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Exchange–Rates Volatility in Nigeria: Application of GARCH Models with Exogenous Break

Bala A. Dahiru
Graduate School of Economics, Kyushu University, Japan

Joseph O. Asemota
Graduate School of Economics, Kyushu University Japan

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[1] Dahiru A. Bala and Joseph O. Asemota

This paper examines exchange–rate volatility with GARCH models using monthly exchange–rate return series from 1985:1 to 2011:7 for Naira/US dollar return and from 2004:1 to 2011:7 for Naira/British Pounds and Naira/Euro returns. The study compare estimates of variants of GARCH models with break in respect of the US dollar rates with exogenously determined break points. Our results reveal presence of volatility in the three currencies and equally indicate that most of the asymmetric models rejected the existence of a leverage effect except for models with volatility break. Evaluating the models through standard information criteria, volatility persistence and the log likelihood statistic, showed that results improved with estimation of volatility models with breaks as against those of GARCH models without volatility breaks and that the introduction of volatility breaks reduces the level of persistence in most of the models. The study recommends the incorporation of significant events in GARCH models in volatility estimation of key asset prices.

Keywords: Exchange rate, Volatility, GARCH, Unit roots, Stationarity, Persistence, Volatility breaks, Time series

JEL Classification: C22; C53; C58; G01; G12

1.0 Introduction

The exchange rate and its volatility are key factors that influence economic activities in Nigeria. That is why foreign exchange (FX) market fluctuations have always attracted considerable attention in both the economics and statistics literature. Examining the FX market by volume reveals that global daily FX transactions exceeded $4 trillion in 2010; bigger than the annual value of global trade (Bank for International Settlement, 2010). The world's total external reserves grew to $9.7 trillion in 2010, while Nigeria's reserves peaked at $64 billion in 2008 before the global financial crisis and dropped to $31.7 billion in late–2011 (BIS, 2010; CBN, 2011). Exchange–rate volatility[2] is swings or fluctuation over a period of time in exchange rate. There has been

[1] Graduate School of Economics, Department of Economic Engineering, Kyushu University, 6–19–1 Hakozaki, Higashi–ku, Fukuoka-shi, 812–8581, Japan, or P.O. Box 12415, General Post Office (GPO), Area 10, Garki, Abuja, FCT, Nigeria. Email: audubm@yahoo.co.uk; bala_dahiru@yahoo.com. Phone Number: +818049387772.

[2] Volatility is the measure of the amount of randomness in an asset return at any particular time. There are different types of volatility measures ranging from actual, historical/realized, implied to forward volatility. There is volatility when the values of a given series change rapidly from period to period in an unpredictable manner (Greene, 2003; and Engle, 2003).

excessive volatility of the *Naira* against major exchange rates in Nigeria since the adoption of flexible exchange–rate regimes in 1986. Consequently sustained exchange rate volatility was thought to have led to currency crises, distortion of production patterns as well as sharp fluctuations in external reserve. Recently, currency debates have taken centre–stage with the euro–zone currency and sovereign debt crises, US dollar volatility, concerns about China's currency rates and strengthening of the Japanese yen, among others.

Greene (2008) observes that uncertainty associated with exchange rates is an unobservable variable of economic importance and since the development of autoregressive conditional heteroscedasticity (ARCH) models in the 1980s; several extensions have been proposed ranging from: GARCH, EGARCH, TARCH, TGARCH, DTARCH, VGARCH, APARCH, STARCH, STAR, STGARCH, to SQGARCH, among others. Several versions of these models have been applied to inflation (e.g. Engle, 1982), the stock market (e.g. Engle, *et al*., 1987; Hammoudeh and Li, 2008 and Zivot, 2009), and the exchange rates (see Andersen and Bollerslev, 1998a and Kasman *et al.* 2011). A related but slightly distinct class of volatility models includes: the stochastic volatility (SV) models (e.g. Shephard and Andersen, 2009), autoregressive conditional duration (ACD) models (Engle and Russel, 1998) and dynamic conditional correlation (DCC) models (see Engle, 2002). While conventional econometric models are estimated based on the assumption of homogeneity of variance, GARCH models allow the conditional variance to change over time as a function of past errors, leaving the unconditional variance constant (see the seminal papers of Engle,1982; and Bollerslev,1990).

Recently, there has been renewed interest in GARCH models with volatility breaks as several studies have documented the importance of sudden shifts in volatility and their implication for estimating volatility persistence, and forecasting power of the model which can lead to biased and misleading GARCH parameters estimates. It is found that incorporating exchange–rate regime shifts leads to reduction in the estimated volatility persistence (see Hammoudeh and Li, 2008). Recent advances in modeling volatility structural breaks and long memory models involves several approaches that include the spline–GARCH model of Engle and Rangel, 2004; the adaptive FIGARCH of Baillie and Morana (2009), and the time varying parameter (TVP) model of Amado and Teräsvirta (2009), among many others.

Nigeria has adopted different exchange–rate arrangements since its exit from fixed to flexible exchange–rate system. The frameworks employed in the FX market from 1986–2012 include: the dual exchange–rate system (1986–1987), the Dutch auction system (DAS) (1987), the unified exchange–rate system (1987–1992), and the fixed exchange–rate system (1992–1998). Others are the re–introduced DAS (1999–2002), the retail Dutch auction system (2002–2006), and the wholesale Dutch auction system (2006–to date). Therefore, modelling attempts have to take into account exchange rate regimes that have been implemented in Nigeria since 1986. This has already influenced a number of recent papers, hence this study examines not only the standard GARCH models, but incorporates volatility breaks into the estimated models. The *Naira,* like other key currencies, has experienced volatility especially following the liberalisation of the FX market in the mid–1980s. As a result, volatility in the FX market tends to be high when supply, demand, or exogenous forces contribute large random shocks to the currency market[3]. Therefore, volatility in the exchange rate of a currency is a reflection of different activities revolving around that currency, either domestically or internationally.

Figure 1 shows time series plots of *Naira* exchange rates vis–a–vis three major trading currencies in Nigeria's FX market and their returns. These are the US dollar (USD), Euro, and British Pounds Sterling (BPS). The BPS from the charts below seems to be the most stable as it is consistent with its average since 2004, while the USD and recently the euro are the most volatile. From the graphs in figure I, two periods stand out as times of pronounced fluctuations: the 2005–2006 period, and during the global financial crisis of 2008–2009. For the US dollar, additional periods are observed due to its larger sample: 1986–1988 periods of exchange–rate reforms and the 1998–1999 periods arising from exchange–rate policy changes. However, there was a period of calm in the FX markets: the guided deregulation era of 1994–1998. The observed stable trend of the *Naira*/US dollar return during this era reflects some credible monetary and exchange–rate policy activities by the central bank to strengthen the *Naira* against other major currencies.

[3] Variables that have been shown to help predict volatility in the literature are: trading volume, macroeconomic news announcements, implied/ realized volatility, overnight returns, and after hour realized volatility (Zivot, 2009).

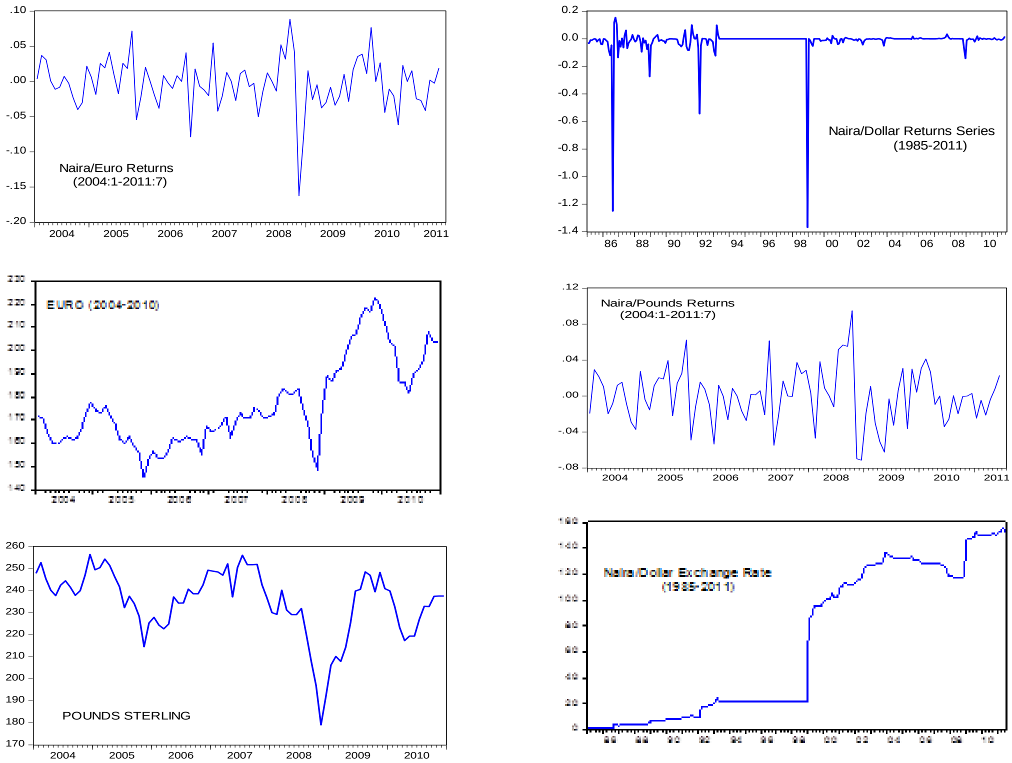

Figure 1: Time Series Plot of Exchange Rates and their Returns in Nigeria: Monthly Naira/Euro, Naira/British Pounds, and Naira/US Dollar rates.

This paper analyses volatility in key exchange rates and compares GARCH variance models with and without volatility breaks[4] with respect to the USD. We also compare estimates from the different models and identify the best performing ones. We equally examine the importance of accommodating breaks in modelling *Naira* exchange rate volatility. The rest of the paper is organized as follows: section 2 reviews the literature while section 3 discusses the methodology. Section 4 presents data and results of the study, while section 5 concludes.

2.0 Literature Review

Since the global adoption of floating exchange rate system in 1973, literature on exchange rate volatility has grown tremendously. A new set of theories evolved, explaining exchange rate behaviour and how exchange–rate

[4] Volatility forecasts are usually used for risk management, option pricing, portfolio allocation, trading strategies, and model evaluation (Zivot, 2009).

dynamics affect macroeconomic variables as well as several attempts to examine volatility of asset prices. Over the years, several studies have applied GARCH type models to examine volatility in relation to trade, stock markets and exchange rates. Adamu (2005) for example explores the impact of exchange–rate volatility on private investment and confirms an adverse effect. Mordi (2006) employing GARCH model argues that failure to properly manage exchange rates can induce distortions in consumption and production patterns and that excessive currency volatility creates risks with destabilizing effects on the economy.

The GARCH model has dominated the literature on volatility since the early 1980s. The model allows for persistence in conditional variance by imposing an autoregressive structure on squared errors of the process. Engle (1982) noted that although OLS maintains its optimality properties, the maximum likelihood is more efficient in estimating the parameters of ARCH models. Similarly, Lastrapes (1989) observe that ARCH provides a good description of the exchange rate process and that it is broadly consistent with exchange rates behaviour. Bollerslev (1990) however introduces a *generalized* ARCH (GARCH) process that allows for a more manageable lag structure. The ARCH/GARCH literature had recently focused on analyzing volatility of high–frequency data and their benefits (see Engle, 2002; Andersen 2000). Shephard and Andersen (2009) on the other hand analysed the development of SV models and several volatility processes including jumps and long memory associated with equity indices, bonds, and exchange rates due to monetary policy announcements. Zivot (2009) provides a tour of empirical analysis of GARCH models for financial time series with emphasis on practical issues associated with model specification, estimation, diagnostics, and forecasting.

Earlier, Andersen and Bollerslev (1998a) examined the DM/USD intraday volatility based on a one–year sample of five minutes returns with emphasis on activity patterns, macroeconomic announcement and calendar effects. They found that market activity is correlated with price variability and that scheduled releases occasionally induce large price changes, but the associated volatility shocks appear short lived. Bollerslev (1990) proposed a multivariate time series model with time–varying conditional variances and co–variances but with conditional correlation. The validity of the model was illustrated for a set of five European/US dollar exchange rates. Similarly, Adubi and Okunmadewa (1999) analysed dynamics of price, exchange–rate volatility and agricultural trade flows in Nigeria, while Taylor (1994) compares and estimates ARCH, autoregressive random variance (ARV) and SV models. In the same vein, Engle (2003) showed how dynamic volatility models can be used to forecast volatility, options valuation and risk over a long horizon. Accordingly, Engle (2002) analysed properties of ARCH, SV, long memory and breaking volatility models by estimating the volatility of volatility and comparing it with option–implied volatilities. In terms of analysing model forecasting power, Hansen and Lunde (2005) compare 330 ARCH–type models in terms of their ability to describe the conditional variance, and finds no evidence that a GARCH (1,1) model is outperformed by more sophisticated models in their analysis of exchange rates. However, Teräsvirta (2009) reviews several univariate models of conditional heteroscedasticity and reports that GARCH models tend to exaggerate volatility persistence.

Markov–switching models of conditional heteroscedasticity constitute another class of nonlinear models of volatility that provides an alternative way of modeling volatility process that contain breaks (see Lange and Rahbek, 2008). As already highlighted, recent advances in the modelling of volatility have focused on examining models that contain volatility breaks. Hammoudeh and Li (2008) have analysed sudden changes in volatility for five Gulf area stock markets and find that accounting for these large shifts in volatility in the GARCH (1,1) models significantly reduces the estimated persistence of the volatility of the Gulf stock markets.

Kasman *et al.* (2011) investigates the effects of interest and exchange rate changes on Turkish bank’s stock returns and finds significant negative impact. Their results further indicate that interest and exchange–rate volatility are the major determinants of conditional bank stock return volatility. Giraitis, *et al.* (2009) examines ARCH(∞) models, their stationarity, long memory properties and the limit behaviour of partial sums of their processes and their modifications like: linear ARCH, and bilinear models. In line with other theoretical studies, Ling and McAleer (2002) derive the necessary and sufficient conditions for the existence of higher order moments for GARCH and asymmetric *power* GARCH models.

3.0 Methodology

The volatility models estimated in this paper include: ARCH, GARCH, EGARCH, PARCH, IGARCH, TGARCH, CGARCH and GARCH–with–

volatility–breaks respectively. Tsay (2005) noted that the manner in which the variance evolves over time distinguishes one volatility model from another. Conditional heteroscedastic models are however classified into two. The first class use exact functions to govern evolution of σ_t^2, while the second category use stochastic equations to describe σ_t^2. GARCH models belong to the first category whereas stochastic volatility models belong to the second category (Tsay, 2005). Therefore, estimated volatility models will be used to examine volatilities in the three exchange rate series under investigation. Recent papers have shown that the GARCH model can be improved in order to better capture the characteristics and dynamics of a particular time series volatility dynamics.

3.1 Distributional Assumptions

In our empirical analysis, three conditional distributions for the standardized residuals of returns innovations will be considered: gaussian, student's t, and the generalised error distribution (GED). Parameter vectors $\theta = [\omega, \alpha, \beta, \gamma, \rho, \delta, \phi$ and $\xi]$ are obtained from the maximization of the log likelihood function:

$$\log L = \sum_{t=1}^{T} l_t = -\frac{T}{2}\log[2\pi] - \frac{1}{2}\sum_{t=1}^{T}\log\sigma_t^2 - \frac{1}{2}\sum_{t=1}^{T}\frac{\mu_t^2}{\sigma_t^2}, \qquad (1)$$

where T is the sample size, and

$$l_t = -\frac{1}{2}\log[2\pi] - \frac{1}{2}\log[\sigma_t^2] - \frac{1}{2}[y_t - x_{t-1}'\gamma]^2/\sigma_t^2$$

For student's t–distribution, log–likelihood contributions are assumed to be of the form:

$$l_t = -\frac{1}{2}\log\left[\frac{\pi[\nu-2]\Gamma[\upsilon/2]^2}{\Gamma[(\upsilon+1)/2]^2}\right] - \frac{1}{2}\log\sigma_t^2 - \frac{[\nu+1]}{2}\log\left[1+\frac{[y_t - x_t'\gamma]^2}{\sigma_t^2[\nu-2]}\right] \qquad (2)$$

where σ_t^2 is the variance at time t, and the degree of freedom $\nu > 2$ controls the tail behaviour. The $t-$distribution approaches the normal as $\nu \to \infty$.

$$l_t = -\frac{1}{2}\log\left[\frac{\Gamma[1/r]^3}{\Gamma[3/r][r/2]^2}\right] - \frac{1}{2}\log\sigma_t^2 - \left[\frac{\Gamma[3/r][y_t - x_t'\gamma]^2}{\sigma_t^2\Gamma[1/r]}\right]^{r/2} \qquad (3)$$

where the tail parameter $r > 0$. The GED is a normal distribution if $r = 2$ and fat–tailed if $r < 2$. Given, $y_t = x_t'\gamma + \mu_t$, note that $\mu_t = (y_t - x_t'\gamma)$. Accordingly, all the necessary regularity conditions are assumed to be satisfied.

3.2 Unit Roots Tests

Prior to modelling the exchange rate return series, we determine the order of integration of the variables. We employ the Augmented Dickey–Fuller (ADF) test based on the following regression:

$$\Delta y_t = \varphi + \beta t + \alpha y_{t-1} + \sum_{i=1}^{k} d_i \Delta y_{t-i} + \mu_t \qquad (4)$$

where μ_t is a white noise error term and $\Delta y_{t-1} = y_{t-1} - y_{t-2}$, $\Delta y_{t-2} = y_{t-2} - y_{t-3}$, etc. Equation (4) tests the null hypothesis of a unit root against a trend stationary alternative. The Philips–Perron (PP) test is equally conducted on the return series, which uses models similar to the Dickey–Fuller tests but with Newey–West non–parametric correction for possible autocorrelation rather than the lagged variable method employed in the ADF test. The Philips–Perron test is computed from the equation below:

$$y_t = \delta_t + \gamma y_{t-1} + \gamma_1 \Delta y_{t-1} + ... + \gamma_p \Delta y_{t-p} + \mu_t \qquad (5)$$

where δ_t may be 0, φ or $\varphi + \beta_t$. The Philips–Perron equation modifies the Dickey–Fuller test (Philips and Perron, 1988).

3.3 Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Models.

There are several GARCH specifications for modeling the conditional variance, or volatility, of a variable. This study uses different GARCH equations to model *Naira* exchange rate volatility during the study period. In the standard GARCH (1,1) model, first derived by Bollerslev (1986) replaces the $AR(P)$ representation with an $ARMA(p,q)$ representation:

$$y_t = x_t'\gamma + \mu_t \tag{6}$$

$$\sigma_t^2 = \omega + \alpha\mu_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

The mean equation given in (6) is written as a function of exogenous variables with an error term. σ_t^2 is the conditional variance equation as it is one–period ahead forecast variance based on past information. This is specified in (7) as a function of three terms: the mean (ω), the ARCH term (μ_{t-1}^2) and the GARCH term (σ_{t-1}^2). The persistence of σ_t^2 is captured by $\alpha+\beta$ and covariance stationarity requires that $\alpha+\beta<1$. GARCH models are usually estimated using the method of maximum likelihood estimation (MLE)[5]. Accordingly,

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}\alpha_i(y_{t-1} - x_{t-1}'\gamma)^2 + \sum_{j=1}^{q}\beta\sigma_{t-1}^2 \tag{8}$$

Since from (6) above

$$\mu_t = y_t - x_t'\gamma \text{ and } \mu_{t-1} = (y_{-1} - x_{t-1}'\gamma) \tag{8b}$$

Where the coefficients $\alpha_i(i=0,1,...,p)$ and $\beta_j(j=0,1,...,q)$ are all assumed to be positive, so as to ensure that the conditional variance σ_t^2 is always positive. Zivot (2009) noted that usually a GARCH (1,1) model with only three parameters in the conditional variance equation is adequate to obtain a good fit for financial time series. These specifications are interpreted in a context where a currency trader predicts this period's variance by forming a weighted average of a long term average (the constant), the forecasted variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the asset return was unexpectedly large in either upward or downward direction, then the trader will increase his estimate of next period's variance. Equation (7) may be extended to allow for inclusion of exogenous regressors or dummy variables to incorporate breaks in the variance equation:

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[5] The method of Maximum Likelihood (MLE) helps in choosing parameters that maximize the probability of a given outcome actually happening (Engle, 1982). In a GARCH(1,1) model, the (1,1) in parentheses is a standard notation in which the first number refers to how many autoregressive lags, or ARCH terms appear in the equation, while the second number refers to how many moving average lags are specified, or GARCH terms.

$$\sigma_t^2 = \omega + \alpha\mu_{t-1}^2 + \beta\sigma_{t-1}^2 + \xi dum_{it} \quad \text{(8c)}$$

where $dum_{1t},...dum_{nt}$ are dummy variables that correspond to periods of key policy changes in the foreign exchange market (0 for normal periods and 1 for periods of high currency movements). The periods of high currency movements were determined by identifying sudden jumps or outliers due to changes in Nigeria's exchange rate policy and other exogenous shocks. Accordingly, a higher order GARCH model, denoted GARCH(p,q), is given by:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 + \sum_{i=1}^{p}\alpha_i\mu_{t-i}^2 + \sum_{k=1}^{k}\xi_k dum_{t-k}, \quad (9)$$

where p is the order of the ARCH term and q is order of the GARCH term and k corresponds to that of the dummy variables. Furthermore, TARCH or *threshold* ARCH model also called the GJR–GARCH model is represented by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}\alpha_i\mu_{t-i}^2 + \sum_{i=1}^{\gamma}\gamma_i\mu_{t-i}^2 d_{t-i} + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 \quad (10)$$

where $d_{t-i} = \begin{cases} 1 & \text{if } \mu_{\text{t-i}} < 0 \\ 0 & \text{if } \mu_{\text{t-i}} \geq 0 \end{cases}$

The *exponential* GARCH (EGARCH) model proposed by Nelson (1991) allows for asymmetric effects between positive and negative asset returns. The specification for conditional variance is:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q}\beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p}\alpha_i\left|\frac{\mu_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r}\gamma_k\frac{\mu_{t-k}}{\sigma_{t-k}} \quad (11)$$

Note that when μ_{t-i} is positive ('good news'), the total effect of μ_{t-i} is $(1+\gamma_i)|\mu_{t-i}|$; while when μ_{t-i} is negative ('bad news'), the total effect of μ_{t-i} is $(1-\gamma_i)|\mu_{t-i}|$. The EGARCH is covariance stationary provided $\sum_{j=1}^{q}\beta_j < 1$ (Zivot, 2009). The *power* ARCH (PARCH) model of Taylor (1986) and Schwert (1989), among others introduces standard deviation GARCH model. In the PARCH model, the power parameter δ of standard deviation is estimated while at times imposed and the optional γ parameters are added to capture asymmetry of up to order r:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} + \sum_{i=1}^{p} \alpha_i (|\mu_{t-i}| - \gamma_i \mu_{t-i})^{\delta} \quad (12)$$

where $\delta > 0$, $|\gamma_i| \le 1$ for $i = 1,...,r, \gamma_i = 0$ for all $i > r$, and $r \le p$. The symmetric model sets $\gamma_i = 0$ for all i. If parameters of GARCH models are restricted to sum to one, and the constant term is dropped, it gives the *integrated* GARCH (IGARCH) model which is given by:

$$\sigma_t^2 = \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \mu_{t-i}^2 \quad (13)$$

The conditional variance in a typical GARCH (1,1) model is given as:

$$\sigma_t^2 = \omega + \alpha(\mu_{t-1}^2 - \omega) + \beta(\sigma_{t-1}^2 - \omega) \quad (14)$$

it shows mean reversion to ω, and is a constant for all time. The component model CGARCH on the other hand allows mean reversion to a varying level q_t, such that:

$$\sigma_t^2 - q_t = \alpha(\mu_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \quad (15)$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\mu_{t-1}^2 - \sigma_{t-1}^2)$$

Combining the transitory and permanent equations above, we have:

$$\sigma_t^2 = (1-\alpha-\beta)(1-\rho)\omega + (\alpha+\phi)\mu_{t-1}^2 - (\alpha\rho + (\alpha+\beta)\phi)(\beta-\phi)\mu_{t-2}^2 + (\beta-\phi)\sigma_{t-1}^2 - (\beta\rho - (\alpha+\beta)\phi)\sigma_{t-2}^2 \quad (16)$$

The above equation shows that the component model is a restricted GARCH (2, 2) model. The asymmetric component model combines the component with asymmetric TARCH model. This equation introduces asymmetric effects in the transitory equation and estimates model of the form:

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\mu_{t-1}^2 - \sigma_{t-1}^2) + \psi_1 z_{1t} \quad (17)$$

$$\sigma_t^2 - q_t = \alpha(\mu_{t-1}^2 - q_{t-1}) + \gamma(\mu_{t-1}^2 - q_{t-1})d_{t-1} + \beta(\sigma_{t-1}^2 - q_{t-1}) + \psi_2 z_{2t} \quad (18)$$

where z is the exogenous variable and d is the dummy variable indicating negative shocks. $\gamma > 0$ indicates presence of transitory leverage effects in the conditional variance.

Table 1: Descriptive Statistics

Variables	Mean	Median	Max	Min	SD	Skewness	Kurtosis	Jarque–Bera
Euro rates	-0.0026	0	0.0889	-0.1624	0.0354	-0.8286	6.8598	66.1706
British Pounds	0.0003	8.33E-05	0.0952	-0.0713	0.0306	0.1102	3.4049	0.7969
US Dollars	-0.0165	0	0.1543	-1.3685	0.1123	-10.068	114.4865	170060

4.0 Data, Results and Discussion[6]

4.1 The Data

The data employed consists of monthly *Naira*/US dollar exchange rate (1985:1–2011:7), *Naira*/British Pounds and *Naira*/Euro return series (2004:1–2011:7). They are obtained from CBN *Statistical Bulletin* (2010) and CBN *Annual Reports*. Monthly exchange–rate return defined as: $r_t = \log(x_t / x_{t-1}) = \log(x_t) - \log(x_{t-1})$, where r_t is the return on exchange rate, x_t is the *Naira*/foreign currency rate at time t, and x_{t-1} the *Naira*/foreign currency rate at time $t-1$ We apply the continuously compounded returns r_t due to its advantages over the simple net returns as well as its attractive statistical properties. Table 1 reports standard summary statistics for returns of the three exchange rate series. The returns distribution is negatively skewed for Euro and USD and positively skewed for BPS. The mean return for *Naira*/British Pounds returns is close to zero and it is 0.025% per month. The kurtosis is substantial for *Naira*/US dollar rate at 114.486, while for BPS and Euro it stood at 3.404 and 6.859 respectively. The extremely large Jarque–Bera (JB) statistic for USD and Euro indicates non–normality of most of the series. Similar evidence is graphically observed in figure III, the quantile–quantile (q–q) plots for the three currencies. The normal qq–plots of standardized residuals do not show strong departures from normality for Euro and BPS returns, except for the USD.

[6] The E–views (Version 7) and Stata (Version 9.2) statistical software are used for all our estimations and computations. The Return series are constructed using E–views 7 commands.

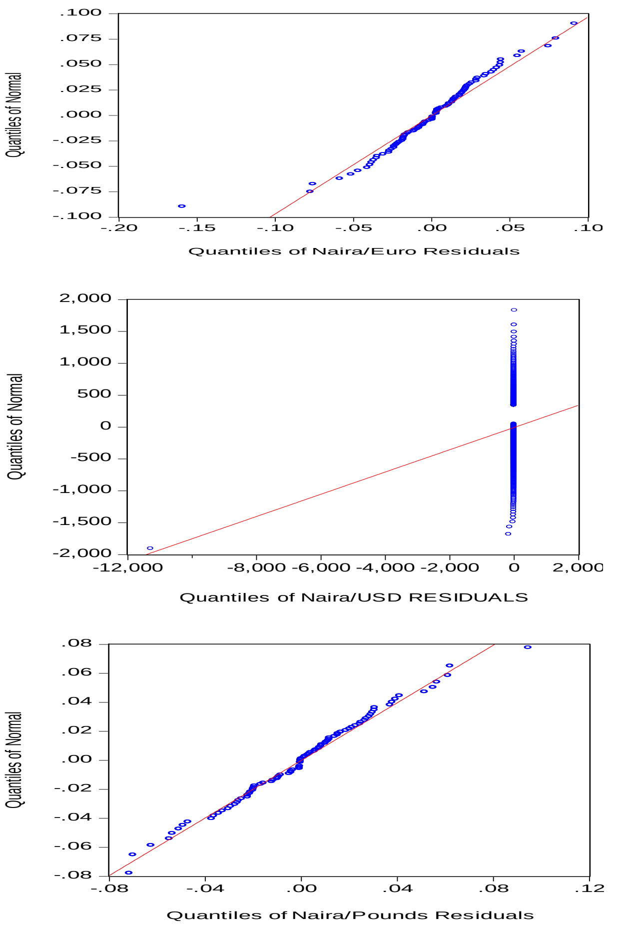


Figure 2: Quantile-quantile plots of standardized residuals fitted from GARCH (1,1) model for Euro, BPS and US Dollars

The monthly standard deviation (SD) shows that US dollar return is the most volatile: 0.1123 while the BPS is the least volatile of the currencies with a value of 0.031 in the given period. However, the US dollar is the most active, in the Nigerian FX market. The maximum return for USD is 0.1543, while for Euro and BPS they stood at 0.0889 and 0.0952 respectively. This shows that within the given periods, the USD had higher return than the other currencies. All the currencies show evidence of fat tails since their kurtosis exceed 3 while negative skewness for BPS and US dollars signify that the left tails are particularly extreme. This implies that significant exchange rate movements in either direction (positive or negative) occur in the FX market with greater frequency than would be predicted under, for example, a normal distribution setting. Part of this non–normality in the case of USD is probably caused by large outliers and jumps around 1986 and during the FX market reforms in the early 1990s, 1999–2000 periods and the global financial crisis of 2008/2009.

Table 2: Unit root tests for the exchange–rate return series (*augmented* Dickey-Fuller Test)

	$\Delta y_t = \psi + \beta t + \alpha y_{t-1} + \sum_{i=1}^{k} d_i \Delta y_{t-i} + \mu_t$					
	Naira/British Pounds		**Naira/Euro**		**Naira/US Dollars**	
	Trend	No Trend	Trend	No Trend	Trend	No Trend
Level	–8.010079	–8.025607	–8.293281	–8.290336	–17.90142	–17.74626
First diff.	–14.01914	–9.111385	–14.03929	–10.72437	–21.34292	–21.37718

Note: The model selection criteria used is the Akaike Information Criterion (AIC). The ADF Critical values are: -3.58 (1%), and -4.15(1%) with constant and with a constant and a trend term in the regression for British Pounds Sterling and Euro, while for US Dollar returns the values for a regression with a constant term are:-3.44 (1%) and -3.98(1%) respectively.

Table 3: Unit root tests for the exchange–rate return series (Phillips–Perron Test)

	$y_t = \delta_t + \gamma y_{t-1} + \gamma_1 \Delta y_{t-1} + ... + \gamma_p \Delta y_{t-p} + \mu_t$					
	Naira/British Pounds		**Naira/Euro**		**Naira/US Dollars**	
	Trend	No Trend	Trend	No Trend	Trend	No Trend
Level	–8.001512	–8.017593	–8.234830	–8.235578	–17.92302	–17.74648
First diff.	–14.43750	–50.86197	–57.84834	–14.53216	–278.4121	–278.9495

Note: The Bartlett Kernel spectral estimation method and the Newey–West Bandwidth selection criteria are used. The ADF critical values are -3.99 and -3.43 at 1% and 5% respectively for models estimated with trend, while the ADF critical values are -3.46 and -2.88 at 1% and 5% for models estimated without trend.

4.2 Unit Root Test Results

Tables 2 and 3, show results of *augmented* Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests for the exchange–rate return series. Since the *t* values are more negative than the test critical values at 1%, 5% and 10% levels, we reject the hypothesis of unit roots (random walk) in the exchange–rate returns series. Thus, there is no need to difference the return series.

4.3 ARCH Effects and Series Residuals Autocorrelation

Table 4 in the appendix shows the AC, PAC, Q–Statistics, and the related probabilities of the exchange rate return series for the key currencies. Examining the results indicates that the euro, BPS and USD returns residuals show the presence of ARCH effects[7]. The three currencies show substantial

[7] Values larger than the critical table value give evidence of the presence of ARCH effects (Greene, 2003).

evidence of ARCH effects as further revealed by autocorrelations of the squared residuals in Table 4. The first order autocorrelation for Euro is 0.937, and they gradually decline to 0.445 after 15 lags. These autocorrelations are not large, and they are mostly positive. The p –values shown in the last column are all zeros, thus rejecting the "no ARCH" hypothesis. Similar results were observed for the BPS and USD returns. Note that the estimated parameters in the variance models are: ω, α, β, γ, ρ, δ, ϕ and the dummy coefficient ξ. Since the exchange–rate return series exhibit departures from normality, the volatility models will be estimated with a student's t and GED error distribution frameworks in some cases. All the models will be evaluated using the Akaike information criterion (AIC), and Schwarz Criterion (SC). The results of estimating equations are presented in Tables 5, 6, 7 and 8 respectively. Figure III plots the Kernel density distribution graphs for BPS, USD and Euro returns (epanechnikov function) with student's t density plot and 1 degree of freedom which equally further revealed the statistical properties of the time series.

Table 4: (a) Euro, (b) British Pounds Sterling (BPS) and (c) US dollars residuals autocorrelation

	(a) Naira/Euro				(b) Naira/ British Pounds (BPS)				(c) Naira/US dollars			
L	AC	PAC	QS	Prob	AC	PAC	QS	Prob	AC	PAC	QS	Prob
1	0.937	0.937	82.54	0.00	0.886	0.886	73.78	0.00	0.992	0.992	317.0	0.00
2	0.857	-0.173	152.3	0.00	0.739	-0.210	125.7	0.00	0.984	-0.036	629.8	0.00
3	0.777	-0.020	210.4	0.00	0.601	-0.023	160.5	0.00	0.976	-0.011	938.3	0.00
4	0.699	-0.035	257.9	0.00	0.465	-0.092	181.6	0.00	0.967	-0.012	1242	0.00
5	0.631	0.036	296.9	0.00	0.321	-0.128	191.7	0.00	0.958	-0.017	1542	0.00
6	0.572	0.013	329.5	0.00	0.172	-0.129	194.7	0.00	0.950	-0.002	1837	0.00
7	0.522	0.025	356.9	0.00	0.035	-0.059	194.8	0.00	0.941	-0.005	2128	0.00
8	0.483	0.037	380.7	0.00	-0.065	0.030	195.3	0.00	0.932	-0.004	2414	0.00
9	0.449	0.006	401.6	0.00	-0.132	0.022	197.1	0.00	0.924	-0.006	2696	0.00
10	0.409	-0.079	419.1	0.00	-0.177	-0.008	200.3	0.00	0.915	-0.008	2973	0.00
11	0.391	0.180	435.3	0.00	-0.206	-0.010	204.8	0.00	0.906	-0.011	3246	0.00
12	0.384	0.033	451.0	0.00	-0.245	-0.157	211.2	0.00	0.897	-0.007	3515	0.00
13	0.392	0.130	467.7	0.00	-0.232	0.176	217.1	0.00	0.888	-0.008	3779	0.00
14	0.422	0.168	487.3	0.00	-0.209	-0.076	221.9	0.00	0.879	-0.006	40.39	0.00
15	0.445	-0.069	509.4	0.00	-0.179	0.026	225.4	0.00	0.870	-0.006	4294	0.00

Note: L, AC, PAC, QS and Prob represents lags, autocorrelation function, partial correlation function, Ljung–Box Q–Statistic and probability respectively.

4.4 ARCH/GARCH Estimation Results of Mean and variance equations

This section interprets key results derived from estimating all the GARCH models in our study. All coefficients of the ARCH models for USD, BPS and Euro returns are positive, including for the model with volatility breaks thereby satisfying the necessary and sufficient conditions for ARCH family models, that $\omega > 0, \alpha > 0$. The constant (ω) in BPS, USD and Euro returns are 0.00056, 0.00049 and 0.00089 which are significant at the 1% levels for all the currencies. The ARCH terms α are equally significant for both USD and BPS returns at the 1% and 5% levels. For USD returns, α is found to be highly significant at the 1 % level (see Table 5). For the *Naira*/USD return model with volatility breaks α is equally statistically significant (see table 6, column 2).

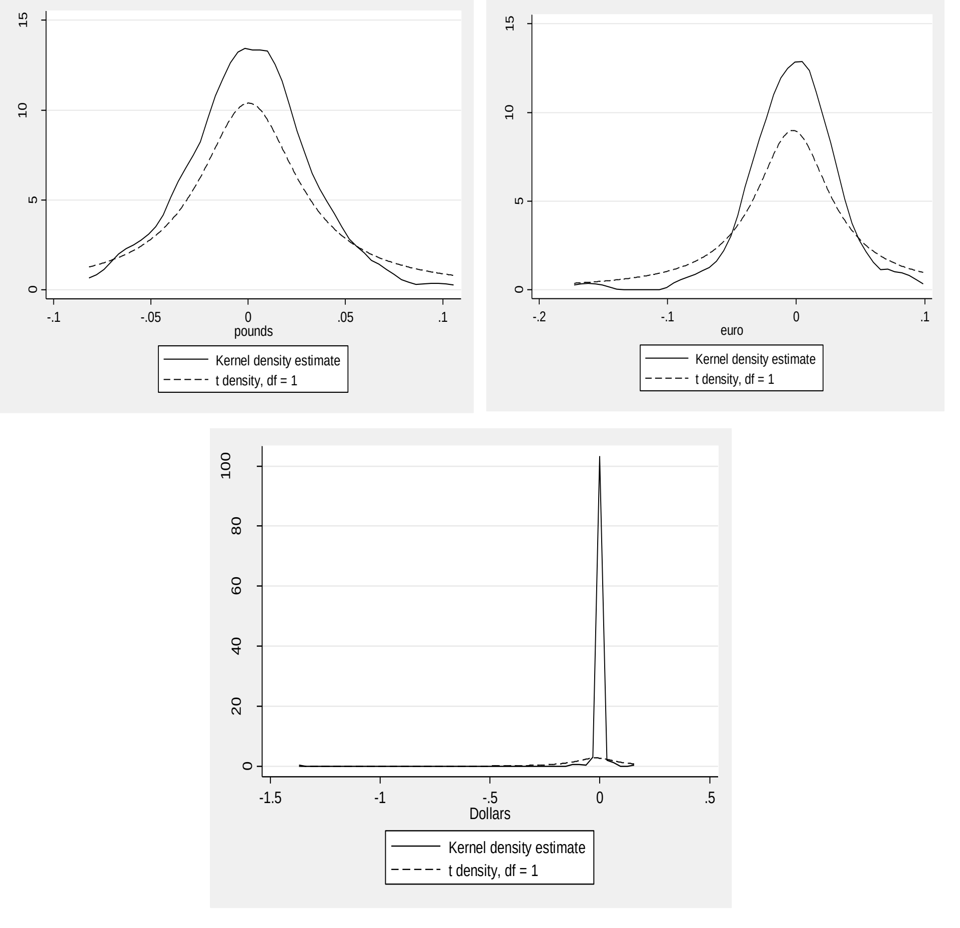


Figure 3: Kernel density distribution graphs for BPS, USD and Euro returns (Epanechnikov function) with student's t density plot and 1 degree of freedom.

The GARCH (1,1) models for the three currencies returns all satisfy the covariance stationary condition that $\alpha + \beta < 1$. For BPS return, results from GARCH (1,1) model reveals that the ARCH term (0.4547) is significant at 5% level, while coefficient of the

Table 5: Parameter Estimates for ARCH/GARCH Models (N/USD Return) without Volatility Breaks

Parameter	ARCH	GARCH (1,1)	EGARCH	PARCH	IGARCH	CGARCH	TGARCH
C	-4.49E-06 (0.001)	-0.0156 (0.018)	-8.86E-08 (0.001)	4.58E-13 (0.000)	1.14E-06 (0.000)	-2.00E-04 (0.002)	-3.50E-03 (0.007)
ω	6.00E-04 (0.000)	0.002 (0.000)	-3.66E+00 (0.223)	1.19E-02 (0.003)		0.0024 (0.001)	0.0009 (0.001)
α	2.66E-01 (0.024)	-0.0055 (0.002)	4.95E-01 (0.077)	8.06E-01 (0.039)	7.16E-01 (0.011)	0.2437 (0.001)	0.0956 (0.123)
β		0.8458 (0.027)	5.89E-01 (0.027)	3.48E-01 (0.015)	2.85E-01 (0.011)	0.4621 (0.099)	0.7736 (0.190)
γ			2.24E-01 (0.077)	4.11E-01 (0.045)			-0.0961 (0.124)
Ø						0.5121 (0.084)	
ρ						0.7791 (0.069)	
δ				1.00E+00			
α + β		0.8403	1.0838	1.1542	1	0.7058	0.8692
Log L	683.72	248.42	700.796	1553.052	1317.27	979.976	417.127
AIC	-4.2749	-1.5372	-4.3761	-9.7299	-8.3659	-6.1131	-2.592
SC	-4.2274	-1.4899	-4.3169	-9.6589	-8.2304	-6.0184	-2.5328
Obs	318	318	318	318	318	318	318

Numbers in parenthesis indicate standard errors

GARCH term β is insignificant and negative (see table 7, column 3)[8]. The unconditional standard deviation of returns $\bar{\sigma} = \sqrt{\omega/(1-\alpha-\beta)}$, for BPS and Euro are 0.029588 and 0.0355 respectively, and are very close to the sample standard deviations of returns reported in Table 1. For the *Naira*/USD return, it is 0.1129. The GARCH (1,1) model for USD returns is equally stationary. With respect to models with volatility breaks, GARCH(1,1) USD return is also stationary. As in many empirical applications of GARCH (1,1) models, our estimates of α are close to zero for all the currencies (volatility models without breaks) and for models with volatility breaks. Furthermore, note that a number of error distributions were assumed in estimating our GARCH

[8] In a GARCH model, the weights are $(1-\alpha-\beta, \beta, \alpha)$, and the long run average variance is $\sqrt{\omega/(1-\alpha-\beta)}$. This only works if $\alpha+\beta<1$ and the weights are positive requiring $\alpha>0, \beta>0, \omega>0$ (Zivot, 2009). This applies to US Dollar and Pounds returns. The magnitude of $\alpha+\beta$ controls the speed of mean reversion (i.e. when a time-series tends to return to its mean). Mean reversion is also known as short memory.

models[9]. Since extreme market events have occurred during the sample period especially in 1986, 1992/93, 1999 and 2008/2009 periods as well as major changes to exchange rate policy, dummy variables associated with these events were added to the conditional mean and variance specifications in order to remove these effects. This is implemented in the GARCH model with volatility break.

Table 6: Parameter Estimates for ARCH/GARCH Models (N/USD Return) with Volatility Breaks

Parameter	ARCH	GARCH (1,1)	EGARCH	PARCH	IGARCH	CGARCH	TGARCH
Dum	-1.27E-02 (0.012)	-0.0179 (0.019)	-2.59E-02 (0.005)	-8.70E-03 (0.003)	9.40E-03 (0.001)	-2.89E-02 (0.015)	-9.30E-03 (0.033)
C	-4.43E-06 (0.001)	-0.0034 (0.007)	3.26E-07 (0.001)	4.45E-06 (0.001)	-1.29E-07 (1.42e-05)	-3.00E-04 (0.006)	-1.62E-02 (0.028)
ω	2.00E-04 (1.88e-05)	0.0008 (0.000)	-4.47E+00 (0.2836)	1.72E-02 (0.001)		0.0315 (0.068)	0.0056 (0.004)
α	1.05E-01 (0.007)	0.0038 (0.003)	5.38E-01 (0.080)	1.07E-01 (0.017)	8.00E-04 (7.36e-05)	0.3796 (0.146)	0.1161 (0.070)
β		0.8224 (0.073)	4.90E-01 (0.034)	1.78E-01 (0.027)	9.99E-01 (7.36e-05)	0.5587 (14.31)	0.7113 (0.201)
γ			2.24E-01 (0.081)	-9.99E-01 (0.206)			-0.1203 (0.067)
Ø						0.3603 (14.57)	
ρ						0.9446 (0.138)	
δ				1.00E+00			
ξ (Dum)	2.20E-03 (0.002)	-0.0012 (0.001)	-3.57E-01 (0.344)	-3.89E-02 (0.003)	-3.00E-04 (1.74e-05)	-0.0019 (0.002)	-0.006 (0.004)
α + β		0.8262	1.0279	0.2853	0.9999	0.9383	0.8274
Log L	624.479	420.636	704.47	717.43	908.28	445.081	243.23
AIC	-3.8898	-2.6077	-4.3866	-4.4618	-5.681	-2.7576	-1.4857
SC	-3.8188	-2.5367	-4.3037	-4.3672	-5.6219	-2.6627	-1.4029
Obs	318	318	318	318	318	318	318

Numbers in parenthesis indicate standard errors

Accordingly, coefficients of the EGARCH model of USD return are highly significant. The EGARCH is covariance stationary since β is 0.58928. The β for EGARCH model for *Naira*/Euro return is equally covariance stationary

[9] The most common fat–tailed error distribution for fitting GARCH models are: the student's t, the double exponential and generalised–error distributions (Zivot, 2009).

since it is 0.7971 which is less than 1, and the coefficient is highly significant. The leverage effect term, γ measures asymmetry of shocks and is equally significant at 1% level. For BPS returns, all the coefficients are insignificant at 5% level except for α . For *Naira*/USD return, all the coefficients are significant and γ , is positive and statistically different from zero, indicating the non–existence of leverage effect in volatility of *Naira*/USD returns (GARCH model without volatility breaks) during the sample period. The same implication affects the *Naira*/BPS series except that the coefficient is not statistically significant. However, for EGARCH equation with volatility breaks, results show the existence of leverage effect (implying that bad news does increase volatility more than good news) and that the coefficient is highly statistically significant.

Table 7: Parameter Estimates for ARCH/GARCH Models (N/BPS Return) without Volatility Breaks

Parameter	ARCH	GARCH (1,1)	EGARCH	PARCH	IGARCH	CGARCH	TGARCH
C	1.00E-04 (0.0028)	0.0003 (0.0029)	6.00E-04 (0.0028)	4.00E-04 (0.0031)	-2.00E-04 (0.0025)	5.00E-04 (0.0024)	7.00E-04 (0.0029)
ω	5.00E-04 (0.0001)	0.0006 (0.0002)	-6.72E+00 (2.5827)	3.80E-03 (0.0033)		0.0009 (0.0007)	0.0005 (0.0002)
α	4.42E-01 (0.2292)	0.4547 (0.2278)	7.45E-01 (0.3157)	1.10E-01 (0.1212)	1.71E-01 (0.0616)		0.5666 (0.3828)
β		-0.1046 (0.2139)	1.41E-01 (0.3498)	7.80E-01 (0.1883)	8.29E-01 (0.0616)	-0.3923 (0.3053)	-0.0716 (0.2745)
γ			8.83E-02 (0.1859)	-9.94E-01 (1.1289)		0.4359 (0.2117)	-0.2356 (0.3996)
Ø						0.1324 (0.1786)	
ρ						0.9372 (0.1323)	
δ				1.00E+00			
α + β		0.3501	0.8861	0.8901	1		0.495
Log L	194.613	194.81	193.8382	194.937	189.366	197.296	195.073
AIC	-4.2358	-4.218	-4.1742	-4.1986	-4.1415	-4.2288	-4.2016
SC	-4.1247	-4.0791	-4.0075	-4.32	-4.0581	-4.0344	-4.035
Obs	90	90	90	90	90	90	90

Numbers in parenthesis indicate standard errors

The IGARCH model for euro returns indicates that β is highly statistically significant at 1% level. The same model also shows that the variances are stationary and volatility persistence will not remain forever[10] (see table 8). The β of IGARCH models for both Euro and BPS return are significant at 1% level, while for USD (model without breaks), both α and β are significant at 1% level, and the sums of all the coefficients are close to one. For the *Naira*/USD return model with volatility breaks, the same results were also found. Results from table 6 reveal that the dummy coefficients (ξ) of the equations for *Naira*/USD GARCH models with breaks are highly significant except for the ARCH, CGARCH, TGARCH and EGARCH specifications. Comparing tables 5 and 6 above, indicates that the results have improved significantly with estimation of *Naira*/USD return GARCH with volatility break model as against the estimation of volatility models without breaks with respect to USD return.

Examining the asymmetric volatility model, *threshold* GARCH (TGARCH), reveals two types of news. The weights are usually computed on the long run average, the previous forecast, the symmetric news, and the negative news. These weights for BPS return are estimated to be 0.623, -0.072, 0.57 and 0.12 respectively (see table 7). For *Naira/*USD return, the weights are (0.17874, 0.77368, 0.09564, and -0.04806). In the case of Euro returns, the weights are 0.1334, 0.60924, 0.58155 and -0.3242 respectively[11]. In a TGARCH model, 'good news' ($\mu_t > 0$) and 'bad news' ($\mu_t < 0$) have differential effects on the conditional variance; good news has an impact of α, while bad news has an impact of $(\alpha + \gamma)$. In the case of *Naira*/BPS return, good news has an impact of 0.567 while bad news has an impact of 0.331. For *Naira*/USD returns, 'good news' has an impact of 0.095, and 'bad news' has an impact of -0.0005 respectively. For *Naira*/Euro returns, 'good news' has an effect of 0.582 and bad news has -0.067. Leverage effect does not exist for the currencies, implying that 'bad news' does not confer higher volatility more than 'good news' of the same magnitude. Thus since $\gamma \neq 0$, the news impact is

[10] There is volatility persistence when volatility in the current month depends on volatility in the preceding months or period (Greene, 2003; and Engle, 2003). Based on documented stylized fact on volatility, it has been showed that GARCH family models are capable of explaining many characteristics ranging from volatility clustering, fat tails, volatility mean reversion and asymmetry (Zivot, 2009).

[11] The TGARCH model is assumed to be $h_t = \omega + \beta h_{t-1} + \alpha r_{t-1}^2 + \gamma r_{t-1}^2 I_{rt-1<0,}$ and the weights are $(1-\alpha-\beta-\gamma/2, \beta, \alpha, \gamma/2)$.

asymmetric. The leverage effect[12] for Euro return model is significant at 5% level, indicating the existence of an asymmetric effect.

Result from *power* ARCH (PARCH) model for BPS returns revealed that β is the only significant coefficient at 1% level with a value of 0.780, when $d = 1$. However, γ is less than 1 (-0.994) which satisfies the condition that $|\gamma_i| \leq 1$. For *Naira*/USD return GARCH model with volatility breaks, all the key coefficients are significant. However, parameter estimates from the *Naira*/USD return CGARCH models shows that α is 0.244 while β is 0.462. Accordingly, ϕ is 0.512 while ρ is 0.779. For BPS return β is –0.392, while ϕ is estimated as 0.133.

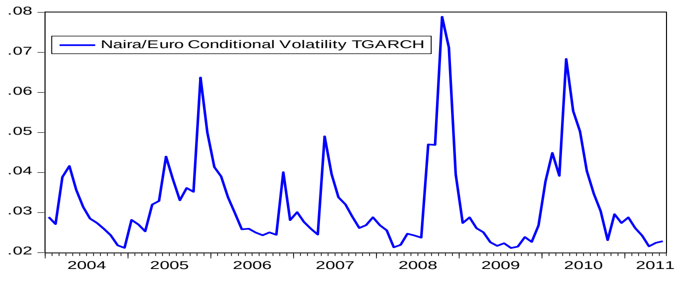
Table 8: Parameter Estimates for ARCH/GARCH Models (N/Euro Return) without Volatility Breaks

Parameter	ARCH	GARCH (1,1)	EGARCH	PARCH	IGARCH	CGARCH	TGARCH
C	-2.80E-03 (0.0032)	-0.003 (0.0032)	-1.30E-03 (0.0034)	-1.50E-03 (0.0034)	-2.50E-03 (0.0026)	-2.60E-03 (0.0013)	-1.20E-03 (0.0034)
ω	9.00E-04 (0.0004)	0.0007 (0.0009)	-1.51E+00 (1.0537)	8.50E-03 (0.0063)		0.0019 (0.0006)	0.0002 (0.0001)
α	2.99E-01 (0.3209)	0.2886 (0.3799)	1.39E-01 (0.1829)	1.83E-01 (0.1320)	3.36E-02 (0.0247)		0.5815 (0.2982)
β		0.1163 (0.6137)	7.97E-01 (0.1424)	5.97E-01 (0.2509)	9.66E-01 (0.0247)	-0.2182 (0.8061)	0.6092 (0.2025)
γ			3.57E-01 (0.1187)	-9.98E-01 (0.7528)		0.1695 (0.2739)	-0.6484 (0.3061)
Ø						-0.0908 (0.0719)	
ρ						0.9918 (0.0089)	
δ				1.00E+00			
α + β		0.4049	0.936	0.7798	1		1.1907
Log L	181.424	181.505	185.657	185.469	176.57	184.921	185.874
AIC	-3.9428	-3.9223	-3.9924	-3.9882	-3.8571	-3.9538	-3.9972
SC	-3.8317	-3.7835	-3.8257	-3.8215	-3.7738	-3.7594	-3.8305
Obs	90	90	90	90	90	90	90

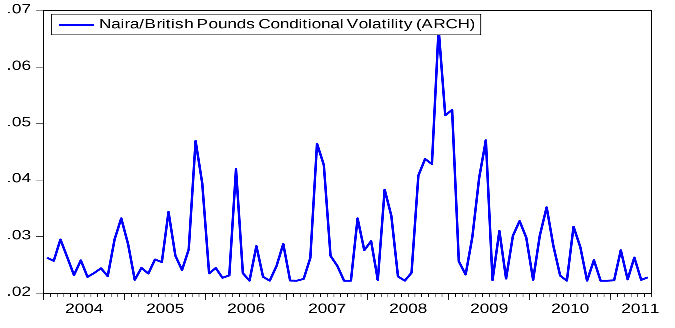
Numbers in parenthesis indicate standard errors

[12] Black (1976) attributes this effect to the fact that bad news tends to drive down stock price, thereby increasing the leverage (i.e. the debt–equity ratio) of the stock and causing the stock to be more volatile. It is based on this that the asymmetric news impact on volatility is referred to as the leverage effect (Zivot, 2009).

(a) Naira/Euro Returns Volatility



(b) Naira/Pounds Returns Volatility



(c) Naira/US Dollar Returns Volatility (with volatility breaks)

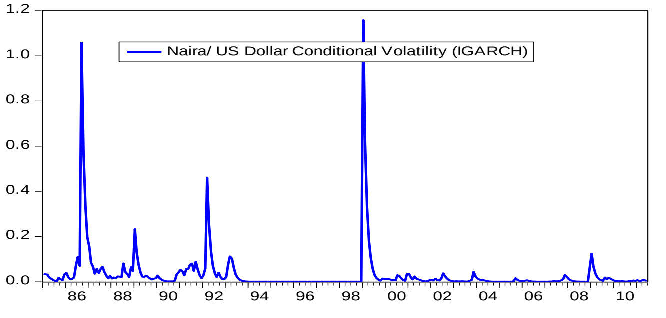


Figure 4: Conditional Volatilities from fitted ARCH/GARCH models for Euro, British Pounds Sterling (BPS) and US Dollars against the Naira.

The figures above indicates that the volatility models selected capture the major trends as well as periods of high and low currency return volatilities as depicted by the charts of the conditional volatilities of fitted GARCH models.

In terms of criteria for selecting the best model, the Akaike information criterion (AIC), and Schwarz Criterion (SC) are estimated and compared for all the specified volatility models. This indicates that TGARCH is the best fitting model for Euro, while ARCH and PARCH (1,1) are the best fitting models for BPS return and *Naira*/USD returns. For the USD return model with volatility breaks, the best fitting model is the IGARCH specification on the basis of the results of AIC, log likelihood statistics, and the level of persistence of the model.

In 2008–2009 periods all the exchange rate return series exhibited higher volatility which was attributed to the impact of global financial crisis that resulted in excessive speculative noise in the FX market[13]. All the estimated models therefore captured these high volatility trends (see figure IV). For the *Naira*/USD, all the estimated volatility models reveal large disturbances in 1986, largely as a result of FX market liberalisation; the late 1990s reforms and the 2008–2009 periods. The estimated volatilities for ARCH, GARCH (1,1), EGARCH, and TGARCH are similar for Euro return, while the IGARCH and PARCH also followed similar volatility patterns. Some of the volatility trends generated by these models are shown in figure IV

5.0 Conclusion and Policy Implications

This paper investigates exchange–rate volatility for three major currencies in the Nigerian FX markets: the Naira/USD, Euro and BPS using variants of GARCH volatility models and compared estimates from these models. The best performing models are identified for each currency and the most volatile currency: the USD is identified as well as the least volatile: BPS. The volatility of the exchange rates is equally further confirmed. The paper finds significant evidence that all the asymmetric models rejected the existence of a leverage effect except for models of GARCH with volatility breaks. Comparing several models, results have improved drastically with the estimation of Naira/USD GARCH models with volatility breaks as against the estimation of volatility models without breaks in respect of USD. In the design of appropriate exchange–rate policies, Nigeria's monetary authorities should take into cognisance key events both domestically and internationally that are likely to affect the fluctuations of the Naira against some key

[13] Fear and greed are some of the key factors that contribute to the volatility of currencies in the FX market.

currencies and to incorporate significant events in the estimation of their currency models as well as other asset prices.

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