0.021 (19.899)*	0.060 (26.540)*
GARCH 1 (V)	0.827 (437.54)*	0.920 (202.51)*	0.809 (210.85)*	0.847 (347.73)*
AIC	-4.189	-2.174	-5.660	-3.622
SIC	-4.181	-2.135	-5.642	-3.604
HQC	-4.186	-2.159	-5.654	-3.616
OBS	3455	533	1461	1461

Source: Computed by the Author

Note:: *, **, *** → 1%, 5%, 10% levels of significance respectively. In addition, the variables are identified as either (M) indicating that the variable features in the conditional mean equation or (V) which implies that the variable is in the conditional variance equation. These notations apply to all the estimations in this paper.

Table 4 shows the results of the estimated GARCH (1,1) model for all the considered periods. Both the ARCH and GARCH effects are statistically significant for all the periods and, therefore, the evidence of volatility initially reported in table 3 appears to have been captured. Also, the sums of the coefficients for the ARCH and GARCH effects are less than one, which is required to have a mean reverting variance process. However, all the sums are close to one indicating that the variance process only mean for each period reverts slowly to the mean. The sums are 0.89, 0.94, 0.83, and 0.91 for FS, SUB1, SUB2 and SUB3 respectively. Thus, among the three sub-samples, SUB1 has the lowest variance reverting process and followed closely by SUB3 while SUB2 has the highest. This trend further authenticates the evidence obtained in tables 2 and 3 and also suggests high level of persistence in the exchange rate volatility over SUB1 and SUB3.

Similarly, the GARCH(1,1) model is compared with the GARCH-M(1,1) model. The results of the latter are presented in table 5. Based on the results obtained under FS, the GARCH-M (1,1) does not seem to improve the GARCH (1, 1) model for

exchange rate as the coefficients on $\left(\sqrt{(\text{GARCH1})}\right)$ included in the conditional mean equation is statistically insignificant and, therefore, does not add any useful information to the volatility of exchange rate in Nigeria. Similar results are evident under SUB1 and SUB2. However, the coefficient on $\left(\sqrt{(\text{GARCH1})}\right)$ is statistically significant and negative under SUB3. This implies that when there was a high volatility in the exchange rate during SUB3, investors shifted to less risky assets and this consequently lowered the exchange rate returns. Apparently, this was the case during the period of the global financial crisis which falls within SUB3.
Nonetheless, there is still evidence of long memory volatility in exchange rate returns. The ranking of the degree of persistence in volatility in exchange rate is the same as the GARCH(1,1) model. In terms of the comparative performance of the two models, the GARCH(1,1) model gives a better fit for all the samples using the SIC.

Table 5: AR(1)-GARCH-M(1,1) model estimation

Dependent Variable: Exchange rate returns (r_t)

Variable	**Coefficient**			
	FS	**SUB1**	**SUB2**	**SUB3**
constant (M)	$-2.03*10^{-4}$ (-1.231)	$-9.16*10^{-4}$ (-0.175)	$5.76*10^{-5}$ (0.173)	$-7.20*10^{-5}$ (-0.238)
AR(1) (M)	-0.003 (-0.070)	-0.022 (-0.194)	-0.007 (-0.092)	0.014 (0.229)
$\left(\sqrt{(\text{GARCH1})}\right)$ (M)	0.036 (1.083)	0.150 (1.177)	-0.045 (-0.486)	-0.010 (-3.188)*
constant (V)	$4.84*10^{-7}$ (22.198)*	$3.04*10^{-5}$ (7.300)*	$1.31*10^{-6}$ (23.489)*	$8.91*10^{-8}$ (7.321)*
ARCH1 (V)	0.058 (37.362)*	0.016 (10.700)*	0.021 (19.870)*	0.056 (27.091)*
GARCH 1 (V)	0.828 (436.43)*	0.920 (206.36)*	0.809 (210.34)*	0.857 (379.59)*
AIC	-4.190	-2.177	-5.660	-3.621
SIC	-4.180	-2.129	-5.638	-3.599
HQC	-4.186	-2.158	-5.651	-3.613
OBS	3455	533	1461	1461

Source: Computed by the Author

The asymmetric GARCH models are also estimated to examine the probable existence of leverage effects. Evidently, the Threshold GARCH (TGARCH) model and the Exponential GARCH (EGARCH) model have become prominent in this regard. Tables 6 and 7 show the results obtained from estimating the two mentioned asymmetric models.

The results obtained from the TGARCH (1,1) model reveals evidence of strong leverage effects for all the samples. These effects indicate that positive shocks increased the volatility of exchange rate more than negative shocks of the same magnitude during the samples under consideration. Notably, the leverage effects were dominant in SUB2 followed by SUB3 with SUB1 having the least. Thus, good news in the foreign exchange market has the potentiality of increasing volatility in the exchange rate than bad news. In addition to the leverage effects, there is evidence of long memory volatility in exchange rate returns using the TGARCH (1,1) model. Unlike the GARCH(1,1) and GARCH-M(1,1) models, the variance process is not mean reverting under SUB3 as the coefficients on ARCH and GARCH effects sum to one indicating that the shocks leading to a change in volatility appear permanent. Although, the variance processes under SUB1 and SUB3 are mean reverting, the movements also seem very sluggish as the sums of coefficients are very close to one.

In terms of the performance of TGARCH(1,1) compared with GARCH(1,1) model, the former gives a better fit under FS, SUB2 and SUB3 while the latter model is preferred under SUB1.

Source: Computed by the Author

Table 6: AR(1)-TGARCH(1,1) model estimation				
Dependent Variable: Exchange rate returns (r_t)				
Variable	**Coefficient**			
	FS	**SUB1**	**SUB2**	**SUB3**
constant (M)	$-8.31*10^{-5}$ (-0.709)	0.004 (1.514	$-5.21*10^{-5}$ (-0.337)	$-2.14*10^{-5}$ (-0.075)
AR(1) (M)	-0.007 (-0.246)	-0.016 (-0.131)	$-4.02*10^{-7}$ (-0.004)	0.001 (0.016)
constant (V)	$2.53*10^{-7}$ (23.217)*	$3.21*10^{-5}$ (6.874)*	$1.07*10^{-6}$ (23.479)*	$4.13*10^{-8}$ (9.756)*
ARCH1 (V)	0.105 (34.373)*	0.018 (10.489)*	0.173 (16.888)*	0.123 (21.691)*
GARCH 1 (V)	0.871 (611.83)*	0.921 (190.24)*	0.792 (202.37)*	0.878 (380.13)*
ASYMMETRY (V)	-0.103 (-34.199)*	-0.005 (-2.168)**	-0.171 (-16.841)*	-0.121 (-21.536)*
AIC	-4.393	-2.172	-5.862	-3.863
SIC	-4.382	-2.123	-5.840	-3.841
HQC	-4.389	-2.153	-5.854	-3.855
OBS	3455	533	1461	1461

Interestingly, the intuition behind the results of the EGARCH (1, 1) model is not different from the TGARCH model. Similarly, for all the samples, the coefficients on $\sqrt{\text{ARCH1/GARCH1}}$ (V) are positive which is the equivalent interpretation for the negative sign of the coefficient on asymmetry in the TGARCH(1,1) model. This further validates the conclusion that positive shocks have the tendency of aggravating the volatility in Nigeria's foreign exchange market. However, based on the SIC values, the EGARCH(1,1) does not seem to alter the modelling preference for the samples. On the basis of the magnitude of impact, the largest asymmetric effects were obtained during SUB2, while the least were recorded during SUB3.

In summary, the estimation results show that different volatility models with different peculiarities fit different democratic regimes in Nigeria.

Table 7: AR(1)-EGARCH(1,1) model estimation

Dependent Variable: Exchange rate returns (r_t)

Variable	Coefficient			
	FS	**SUB1**	**SUB2**	**SUB3**
constant (M)	$2.67*10^{-6}$ (0.005)	0.005 (1.680)***	$-1.13*10^{-6}$ (-0.006)	$7.41*10^{-7}$ (0.001)
AR(1) (M)	0.013 (0.426)	-0.014 (-0.166)	0.003 (0.070)	-0.019 (-0.997)
constant (V)	-1.211 (-70.420)*	-0.182 (-12.690)*	-1.176 (-36.135)*	-0.238 (37.677)*
$\left\|\sqrt{\text{ARCH1/GARCH1}}\right\|$ (V)	0.125 (60.949)*	0.089 (11.825)*	0.074 (27.365)*	0.053 (39.532)*
$\sqrt{\text{ARCH1/GARCH1}}$ (V)	0.035 (21.083)*	0.039 (6.303)*	0.051 (19.994)*	0.026 (21.454)*
LOG(GARCH 1) (V)	0.859 (401.37)*	0.983 (418.06)*	0.896 (298.81)*	0.975 (1331.05)*
AIC	-3.554	-2.150	-5.591	-3.424
SIC	-3.544	-2.101	-5.570	-3.402
HQC	-3.551	-2.130	-5.583	-3.416
OBS	3455	533	1461	1461

Source: Computed by the Author

Note: EGARCH (1,1) Model is given as : $\ln(\sigma_t^2) = \emptyset + \vartheta\left|\sqrt{\varepsilon_{t-1}^2/\sigma_{t-1}^2}\right| + \propto\sqrt{\varepsilon_{t-1}^2/\sigma_{t-1}^2} + \gamma\ln(\sigma_{t-1}^2)$. If the asymmetry effect is present, $\propto < (>) 0$ implying that negative (positive) shocks increase volatility more than positive(negative) shocks of the same magnitude while if $\propto = 0$, there is no asymmetry effect.

V.3 Post-Estimation Analysis

Recall that the pre-estimation test confirms the existence of ARCH effects in Nigeria's exchange rate necessitating the estimation of different volatility models as presented above. As a follow up on this, the paper also provides some post-estimation analyses to ascertain if the volatility models have captured these effects. The post-estimation ARCH test is carried out using both the *F*-test and chi-square distributed nR^2 test. The results obtained for all the samples as presented in table 8 do not reject the null hypothesis of no ARCH effects. All the values are statistically insignificant at all the conventional levels of significance. Thus, this study further authenticates the theoretical literature that ARCH/GARCH models are the most suitable for dealing with volatility in financial time series. Thus, ignoring the volatility in the Nigeria's foreign exchange market when in fact it exists yields inefficient results and policy prescriptions offered from such analyses will be invalid.

Table 8: ARCH TEST

Dependent Variable: Exchange rate returns (r_t)

Model	Period	P =1		P = 5		P = 10	
		F-test	nR^2	*F-test*	nR^2	*F-test*	nR^2
GARCH(1,1)	FS	0.001	0.001	0.007	0.034	0.010	0.104
	SUB1	0.113	0.114	0.090	0.455	0.622	6.276
	SUB2	0.478	0.480	0.127	0.636	0.081	0.820
	SUB3	0.003	0.003	0.014	0.068	0.008	0.083
GARCH-M(1,1)	FS	0.001	0.001	0.007	0.034	0.010	0.104
	SUB1	0.111	0.112	0.090	0.454	0.613	6.185
	SUB2	0.471	0.471	0.125	0.626	0.080	0.809
	SUB3	0.003	0.003	0.013	0.068	0.008	0.083
TGARCH(1,1)	FS	0.019	0.019	0.026	0.129	0.025	0.252
	SUB1	0.130	0.130	0.100	0.506	0.615	6.208
	SUB2	0.061	0.061	0.078	0.392	0.275	2.767
	SUB3	0.020	0.020	0.017	0.090	0.018	0.180
EGARCH(1,1)	FS	0.002	0.002	0.002	0.009	0.002	0.016
	SUB1	0.150	0.150	0.128	0.647	0.612	6.174
	SUB2	0.244	0.244	0.120	0.603	0.503	5.052
	SUB3	0.015	0.015	0.011	0.058	0.012	0.125

Source: Computed by the Author

Note: p is the lag length for the test statistics. The mean equations for all the models follow first order autoregressive process as previously estimated.

V.4 Forecast Evaluation of the Volatility Models

This section evaluates the forecast performance of the volatility models using standard forecast measures. Essentially, the forecast allows the projection of *s*-step ahead of *T* (the sample size) for r_t. Thus, the forecast function can be obtained by taking the conditional expectation of r_{T+s} In the case of the estimated mean equation in this paper, the forecast function for *s*-steps ahead can be expressed as:

$$E\left(r_{T+s}|\Omega_T\right)=\eta+\delta_1 r_{T+s-1}; \quad \varepsilon_t \sim \mathrm{IID}\left(0,\sigma^2\right) \tag{22}$$

where Ω_T denotes the available information set. Given equation (22), one-step ahead forecast of r_t will be $\eta + \delta_1 r_T$; two-step ahead will be $\eta + \delta_1 r_{T+1}$ and so on. The corresponding *s*-step ahead forecast for the conditional variance in a GARCH(1,1) model for example, can be expressed as:

$$E\left(\sigma^2_{T+s}|\Omega_T\right)=\beta_0+\beta_1\varepsilon^2_{T+s-1}+\gamma_1\sigma^2_{T+s-1} \tag{23}$$

Thus, one-step ahead forecast of σ_t^2 will be $\beta_0+\beta_1\varepsilon^2_T+\gamma 1\sigma^2_T$; two-step ahead will be $\beta_0+\beta_1\varepsilon^2_{T+1}+\gamma 1\sigma^2_{T+1}$; and so on. Forecasts of σ^2_T for some of the extensions can also be obtained in a similar way. Measures of forecast performance employed in this paper are the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), the Theil's Inequality Coefficient (TIC) and the Mean Absolute Percent Error (MAPE). These measures are given as:

$$\mathrm{RMSE}=\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{r}_t-r_t\right)} \tag{24}$$

$$\mathrm{MAE}=\frac{1}{T}\sum_{t=1}^{T}\left|\hat{r}_t-r_t\right| \tag{25}$$

$$\mathrm{MAPE}=\frac{1}{T}\sum_{t=1}^{T}\hat{r}_t-r_t/r_t \tag{26}$$

$$\mathrm{TIC}=\frac{\sqrt{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left(\hat{r}_t-r_t\right)^2}}{\sqrt{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left(\hat{r}_t\right)^2}-\sqrt{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left(r_t\right)^2}} \tag{27}$$

Where r_t and $\hat{r}_t$ denote actual and forecasted volatility of exchange rate returns, respectively. These measures are used to evaluate the performance of the models in forecasting daily volatility for 2 weeks ahead of each period considered. Both the actual and relative statistics are computed to provide a comprehensive picture of the forecasts. The former are obtained for each model from the computation of RMSE, MAE, MAPE and TIC for all the samples. However, the relative statistics are obtained by dividing the actual statistics by that of the worst performing model under each measure. Based on the evidence obtained from the estimation, the EGARCH (1,1) model appears to be the worst model for all the subsamples based on the SIC values and was consequently used as the base category for computing the relative statistics. Two things are achieved with this division: (i) the ranking of the models by their forecast performance is ascertained; and (ii) the magnitude of forecasting accuracy of each model relative to the worst performing model is quantified. The volatility model with the least RMSE, MAE, and MAPE and highest TIC for both actual statistics and relative statistics is the best forecasting model. To achieve (ii), under each measure, the difference between the relative statistics of each model and that of the worst performing model is computed. The results are presented in tables 9 and 10. Table 9 shows the actual and relative statistics for all the models, while table 10 provides the magnitude of forecasting accuracy relative to the worst performing model.

Table 9: Forecast Evaluation Measures for the Volatility Models

Dependent Variable: Exchange rate returns (r_t)

Model	**Period**	**MAE**		**RMSE**		**MAPE**		**TIC**	
		Actual	Rel (%)	Actual	Rel (%)	Actual	Rel (%)	Actual	Rel (%)
GARCH(1,1)	FS	0.04	100.00	0.25	100.00	16.58	99.97	1.00	100.00
	SUB1	0.06	98.46	0.28	100.00	17.17	100.23	0.99	98.90
	SUB2	0.02	10.37	0.11	100.90	13.89	99.96	1.00	99.90
	SUB3	0.05	100.00	0.32	100.00	19.02	99.97	1.00	100.00
GARCH-M(1,1)	FS	0.04	100.00	0.25	100.00	16.58	99.96	1.00	99.90
	SUB1	0.06	96.92	0.28	100.00	17.22	100.56	0.99	99.30
	SUB2	0.17	100.61	0.11	100.00	13.89	99.97	1.00	99.90
	SUB3	0.05	100.00	0.32	99.69	19.02	99.97	1.00	100.00
TGARCH(1,1)	FS	0.04	100.00	0.25	100.00	16.58	99.98	1.00	100.00
	SUB1	0.07	100.00	0.28	100.00	17.16	100.18	0.99	98.90
	SUB2	0.02	10.37	0.11	100.00	13.90	99.98	1.00	100.00
	SUB3	0.05	100.00	0.32	100.00	19.03	99.99	1.00	100.00
EGARCH(1,1)	FS	0.04	100.00	0.25	100.00	16.59	100.00	1.00	100.00
	SUB1	0.07	100.00	0.28	100.00	17.13	100.00	1.00	100.00
	SUB2	0.16	100.00	0.11	100.00	13.90	100.00	1.00	100.00
	SUB3	0.05	100.00	0.32	100.00	19.03	100.00	1.00	100.00

Source: Computed by the Author

Based on the actual statistics for all the measures of forecast accuracy, with the exception of MAE values for SUB2, the forecast performance of the EGARCH (1,1) model is not significantly different from other volatility models. However, particularly in relation to the MAE values under SUB2, the EGARCH model is resoundingly less accurate than GARCH (1,1) and TGARCH (1,1) models and the latter two models relatively have the same level of forecast performance. In quantitative terms, the relative statistics for MAE obtained from the GARCH (1,1) and TGARCH (1,1) models during SUB2 relative to EGARCH are 10.37% which was the least recorded and substantially lower than the second least value of 96.92% for GARCH-M (1,1) model during SUB1. Except for these trends, the relative statistics are essentially approximately 100% showing that the forecast performance of the EGARCH (1,1) model is more or less as accurate as other competing volatility models.

Table 10: Magnitude of Forecasting Accuracy Relative to EGARCH(1,1) Model

Dependent Variable: Exchange rate returns (r_t)

Model	**Period**	**MAE (%)**	**RMSE (%)**	**MAPE (%)**	**TIC (%)**
GARCH(1,1)	FS	0	0	0.03	0
	SUB1	1.54	0	-0.23	1.1
	SUB2	89.63	-0.9	0.04	0.1
	SUB3	0	0	0.03	0
GARCH-M(1,1)	FS	0	0	0.04	0.1
	SUB1	3.08	0	-0.56	0.7
	SUB2	-0.61	0	0.03	0.1
	SUB3	0	0.31	0.03	0
TGARCH(1,1)	FS	0	0	0.02	0
	SUB1	0	0	-0.18	1.1
	SUB2	89.63	0	0.02	0
	SUB3	0	0	0.01	0

Source: Computed by the Author

As presented in table 10, the magnitudes of forecasting also confirm the results in table 9. With the exception of MAE values for SUB2, the magnitudes of forecasting accuracy of the volatility models relative to EGARCH(1,1) reveal infinitesimal differences and in fact, in most cases were not different from zero, therefore, indicating that the forecasting performance of the EGARCH (1,1) model is not different from other models. However, under SUB2 and in relation to MAE, GARCH(1,1) and TGARCH (1,1) models were substantially more accurate than EGARCH(1,1) by 89.63%, while minimal differences were recorded for the other forecasting measures.

V5. Implications of Findings and Concluding Remarks

The paper provides empirical support for the arguments that flexible exchange rate regime under different democratic transitions may give substantially different volatility trends and may affect the choice of the modelling framework for such volatility. The domestic currency (*Naira*) relative to the US dollar has suffered large depreciations over the years, hence, the evidence of volatility in the exchange rate for all the samples studied. Three implications can be drawn from these findings:

(i) The behaviour of exchange rate tends to change over short periods of time with inconsistent leverage effects and permanent shocks. The TGARCH (1,1) model gives the best fit under SUB1 and SUB3, while the GARCH (1,1) is preferred under SUB2. While the variance processes under SUB1 and SUB2 were mean reverting, the shocks under SUB3 (the most recent period) seem permanent;

(ii) Applying one-model-fits-all approach for exchange rate volatility in Nigeria will yield misleading and invalid policy prescriptions.

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