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Volatility Persistence in Naira Exchange Rates: A Pre- and Post- Global Financial Crisis Analysis

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The exchange rates of naira against other currencies around the world have been affected by market reactions, with the greatest crash during the 2008 global financial crisis. As a result, structural pattern and volatility persistence in the pre-global and post-global crisis periods might have undergone a shift. This paper considered high frequency naira exchange rate time series for pre-global and post-global crisis periods to investigate the volatility persistence in the financial time series. Long range dependence techniques and volatility modelling approaches were applied on level series, absolute and squared log-returns of six daily naira exchange rate series between 12 October, 2001 and 19 December, 2014. Significant persistence of volatility in both absolute and square returns of the exchange rates series was observed, and there was the difference in the level of persistence between the two time series sub-samples, that is, the pre-crisis period seemed to exhibit lower level of volatility than the post-global crisis period. Further investigation using estimates of volatility modelling confirmed lower volatility persistence in the pre-crisis period, and possible asymmetry in the entire time series sample. The higher persistence of volatility observed in naira exchange rates during the post crisis period was as a result of the residual impacts of the global crisis on the economy that we experienced till the end of the sampled period.

Keywords: Exchange rates; fractional persistence; global financial crisis; heteroscedasticity; volatility

1. Introduction

Since the 2008 global financial market crisis, the interest of financial time series analysts have been gingered towards studying volatility market behaviours of financial assets, particularly the volatility of exchange rates. As a result of denomination of local currency by a unit of US dollars, developing nations such as Nigeria feel the spillover effect whenever there is a shock from the US or other technological dependent nations. For example, advanced economies such as Organization for Economic Cooperation and Development (OECD) and the BRICS (Brazil, Russia, India, China and South Africa) might have established a strong US dollar exchange rates as a result of strong economic development and policies (see Salisu et al., 2016).

Previous work on naira exchange rates by Yaya and Shittu (2014) tested for nonlinearity in exchange rates, and concluded that the dynamics of market volatility is linear. As a follow up, we rather consider studying exchange rate volatility using fractional integration approach on both the mean and variance series, and as well by using volatility modelling approach to validate the results.

Nigeria is one of the countries that adopted the floating exchange rate system in the early 1970s after the demise of the Bretton Woods system (Ajibola et al., 2015). The floating exchange rate allowed the exchange rates to be determined by market pressure. The fluctuations in exchange rates perceived under the floating system was later found to have adverse repercussions for investment and trade. As a result of this negative correlation between trade and exchange rate volatility, both imports and exports were significantly reduced since firms had to add risk premiums to the costs of traded goods leading to higher prices and lower trade volume (Akpokodje, 2009). Apart from trade, there is an expansive literature indicating that exchange rate volatility has a direct, deleterious effect on Foreign

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Direct Investment (FDI) in Nigeria and South Africa (Benassy-Quere et al., 2001; Kiyota and Urata, 2004; Ruiz, 2005). Exchange rate volatility generates an air of uncertainty as the variance of expected profits rises and its net present value falls.

The present recession in Nigeria is believed to have been caused by the spill-over in the fall in the pricing of oil at the markets, which affected the foreign reserves. Due to the fact that oil is believed to have direct spill-over impacts on exchange rates, there is the need to investigate the structural pattern and volatility persistence of naira exchange rates (Salisu and Mobolaji, 2013).

The dynamic modelling of exchange rate volatility persistence in this paper follows the idea of Mikosch and Starica (2004). In the paper, it is observed that the assumption of the standard Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model having constant parameters may not hold in practice unless the series to be modelled are sufficiently short. The series are divided into sub-series according to the location of the break points and separate volatility models are fitted to the subseries. In this regards, the problem is how to obtain the sub-series. This may not pose much difficulty in a case where the financial series reacts to external forces at almost the same time. For example the influence of Central Bank of Nigeria (CBN)s intervention and global financial crisis, which drastically increased and decreased the exchange rates, respectively. Another motivation for modelling volatility processes is related to the high persistence that is commonly observed in the squared or absolute returns. This persistence refers to the typical pattern for the Autocorrelation Function (ACF) of the squared/absolute returns, that are positive and slowly decreasing (van Bellegem, 2012). The main stylized feature of the GARCH models is their ability to capture volatility clustering, that is, large changes of log-returns tending to be followed by large changes, of either sign, or small changes tending to be followed by small changes of log- returns. This results in positive autocorrelation coefficients of absolute or squared returns.

This paper therefore investigates the volatility persistence and asymmetry in naira exchange rates during pre-crisis and post-crisis periods. Both fractional dependence and Generalized Autoregressive Conditionally Heteroscedasticity (GARCH) modelling approaches are applied in achieving this aim. The level of volatility persistence is first investigated in the exchange rates series by estimating the fractional differencing parameter in exchange rates, absolute and squared log-returns time series of exchange rates. Then GARCH modelling approach is considered to study the persistence of volatility in the returns series, and asymmetry is examined using the Glosten Jaganathan and Runkle-GARCH (GJR-GARCH) models (see Goffe et al., 1994).

The rest of the paper is structured as follows: Section 2 presents the theoretical framework. Section 3 presents the statistical methodology involved in the work. Section 4 presents the data and the empirical analysis, while Section 5 gives the concluding remarks.

2. Theoretical Framework

2.1 *Long Range Dependence (LRD) and fractional integration*

The idea of Long Range Dependency (LRD) was originated from the fractional Brownian motion studied by hydrologist, Hurst in 1951. The prominence was achieved in this line of research by Granger and Hosking between 1980 and 1981. This methodology has been widely used in estimating and testing long range dependency in finance, economics and in many other disciplines. LRD has been observed in financial series and these dependencies are substantially larger than those allowed for stationary ARMA processes (Xekalaki and Degiannakis, 2010). Ding et al. (1993) found that the absolute or squared values of returns on the Standard and Poors (SP500) index tend to have very slowly decaying autocorrelations. Similar evidence of LRD is documented in Mills (1996), Perron and Qu (2010), Yaya (2013), Gil-Alana et al. (2014), among others.

2.2 *GARCH modelling approach*

A number of papers in the literature have stressed the applicability of GARCH modelling on exchange rates and other volatility time series. The extended GARCH model is the GJR-GARCH model proposed in Glosten et al. (1993). This is an asymmetric GARCH variant capable of determining the leverage effect in the return series. Other GARCH models that allow for an asymmetric news impact effect are the Exponential GARCH (EGARCH) model of Nelson (1991) and the Asymmetric Power ARCH (APARCH) model of Ding et al. (1993). The fractionally integrated versions of some of these models have also been developed. The positive asymmetric response of assets return volatility to past shocks is considered as a stylized fact, but there is no consensus that the findings of positive asymmetric parameter corresponds actually to the financial leverage effect. Negative asymmetric parameter estimates are found for commodity returns series in Carpantier (2010), and this is named the inverse leverage effect. Engle (2011) investigated returns series of gold prices, exchange rates and some other series and interprets the asymmetric parameter as a hedge effect. Beine et al. (2012) remarked that GARCH and Integrated GARCH (IGARCH) models tend to underestimate the effect of Central Bank interventions on the volatility of asset prices. On asymmetric volatility modelling, Engle and Ng (1993) argued that the GJR-GARCH model is better than the EGARCH model of Nelson (1991) since the conditional variance of EGARCH model is too high due to its exponential form. Yaya et al. (2015) studied the high frequency data of European, American and Asian stocks using GJR-GARCH model, following the findings of Huang (2011). The GARCH model assumes that the volatility series follows a stationary symmetric volatility process with conditional variance series. The GJR-GARCH model checks for the presence of asymmetry in the returns series based on the estimates of its parameters.

3. Methodology

The approach in this paper is centred on the fractional integration technique. This technique has been applied in studying the persistence of volatility in assets prices and returns series. The persistency in the transformed returns series is confirmed using the volatility model-based approach.

3.1 *The fractional integration techniques*

The fractionally integrated time series is defined with the backward shift operation as

$$\begin{gathered}(1-B)^d y_t = u_t,\ t = 1, 2, \cdots \\ y_t = 0,\ t \leq 0,\end{gathered} \tag{1}$$

where B is the backward shift operator; y_t is the observed time series (level series, returns, absolute or squared returns), supposed to be fractionally differenced, d is the fractional differencing parameter, and u_t is the resulting covariance stationary $I(0)$ process, that is, a purely stationary time series process. The estimation of the fractionally differencing parameter is carried out using non-parametric, semi-parametric and parametric approaches. The non-parametric approach is updated in Mills (1996). The semi-parametric approach is the Local Whittle (LW) estimation of Robinson (1995a). The parametric approach is the Exact Maximum Likelihood (EML) method in Ooms and Doornik (1999, 2004, 2006). All these methods are sensitive to estimating the differencing parameter within the long memory range, i.e., $0 < d < 0.5$. The semiparametric LW estimator estimates the differencing parameter in the nonstationary range $0.5 < d < 2$. The estimation procedure is similar to Geweke and Porter-Hudak (GPH) log-periodogram regression approach given in Robinson

(1995b), as implemented in most statistical software.

The non-parametric approach of Lo (1991) is based on a rescaled range statistic (R/S) defined as:

$$R/S = \frac{1}{S_N(q)}\left(\sup_{1\leq m\leq N}\sum_{j=1}^{m}(y_j-\bar{y}) - \inf_{1\leq m\leq N}\sum_{j=1}^{m}(y_j-\bar{y})\right), \tag{2}$$

where S_N is the standard deviation defined in Lo (1991) as

$$S_N(q) = \left(S_N^2 + 2\sum_{j=1}^{Q} w_j(q)\hat{\gamma}_j\right)^{1/2}$$

and $w_j = 1 - j/(q+1)$ such that $q < N$ and S_N is the standard deviation of the time series y_j and the jth-order sample autocovariance by $\hat{\gamma}_j$. The Hurst coefficient, H, is estimated by

$$\hat{H} = \frac{1}{\log(N)}\log(R/S) \tag{3}$$

and the fractional differencing parameter, d is obtained as

$$\hat{d} = \hat{H} - 0.5, \tag{4}$$

The semi-parametric estimator of the LW estimator represents an approximation to the MLE in the frequency domain for large N. This estimator is defined as

$$\hat{d} = arg\min_{d}\left(\log\overline{C(d)} - 2d\frac{1}{m}\sum_{s=1}^{m}\log\lambda_s\right), \tag{5}$$

$$\overline{C(d)} = \frac{1}{m}\sum_{s=1}^{m} I(\lambda_s)\lambda_s^{2d},\ \lambda_s = \frac{2\pi s}{N},\ \frac{m}{N} \to 0,$$

where m is a bandwidth number, and $I(\lambda_s)$ is the periodogram of the raw time series, y_t, given by

$$I(\lambda_s) = \frac{1}{2\pi N}\left|\sum_{t=1}^{N} y_t\exp(i\lambda_s t)\right|^2. \tag{6}$$

The estimator is consistent for $d \in (-0.5, 0.5)$ and this consistency depends on the bandwidth, m which satisfies $\frac{1}{m} + \frac{m}{N} \to 0$ as the sample size $N \to \infty$. Velasco (1999) further showed that the estimator is consistent for $d \in (-0.5, 1)$ and asymptotic normal for $d \in (-0.5, 0.75)$. Further refinements of the estimation approach are given in Robinson and Hendry (1999), Velasco and Robinson (2000), Phillips and Shimotsu (2004), Shimotsu and Phillips (2005) and Abidir et al. (2007). Another semi-parametric method is the GPH approach which assumes that the spectrum of a time series process takes the form,

$$f(\lambda) = |\lambda|^{-2d} g(\lambda),\ \text{as}\ \lambda \to 0, \tag{7}$$

where $g(\bullet)$ is an even function on the Nyqvist range $[-\pi, \pi]$ that determines the short run dynamics of the stationary process y_t and this satisfies $0 < g(0) < \infty$. Then, the GPH estimator is based on the least-square regression using spectral ordinates $\lambda_1, \lambda_2, \cdots, \lambda_m$ from the periodogram of $I_y(\lambda_j)$ for y_t with $j = 1, 2, \cdots, m$ where m is the bandwidth which is less than the sample size N. Then, (7) is re-written as

$$\log\left[I_y(\lambda_j)\right] = a + b\log(\lambda_j) + v_j, \tag{8}$$

where v_j is assumed to be i.i.d. Then, from the least square estimator $\hat{b}$, the fractional differencing operator is computed as,

$$\hat{d} = -\frac{1}{2}\hat{b}, \tag{9}$$

which is asymptotically normal, and the theoretical standard error is computed as $\pi(24m)^{-1/2}$. Diebold and Inoue (2001) showed that the choice of a large value for m would result in reducing the standard error at the expense of biasness in the estimator, as the relationship that the GPH regression is based on holds only at low frequencies.

The parametric EML approach jointly estimates the fractional differencing parameter with the parameters in the Autoregressive Fractionally Integrated Moving Average (ARFIMA(p, d, q)) model where p and q are the orders of AR and MA parts of the model, and d is the value of the fractional difference. Following Ooms and Doornik (1999), y_t is assumed to follow the Gaussian process, then the resulting log-likelihood function is

$$L(\theta) = -\frac{N}{2}\log(2\pi) - \frac{1}{2}\log|\Omega| - \frac{1}{2}y_t'\Omega^{-1}y_t \tag{10}$$

The Gaussian Maximum Likelihood estimates are then obtained by maximizing $L(\theta)$, and this requires the calculation of the determinant and the inverse of the variance-covariance matrix Ω which is carried out by the Cholesky decomposition method. For details of ML estimation approach for ARFIMA$(0, d, 0)$ process implemented in ARFIMA package in Ox and GiveWin software, readers are referred to Doornik and Hendry (2001). The EML approach therefore estimates the differencing parameter in the range $0 < d < 0.5$.

3.2 *The volatility modelling approaches*

First differences of the log-transformed volatility time series (E_t) produces the return series, ϵ_t. The absolute returns, $|\epsilon_t|$, and the squared returns, ϵ_t^2, are then obtained. A common framework for modelling volatility of asset returns is based on the GARCH model. The basic idea of this model is that the shocks of an asset are serially uncorrelated but dependent and this can be described by a simple quadratic function of the lagged values. Using the returns/shocks, ϵ_t, then the GARCH(1,1) model assumes that the conditional volatility series σ_t^2 is modelled as

$$\sigma_t^2 = a_0 + a_1\epsilon_{t-1}^2 + b_1\sigma_{t-1}^2, \tag{11}$$

where a_1 and b_1 are non-negative parameters and a_0 is a strictly positive constant. The sum $a_1 + b_1 < 1$ for stationary GARCH(1,1) specification. For $a_1 + b_1 \geq 1$, the process realizes nonstationary conditional variances and this case is termed IGARCH process. The conditional variance is expressed as a linear function of the squared past values of the series. This specification is able to capture and reproduce several important characteristics of financial time series (Francq and Zakoian, 2010). These include a succession of turbulent periods; autocorrelation of the squares but absence of autocorrelation of returns, and leptokurticity of the marginal distributions. The unconditional variance (volatility) is computed as,

$$\sigma^2 = a_0/\left(1 - a_1 - b_1\right). \tag{12}$$

The level of persistence is

$$a_1 + b_1$$

and the closer the persistence value is to unity, the more persistent the volatility of the return series. The half-life of volatility, a measure of the average time it takes the persistence to reduce by one-half is obtained by

$$\ln(0.5)/\ln(a_1 + b_1).$$

This implies that, the closer $a_1 + b_1$ is to unity, the larger the half-life of volatility. The first order autocorrelation coefficients of the returns is computed as

$$\rho_1 = \left\{a_1(1 - b_1^2 - a_1 b_1)\right\} / \left\{1 - b_1^2 - 2a_1 b_1\right\} \tag{13}$$

and this value is usually larger than a_1.

A widely used extension of the GARCH(1,1) model is the GJR-GARCH model. This is given as

$$\sigma_t^2 = a_0 + a_1\epsilon_{t-1}^2 + b_1\sigma_{t-1}^2 + c_1\epsilon_{t-1}^2 I(\epsilon_{t-1} < 0) \tag{14}$$

with the additional parameter c_1 as the asymmetric parameter, and indicator function $I(\epsilon_{t-1} < 0)$. This model implies that at $c_1 = 0$, the conditional variance response to a past shock ϵ_{t-1} of given absolute value is the same whether the shock is positive or negative. The news impact curve which traces σ_t^2 as a function of ϵ_{t-1} for values of $a_0 + b_1\sigma_{t-1}^2$ and a_1 is a parabola having its minimum at $\epsilon_{t-1} = 0$. At this point, the realized volatility perfectly matched that of the GARCH model. If $c_1 > 0$, the response of conditional variance to past negative shock is stronger than the response to past positive shocks of the same magnitude, and the news impact curve is asymmetric. A clarification is needed here in order to avoid the general misconception between asymmetry and leverage: (i) asymmetry is a case where positive and negative shocks of equal magnitude have different impacts on volatility and (ii) leverage is intended to capture the possibility that negative shocks increase volatility while positive shocks decrease volatility or equivalently, a negative correlation between current returns and future volatility (see Xekalaki and Degiannakis, 2010). As a matter of fact, the asymmetric volatility models (EGARCH, GJR-GARCH, APARCH, etc.) may not indicate leverage effect. For leverage to occur, the coefficient of the ARCH term must be negative. The EGARCH model may display both asymmetry and leverage while the GJR-GARCH model is unlikely to have leverage.

For many asset prices and indexes, a positive effect is observed. The symmetric effect is then computed as

$$a_1 + b_1$$

while the asymmetric effect is computed as

$$a_1 + b_1 + c_1.$$

4. The Data, Results and Discussion

The data used in this work are the six daily official naira exchange rates with Central and West African Francs (naira-CFA); with European Euro (naira-EURO); with British Pound (naira-GBP); with United States Dollars (naira-USD); with International Monetary Fund West African Unit of Account (naira-WAUA) and Japanese Yen (naira-JPY). The data were sourced from Central Bank of Nigeria website (www.cenbank.org) and spanning between 12 October, 2001 and 19 December, 2014. An algorithm set up by Pagan and Soussounov (2003) to determine market peaks and trough was applied to identify the peak point in the exchange rate series. This date was identified as 6 June 2008 for most of the exchange rates. At this date, a US dollar was exchanged for 116.10 Naira. We observe that the exchange rates picked up astronomically in all the series during the post crisis period, and gained its stability back within one or two months, that is, in July and August, 2008. During this period, Naira-USD rose from 116.10 naira to about 140 naira, that is, with about 21% fall in the exchange rate. Other exchange rates also increased within the range 18% to 37%. We omitted the two months (July and August 2008) of sharp drop and recovery of the rates, since the inclusion of this might affect the results and the small sample could bias the results, and as well lead to misleading results. Plots of the six naira exchange rates are given in Figure 1, with the exchange rates on the vertical axis and time periods (dates) on the horizontal axis. The breaks in the rates in 2008 are very conspicuous. Over the sampled years, naira exchange rates have fractured the economy of Nigeria, as naira was depreciating at the international market. Naira-USD exchange exchanges rates displays lesser fluctuations compared to other naira exchange rates, therefore this seems to be less volatile

Table 1 presents the results of fractional integration for the exchange rates. Having partitioned each series into two, we found the estimates of integration parameter to be dissimilar from the two estimation methods. This further indicates that the nonstationary persistence after the global financial crisis is higher. Since volatility may not be observable by mere looking at the plot of the exchange rates, we then carried out log-differenced transformation to obtain exchange rates returns series, which acted as proxy for the volatility series. The descriptive statistics on the log-returns are presented in Table 2. We observe average returns to be higher after the crisis in five exchange rates (naira-CFA, naira Euro, naira-GBP, naira-USD, and naira-WAUA) and for naira-JPY exchange rate, the returns are larger during pre-crisis period. Looking at the full sample series, the average returns for naira-USD exchange rate (3.86E-05) is smaller than average returns for the remaining five exchange rates and that is why US dollar is used as a global currency.

Further analysis on the persistence of naira exchange rates volatility is based on fractional persistence approach on log-returns, absolute and squared log-returns series and the results are presented in Tables 3 and 4 for non-parametric, semi-parametric and parametric estimation methods. Actually the estimates are given in the range for long range dependence (LRD) ($0 < d < 0.5$) implying significant dependency of the transformed log-returns of the exchange rates over the years. In Table 3, we observe the LRD estimates to be larger during post-crisis period, implying higher market volatility during this period.

Similar results are obtained on Table 4 when the squared log-returns were used as proxy for volatility series, only that squared log-returns of Naira-GBP, Naira-USD and Naira-WAUA exchange rates indicated lower LRD value after the global crisis based on semi-parametric and parametric methods.

Using the model based approach (Table 5), we obtained significant GARCH (1,1) estimates for the exchange rates models, these were computed based on Student-t distribution. The ARCH parameter estimates were computed within the interval (0.02, 0.25) while the GARCH parameters were computed within (0.75, 0.98), this, implying reliable estimates according to Giraitis et al. (2006), Xekalaki and Degiannakis (2010), Tsay (2010) and Bauwens et al. (2012). This condition is in exception to the naira-USD exchange rates whose GARCH parameter is as low as 0.60. We observe the persistence before the global

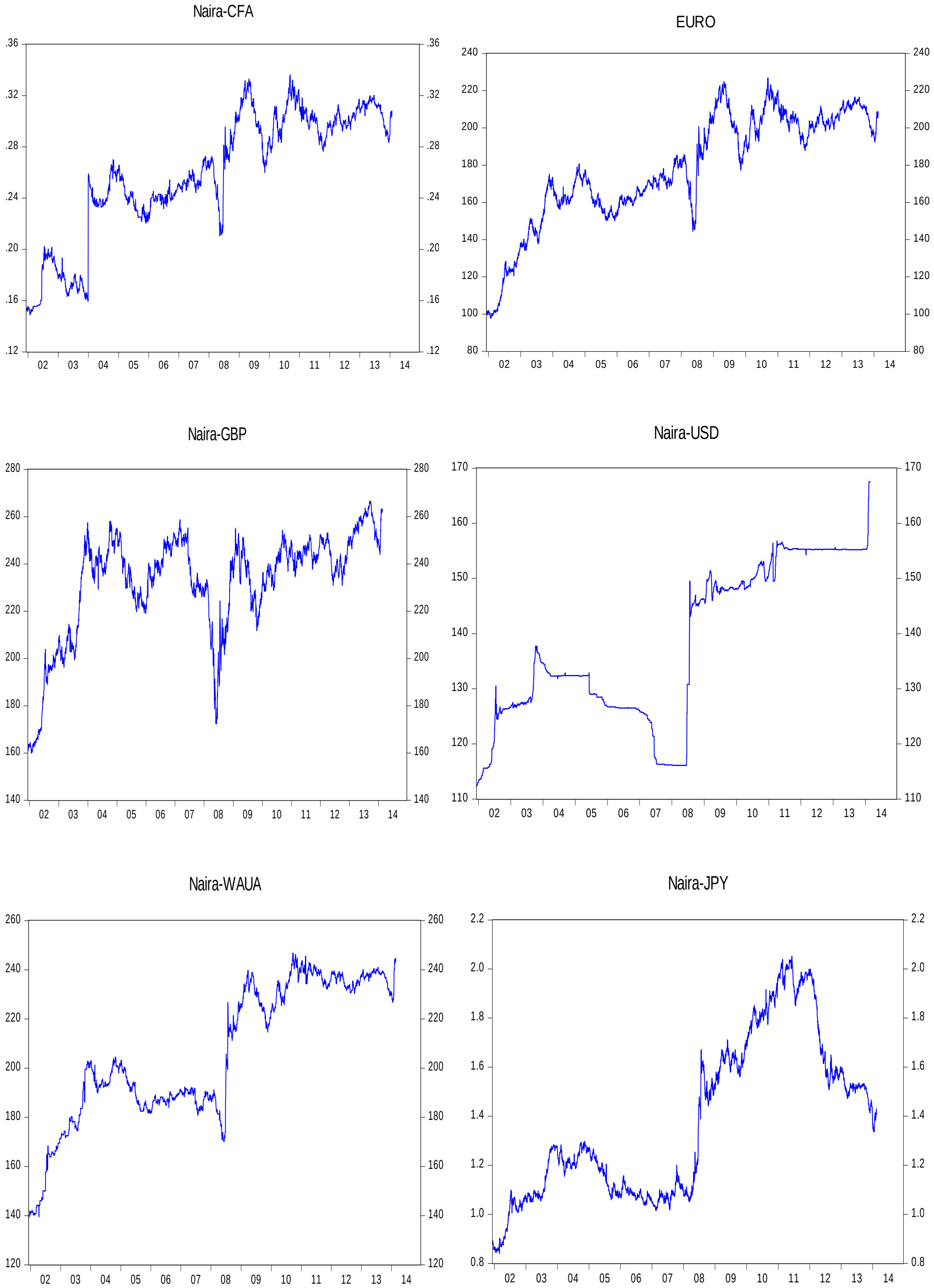

Figure 1: Plots of Naira Exchange rates

crisis to be lower than persistence in the post-crisis period implying the riskier financial marketing after the crisis. Using the unconditional volatility measures for the realized conditional series $\hat{\sigma}_t^2$, there is a little contrary result. In naira-CFA and naira-GBP exchange rates, the conditional volatilities realized are highly persistent after the global crisis. The half-life of volatility actually confirms longer period of time for the persistence in the re-

Table 1: Estimates of Persistence for Exchange rates series

Methods		Semiparametric	Semiparametric Log-
Naira-CFA	Pre-crisis	0.9373***	1.0073***
	Post-crisis	0.9630***	1.0176***
	Full sample	0.9430***	0.9949***
Naira-EURO	Pre-crisis	0.9448***	1.0190***
	Post-crisis	0.9620***	1.0227***
	Full sample	0.9364***	0.9882***
Naira-GBP	Pre-crisis	0.9481***	1.0283***
	Post-crisis	0.9556***	0.9961***
	Full sample	0.9475***	0.9975***
Naira-USD	Pre-crisis	0.9378***	1.0085***
	Post-crisis	0.9550***	0.9993***
	Full sample	0.9468***	1.0030***
Naira-WAUA	Pre-crisis	0.9395***	1.0071***
	Post-crisis	0.9546***	1.0066***
	Full sample	0.9452***	0.9983***
Naira-JPY	Pre-crisis	0.9312***	1.0016***
	Post-crisis	0.9639***	1.0102***
	Full sample	0.9389***	0.9930***

*** Indicates significant estimate of *d* at 5% level.

Table 2: Descriptive statistics on log-returns of exchange rates

Exchange rates	Samples	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Naira-CFA	Pre-crisis	9.33E-05	0.2055	-0.0270	0.0064	20.0431	640.8220
	Post-crisis	1.05E-04	0.0367	-0.0212	0.0035	1.3047	21.0840
	Full sample	1.36E-04	0.2055	-0.0270	0.0065	19.2429	603.3226
Naira-EURO	Pre-crisis	1.02E-04	0.0228	-0.0225	0.0032	-0.2620	10.1761
	Post-crisis	8.83E-05	0.0377	-0.0375	0.0036	1.1351	31.0092
	Full sample	1.36E-04	0.0277	-0.0225	0.0033	0.3911	13.7599
Naira-GBP	Pre-crisis	2.62E-05	0.0288	-0.0242	0.0030	-0.2115	15.5485
	Post-crisis	9.87E-05	0.0418	-0.0220	0.0032	1.6972	29.4679
	Full sample	5.49E-05	0.0288	-0.0242	0.0032	0.3175	17.4779
Naira-USD	Pre-crisis	8.29E-05	0.0089	-0.0170	0.0009	-5.2102	144.6487
	Post-crisis	8.74E-05	0.0278	-0.0196	0.0015	8.3047	193.4576
	Full sample	3.86E-05	0.0278	-0.0170	0.0012	6.6346	230.8687
Naira-WAUA	Pre-crisis	5.22E-05	0.0301	-0.0173	0.0022	2.8747	58.8514
	Post-crisis	8.41E-05	0.0325	-0.0190	0.0022	4.9256	81.1627
	Full sample	7.38E-05	0.0304	-0.0173	0.0023	3.7661	65.3908
Naira-JPY	Pre-crisis	7.70E-05	0.0309	-0.0266	0.0035	0.6518	16.0328
	Post-crisis	4.10E-05	0.0286	-0.0205	0.0033	0.8719	15.3808
	Full sample	1.18E-04	0.0309	-0.0266	0.0036	0.9397	16.9593

Source: Author's computation using EViews 8.0 software

turns after the crisis. After the global crisis, naira-USD exchange rate was taking about 8 days to re-adjust to the effect of the shocks, and this is the smallest half-life period among the exchange rates. Even in the full sample, the half-life is 2.5 days. The highest half-life of persistence of volatility was obtained for naira-WAUA exchange rates at 866 days for the full sample, while after the crisis, this and the naira-EURO exchange rates experienced

Table 3: Persistence of volatility using absolute log-returns series

Methods		Non-parametric	Semiparametric	Parametric
Naira-CFA	Pre-crisis	0.0877***	0.0424***	0.0423***
	Post-crisis	0.2036***	0.1690***	0.1736***
	Full sample	0.1229***	0.0761***	0.0760***
Naira-EURO	Pre-crisis	0.1815***	0.1232***	0.1228***
	Post-crisis	0.2140***	0.1891***	0.1928***
	Full sample	0.1864***	0.1613***	0.1611***
Naira-GBP	Pre-crisis	0.1350***	0.1679***	0.1674***
	Post-crisis	0.2396***	0.1583***	0.1646***
	Full sample	0.2081***	0.1599***	0.1597***
Naira-USD	Pre-crisis	0.1585***	0.1650***	0.1646***
	Post-crisis	0.1856***	0.1617***	0.1630***
	Full sample	0.1385***	0.1561***	0.1559***
Naira-WAUA	Pre-crisis	0.1654***	0.1430***	0.1426***
	Post-crisis	0.1514***	0.1600***	0.1650***
	Full sample	0.1608***	0.1063***	0.1062***
Naira-JPY	Pre-crisis	0.0419***	0.0135***	0.0135***
	Post-crisis	0.1892***	0.1838***	0.1848***
	Full sample	0.1749***	0.1617***	0.1615***

*** Indicates significant estimate of *d* at 5% level.

Table 4: Persistence of volatility using squared log-returns series

Methods		Non-parametric	Semiparametric	Parametric
Naira-CFA	Pre-crisis	-0.0006	-	
	Post-crisis	0.1394***	0.1883***	0.1938***
	Full sample	-0.0007	-	-
Naira-EURO	Pre-crisis	0.1335***	0.1669***	0.1662***
	Post-crisis	0.1132***	0.2320***	0.2357***
	Full sample	0.1302***	0.2194***	0.2188***
Naira-GBP	Pre-crisis	0.0945***	0.2432***	0.2419***
	Post-crisis	0.1559***	0.1004***	0.1075***
	Full sample	0.1509***	0.1308***	0.1306***
Naira-USD	Pre-crisis	0.0974***	0.2193***	0.2181***
	Post-crisis	0.1410***	0.1747***	0.1771***
	Full sample	0.0784***	0.0985***	0.0984***
Naira-WAUA	Pre-crisis	0.0718***	0.1140***	0.1136***
	Post-crisis	0.0934***	0.0965***	0.1029***
	Full sample	0.0637***	0.1137***	0.1135***
Naira-JPY	Pre-crisis	0.0891***	0.0374***	0.0373***
	Post-crisis	0.1027***	0.1783***	0.1792***
	Full sample	0.1142***	0.1946***	0.1942***

*** Indicates significant estimate of *d* at 5% level.

half-life of about 93 days. The estimates of autocorrelation at lag 1 for the returns are given in the last column of Table 5, and these values are large enough to judge the linear relationship between the current value of returns and its immediate value.

Looking at the possible asymmetry in each of the episodes of exchange rates using GJR-GARCH estimates in Table 6. The leverage effects, as depicted by the estimates of asym-

Table 5: The GARCH (1,1) estimates and persistence measures

Exchange	Samples	$\hat{a}_0$	$\hat{a}_1$	$\hat{b}_1$	Persistence	Volatility, $\hat{\sigma}^2$	Half-life	Autocorr. $\hat{\rho}_1$
Naira-CFA	Pre- Crisis	2.63E-06	0.0992	0.5916	0.6908	9.00E+00	1.9	0.1101
	Post-crisis	1.72E-07	0.0328	0.9453	0.9781	7.85E-06	31.3	0.0557
	Full sample	2.28E-06	0.1156	0.6772	0.7928	1.10E-05	3.0	0.1391
Naira-EURO	Pre- Crisis	8.27E-08	0.0245	0.9631	0.9876	6.67E-06	55.6	0.0474
	Post-crisis	8.91E-08	0.0620	0.9306	0.9926	1.20E-05	93.3	0.2544
	Full sample	7.82E-08	0.0463	0.9491	0.9954	1.70E-05	150.3	0.2260
Naira-GBP	Pre- Crisis	5.26E-07	0.0755	0.8368	0.9123	6.00E-06	7.6	0.1030
	Post-crisis	4.98E-08	0.0350	0.9551	0.9901	5.03E-06	69.7	0.0909
	Full sample	1.07E-07	0.0562	0.9340	0.9902	1.09E-05	70.4	0.1864
Naira-USD	Pre- Crisis	3.30E-17	0.1503	0.6001	0.7504	1.32E-16	2.4	0.1798
	Post-crisis	8.23E-17	0.2314	0.6811	0.9125	9.41E-16	7.6	0.3965
	Full sample	1.86E-09	0.1522	0.6025	0.7547	7.58E-09	2.5	0.1830
Naira-WAUA	Pre- Crisis	1.59E-07	0.0071	0.8638	0.8709	1.23E-06	5.0	0.0073
	Post-crisis	2.73E-08	0.0577	0.9349	0.9926	3.69E-06	93.3	0.2299
	Full sample	3.40E-08	0.0518	0.9474	0.9992	4.25E-05	866.1	0.6454
Naira-JPY	Pre- Crisis	1.52E-06	0.1236	0.6999	0.8235	8.61E-06	3.6	0.1553
	Post-crisis	1.10E-07	0.0415	0.9473	0.9888	9.82E-06	61.5	0.1095
	Full sample	1.27E-06	0.1693	0.7272	0.8965	1.23E-05	6.3	0.2620

Note: significant model estimates at 5% level are in bold

Table 6: The GJR-GARCH(1,1) estimates

Exchange rates	Samples	$\hat{a}_0$	$\hat{a}_1$	$\hat{b}_1$	$\hat{c}_1$	Symmetric effect	Asymmetric effect
Naira-CFA	Pre- Crisis	1.34E-04	0.0714	0.9217	0.1529	0.9931	1.1460
	Post-crisis	2.09E-05	0.0334	0.9600	0.1060	0.9934	1.0994
	Full sample	2.23E-06	0.1294	0.6704	-0.0257	0.7998	0.7741
Naira-EURO	Pre- Crisis	2.47E-04	0.0366	0.9646	0.0284	1.0012	1.0296
	Post-crisis	4.90E-07	0.0648	0.9352	0.1141	1.0000	1.1141
	Full sample	7.69E-08	0.0442	0.9493	0.0038	0.9935	0.9973
Naira-GBP	Pre- Crisis	6.67E-06	0.0839	0.8552	0.0986	0.9391	1.0377
	Post-crisis	1.56E-04	0.0234	0.9817	0.9999	1.0051	2.0050
	Full sample	1.07E-07	0.0577	0.9336	-0.0023	0.9913	0.9890
Naira-USD	Pre- Crisis	1.13E-16	0.2009	0.6888	0.0555	0.8897	0.9452
	Post-crisis	5.22E-17	0.2378	0.7020	0.0405	0.9398	0.9803
	Full sample	4.58E-16	0.2138	0.6932	0.0425	0.9070	0.9495
Naira-WAUA	Pre- Crisis	2.36E-07	0.0217	0.8304	0.0332	0.8521	0.8853
	Post-crisis	7.57E-08	0.0518	0.9333	-0.2817	0.9851	0.7034
	Full sample	4.17E-08	0.0777	0.9401	-0.0410	1.0178	0.9768
Naira-JPY	Pre- Crisis	1.02E-04	0.0758	0.872	-0.6328	0.9478	0.3150
	Post-crisis	1.48E-05	0.0680	0.9302	-0.2136	0.9982	0.7846
	Full sample	1.20E-06	0.1990	0.7404	-0.0756	0.9394	0.8638

Note: significant model estimates at 5% level are in bold

metric parameters $\hat{c}_1$ in all the models for bank shares returns are significant in at least a phase of the financial crisis. In naira-USD, naira-WAUA and naira-JPY exchange rates, leverage effect is present in the series in pre-crisis and post-crisis periods. In pre-crisis period, naira-CFA exchange rates indicated asymmetric returns, while naira-EURO and naira-USD exchange rates indicated asymmetric return in the returns series in the post-crisis period. These three exchange rates generally, do not indicate evidence of significant leverage effect in their full series.

5. Conclusion and Recommendations

This paper investigated the volatility persistence in naira exchange rates during pre-global and post-global crisis periods by using six major naira exchange rates, sampled between 12 October, 2001 and 19 December, 2014. These are the naira-CFA, naira-EURO, naira-GBP, naira-USD, naira-WAUA and naira-JPY exchange rates. Having identified the two subsamples based on an algorithm by Pagan and Soussounov (2003), the results showed dramatic differences in the level of volatility persistence in the time series subsamples. Long range dependence approach on the exchange rates and the returns indicate lesser persistence of volatility before the global crisis in the six exchange rates. For instance, the naira-USD exchange rates presented the least volatility in the overall series. This stability between naira and US dollar has often recognized US dollars as a general foreign currency in Nigeria. Furthermore, applying the GARCH and GJR-GARCH estimates on the returns of the exchange rates, we obtain higher persistence of volatility in the post crisis period. The volatility shocks of the exchange rates after the crisis last for longer periods as indicated by the estimates of half-life of volatility.

The higher volatility in exchange rates in the post crisis period is due to many factors. One, the residual impact of the financial crisis on the economy was felt during the post crisis period as indicated in the very high half-life estimates. Two, interest rates differentials for banks by central banks between 2008 and 2009 is responsible for the sharp transition of exchange rates in 2008, until it stabilized, since money had to be injected into the economy by assisting banks with loan with low interest rates that helped then in cushion the global effect quickly. Due to the fact that volatility is higher during post 2008 global crisis, the monetary agency (Central Bank of Nigeria) therefore needs to put down measures to curb high exchange rate fluctuations.

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