Nigerian Foreign Exchange: Stylised Facts and Volatility Modelling

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Exchange rate plays an increasingly significant role in any economy as it directly affects domestic price level, profitability of traded goods and services, allocation of resources and investment decisions. The exchange rate and its risk are key factors that influence economic activities in Nigeria. An important measure in finance is the risk associated with an asset and asset volatility is perhaps the most commonly used risk measure. Volatility is used in risk management, value-at risk, portfolio analysis and derivatives pricing. It is well-known that economic and financial news have an impact on volatility and that "good" news and "bad" news do not have the same impact on future volatility. In Nigeria, the 2014 and 2015 exchange rate decisions by the Central Bank of Nigeria (CBN) have been of interest to risk managers, researchers, regulators, traders and other financial market participants.

In this paper, statistical analysis of Nigerian exchange rate (Naira/USD, Naira/Pound, Naira/Euro and Naira/Yuan) data is performed and a set of stylized empirical facts is observed in the data. We find that a good volatility model for the Naira and other currencies return series should capture serial correlation, time-varying variance, peakedness as well as fat tails. Furthermore, due to the existence of asymmetry of the return distributions observed, it is necessary to model left and right tails separately in order to capture their distinct characteristics. We also find that FIGARCH models with fat-tailed distributions are capable of capturing serial correlation, time-varying variance, long-memory, peakedness as well as fat tails for the Naira/USD. For the Naira/Yuan, Naira/Pound and Naira/Euro, the APARCH (1,1) model with student-t or skewed student-t error distributions are able to capture the stylised facts observed in the data.

1.0 INTRODUCTION

Academics, policymakers, regulators, and market practitioners have for long studied and modelled foreign exchange volatility in recognition of its importance for risk management and policy evaluation. Both financial market participants and regulators use volatility forecasts as inputs to models of risk management such as Value-at-Risk (VaR). Academics sought to model foreign exchange volatility because the volatility process reveals how news affects asset prices and what information is important. Policymakers are interested in measuring asset price volatility to learn about market expectations and uncertainty about policy. For instance, according to Erdemlioglu et. al. (2012), all things being equal, a clear understanding of policy objectives and tools would tend to reduce market volatility.

Volatility measures the dispersion of asset price returns. Asset price returns exhibit stylized facts that include non-normality, serial correlation, time-varying variance, peakedness and fat tails (Bollerslev et. al. (1992), Campbell et. al. (1997), Granger et.al. (2000), Engle (1993), Engle (2002), Figlewski (2004)). Risk forecasting is central to financial regulations, risk management, and macroprudential policy. Regulators and financial institutions increasingly depend on statistical risk forecasting. VaR is the most prominent statistical risk measure adopted by the Bank for International Settlement in its Basel II/III regulatory framework to set minimum capital requirements and to measure general financial risks. VaR has become the standard measure that financial analysts use to quantify market risk. Volatility is a key parameter in some of the VaR models that are used for risk capital estimation as introduced by the Basel Committee as well as for setting risk limits used by banks' trading desks.

As noted by Engle (2001), volatility models have been applied in a wide variety of applications. In most cases, volatility is itself an interesting aspect of the problem. In some cases, volatility is an input used for purposes of measurement, like in the example of estimating value at risk given earlier. In other cases, volatility may be a causal variable in models where expected volatility is a determinant of expected returns.

Moreover, most researchers agree that volatility is predictable and there is considerable disagreement on how volatility predictability should be modelled

(Engle and Ng, 1993). In addition, economic and financial news has an impact on volatility and that "good" news and "bad" news do not have the same impact on future volatility, a key stylized fact of volatility dynamics, (Engle and Ng, 1993; Glosten et.al. 1993). Therefore, several models have been proposed to model and forecast volatility in an attempt to capture the stylised facts of asset and volatility dynamics (Danilesson and Macrae, 2011).

After the CBN Monetary Policy Committee meeting of the 24th and 25th November 2014, the midpoint of the official window of the foreign exchange market was moved from ₦155/US$ to ₦168/US$[1]. In effect, the CBN devalued the currency by 8.3 per cent or ₦13 by moving the midpoint of the official window of the foreign exchange market.

In addition, on 19 February, 2015, the CBN closed the Retail and Wholesale Dutch Auction System of the foreign exchange market, signalling a further devaluation of the exchange rate from N168/US$ to N198/US$. The interbank forex market rate would represent a unified foreign exchange market rate. Along with the RDAS/WDAS closure, the naira exchange rate was devalued from N168/US$1 to N198/$1.

In this paper, we analyse the stylized facts of asset returns to the four pairs of Nigerian foreign exchange data. Specifically, we used the returns of the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates both on the day of the announcement and two business days after and then characterise the stylised facts in each of the four series based on the two announcement days. We seek answer to the following question: Do the asset returns of the four pairs of Nigerian exchange rate exhibit the widely observed stylised facts of asset returns based on the CBN policy announcements of **25th November 2014 and** 19 February, 2015?

[1] Central Bank of Nigeria Communique No. 98 of the Monetary Policy Committee Meeting of held on November 24 and 25, 2014, http://www.cenbank.org/documents/mpc.asp, Published 12/15/2014

This paper therefore also applies Autoregressive Conditional Heteroscedasticity (ARCH), symmetric GARCH and three asymmetric GARCH models (which are Exponential GARCH or EGARCH, GJR-GARCH and Asymmetric Power ARCH), unit-root GARCH models (IGARCH) and long memory in volatility, that is Fractionally Integrated GARCH or FIGARCH with variations in the distribution of the errors to be normal, student t and skewed student t that capture most stylized acts about exchange rate returns such as volatility clustering and leverage effect to the four pairs of Nigerian foreign exchange data. The question asked in this regard is 'Which volatility model best fits each of the four pairs of Nigerian foreign exchange data?'

There are several reasons for the analysis of returns and empirical volatility modelling. First, volatility is a statistical risk forecast, which according to the Basel Committee (2013, 2014), increasingly drives decisions of financial institutions and financial regulators. The choice of a model for volatility can influence the market risk capital charge by several percentages, either lower or higher by 0-200% as shown in the analysis of the Swiss foreign exchange risk modelling (Danielson, 2015b). Volatility is a key input in market risk capital estimation. Danielson (2008, 2015) showed that two risk measures behave differently in smaller sample sizes because of the choice of the model. Second, the hazard of working with a potentially incorrect model is called model risk. There are several volatility models and the accuracy of the volatility risk models depends crucially on the extent to which the data can be reliably modelled. Therefore, choosing an appropriate model to compute market risk measures like volatility estimates is an important and difficult task and helps in model risk management. Third, it is widely stated that model risk produced the crisis and that risk models don't perform well during crisis periods. Finally, there is the belief that a really complicated statistical model is needed for risk forecasting and that regulators should not rely on simpler methods.

Our goals are:

(i) To demonstrate empirical analysis of GARCH processes.

(ii) To compare different GARCH models.

(iii) Explore the role of alternative distributional assumptions in the estimation of GARCH models using the conditional normal, the Student-t and the skewed Student-t.

(iv) for bank regulators, the choice of the wrong VaR estimate, which in most cases rely on the particular volatility model, can make a great deal of difference in the actual capital to be set aside by the bank. Similarly, the bank risk managers can set the wrong or inappropriate limit for trading based on the wrong choice of volatility model.

We find that the Naira/Euro had the highest standard deviation value while the Naira/USD reported the lowest value of standard deviation. Furthermore, 2 days after the 19th February, 2015 policy announcement produced the highest value of standard deviation for each of the 4 exchange rates in comparison to the other periods used for the analysis. In terms of skewness, the four pairs of exchange rates produced positive skewness except the data used for 2 days after the 19th February, 2015 policy announcement, where all the rates produced negative skewness. Furthermore, the period that produced the highest skewed values, in decreasing order, are 2 days after 19th February, 2015 policy announcement, on 25th November 2014 policy announcement, on 19th February, 2015 policy announcement and 2 days after November 2014 policy announcement.

These findings suggest that a good volatility model for the Naira vs other currencies return series should capture i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails. Furthermore, due to the existence of asymmetry of the return distributions observed, it is necessary to model left and right tails separately in order to capture their distinct characteristics. In the case there is evidence of positive (negative) skewness, which means that the right (left) tails are particularly extreme.

Generally, modelling volatility of the four pairs of the exchange rate based on the announcements, the ARCH models produced lowest log-likelihood values compared to the GARCH-based models. The GARCH models are therefore preferred. In the GARCH models, APARCH models with skewed student t distribution is preferred for modelling volatility in all currency pairs except in the case of Naira/USD that portrayed FIGARCH as the best model. Also, the Naira/USD exchange rate produced the highest log-likelihood values while the Naira/Euro exchange rate produced the lowest fit in terms of the log-likelihood values. Moreover, the models with Student t and Skewed Student t distribution of residuals produced better fit for the exchange rate than those based on Normal distribution.

This paper is structured as follows. Section 2 presents the literature review of stylized facts of asset returns and GARCH volatility models. Section 3 analyses the stylized facts of the four pairs of the exchange rate both on the day of the announcement and two business days after the announcements of 24 November 2014 and 19 February 2015. Section 4 empirically models the four pairs of the exchange rate using several GARCH volatility models. The last Section concludes, presents findings and offers some policy implications of modelling foreign exchange volatility.

2.0 STYLIZED FACTS OF ASSET RETURNS

There are characteristics that asset returns and its associated volatility, as empirically observed over the years, should follow and referred to as Stylised Facts/Behaviour of Asset Returns. **In the light of the previous research of (**Bollerslev et. al. (1992), Campbell et. al. (1997), Granger et.al. (2000), Engle (1993), Engle (2002), Figlewski (2004))**, we focus on the following stylised facts in this paper (especially the first four).**

i. **Log returns are not Gaussian: The (unconditional) distribution of log returns seems to display fat-tails (a power-law or Pareto-like tails) for most data sets studied.**

ii. Slow decay of autocorrelation in absolute returns: The autocorrelation function of absolute returns decays slowly as a function of the time lag, roughly as a power law. This is sometimes interpreted as a sign of long-range dependence**.**

iii. **Volatility clustering: Different measures of volatility display a positive autocorrelation indicating that high-volatility events tend to cluster in time.**

iv. **Gain/loss asymmetry: Large drawdowns in stock prices and stock index values but not equally large upward movements. In other words, the distribution is skewed.**

v. **Aggregational gaussianity: As one increases the time scale over which returns are calculated, their distribution looks more and more like a normal distribution.**

vi. Leverage effect: Most measures of volatility of an asset are negatively correlated with the returns of that asset.

vii. Volume/volatility correlation: Trading volume is correlated with all measures of volatility.

2.1 MODELLING AND FORECASTING VOLATILITY

Volatility simply measures the degree randomness plays in price behaviour. Figlewski (2004) argues that, in practice volatility is very hard to predict. It is a function of time, exhibiting a combination of deterministic and random behaviour and should therefore be measured for each project. The volatility of the main financial prices - exchange rates, interest rate futures, stock indexes - is often understood or perceived as a measure of risk. Volatility is indeed one of the most important risk indicators that is available to market participants and market observers. Volatility is a key determinant of the value of commodity-based contingent claims, whether financial or "real". Volatility is simply the standard deviation of returns.

2.2 METHODS OF ESTIMATING VOLATILITY

Two of the most commonly used volatility estimates in financial analysis are: historical volatility (volatility is estimated from historical data) and implied volatility (volatility is estimated by examining the prices at which options on these assets trade). A third type, stochastic volatility, is harder to model but gives more accurate representation of actual volatility (Fouque et al., 2000). The method to use in estimating volatility depends on the data. Each method has its merits and may work well in some circumstances.

Historical volatility are simple average measures – for example, the standard deviation of daily, weekly or monthly returns over a 4-year period. They are therefore the simplest of the volatility models to calculate. If the data is reasonably constant through time then historical volatility can serve as a good estimate of future volatility. However, if the volatility exhibits high random behaviour, then historical volatility will over or underestimate the future volatility (Clewlow & Strickland, 2000).

Historical volatility possess a number of drawbacks. First, it would not take advantage of short-term persistence in volatility that could lead to more accurate short-term forecasts given that historical volatility can be slow to respond to changing market circumstances and the observations are unweighted. Second, it is not able to accurately capture an extreme event like a big currency devaluation or market crash (Brooks, 2008).

Implied volatility is the volatility embedded in the Black-Scholes Options formula. According to Darrel (1998), implied volatility can be calculated from Black-Scholes by inverting the volatility implied by the option price.

Stochastic volatility, like Autoregressive Conditional Heteroscedasticity (ARCH) models have been extensively used to model financial data and have been regarded as stochastic volatility models. Generalised ARCH (GARCH) models are used to estimate volatility instead of ARCH. GARCH models use lagged values for the dependent variable in addition to the residuals to estimate volatility whereas ARCH models rely only on the residuals and hence give a better estimate. Jarrow (1998) state that GARCH models provide a better estimate of volatility than ARCH and GARCH (1,1) is adequate for almost all financial econometrics.

GARCH models overcome the problems associated with historical volatility model due to the fact that a GARCH model that is "stationary in variance" will have forecasts that converge upon the long-term average as the horizon increase. GARCH models will also overcome the two problems with unweighted averages described above. Thus it is important to apply a "reality check" to estimated GARCH models to ensure that the coefficient estimates are intuitively plausible. An interesting property of ARCH models is that the kurtosis of shocks is strictly greater than the kurtosis of a normal distribution. This is because, an ARCH model is a variance-mixture of normals which must produce a kurtosis greater than three.

For detailed discussion on volatility estimation, forecasting and diagnostics, the reader is referred to Brooks (2008) and Figlewski (2004).

This paper is concerned with the following volatility models.

2.3 Historical Volatility

If n denotes number of observations, S exchange rate at at time period t=1,2,3,4… *T* then our continuously compounded rate of return as given in (1) is defined as:

r_t = ln(S_t /S_{t-1})

(1)

To calculate the historical volatility σ, we first calculate the logarithmic price returns r_t, then calculate the standard deviation of the logarithmic price returns and annualize the standard deviation by multiplying it by the current factor.

The best forecast of volatility at time t σ is the average of all past realized volatilities at time *t*.

$$\sigma^2(r_t) = \frac{1}{t-1}\sum_{t=1}^{T}\left(r_t - \bar{r} \right)^2 \tag{2}$$

Where the sample average of the returns, $\bar{r} = \sum_{t=1}^{T} r_t$

2.4 ARCH Model

Let the dependent variable be labeled r_t be the return on an asset or portfolio. The mean value m and the variance *h* will be defined relative to a past information set. Then, the return *r* in the present will be equal to the mean value of *r* (that is, the expected value of *r* based on past information) plus the standard deviation of *r* (that is, the square root of the variance) times the error term for the present period.

ARCH models based on the variance of the error term at time *t* depends on the realized values of the squared error terms in previous time periods. The model is specified as:

$$y_t = u_t \tag{3}$$

$$u_t \sim N(0, h_t)$$

$$h_t = \alpha_0 + \sum_{t=1}^{q} \alpha_j u_{t-i}^2 \tag{4}$$

This model is referred to as ARCH (q), where q refers to the order of the lagged squared returns included in the model. The complete ARCH (q) model of Engle (1982) relates the current level of volatility to the past q squared shocks. If we use ARCH (1) model it becomes

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{5}$$

Since h_t is a conditional variance, its value must always be strictly positive; a negative variance at any point in time would be meaningless. To have positive conditional variance estimates, all of the coefficients in the conditional variance are usually required to be non-negative. Thus coefficients must be satisfy $\alpha_0 > 0$ and $\alpha_1 \geq 0$. Unfortunately, like most models, ARCH models typically require 5-8 lags of the squared shock to adequately model conditional variance (Sheppard, 2013).

2.5 GARCH Model

Bollerslev (1986) developed the GARCH (p,q) model. The model allows the conditional variance of variable to be dependent upon previous lags; first lag of the squared residual from the mean equation and present news about the volatility from the previous period which is as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{6}$$

This model is also a weighted average of past squared residuals, but it has declining weights that never go completely to zero. The most used and simple model is the GARCH (1,1) process, for which the conditional variance can be written as follows:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{7}$$

We can easily find that

$$h = \alpha_0 + \alpha_1 h + \beta_1 h. \tag{8}$$

Solving the equation we have

$$h = \frac{\alpha_0}{1 - \alpha_1 - \beta_1} \tag{9}$$

For this unconditional variance to exist, it must be the case that $\alpha_1 + \beta_1 < 1$ and for it to be positive, we require that $\alpha_0 > 0$.

This model forecasts the variance of date t return as a weighted average of a constant, yesterday's forecast, and yesterday's squared error. Of course, if the mean is zero, then from the surprise is simply r_{t-1}^2. Thus the GARCH models are conditionally heteroskedastic but have a constant unconditional variance. According to GARCH, the best predictor of the variance in the next period is a weighted average of the long-run average variance, the variance predicted for this period, and the new information in this period that is captured by the most recent squared residual. Such an updating rule is a simple description of adaptive or learning behavior and can be thought of as Bayesian updating (Engle, 2001).

2.6 GJR GARCH

Glosten, et.al (1993) develop the GARCH model which allows the conditional variance to have a different response to past negative and positive innovations. The GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries (Brooks, 2008). GJR GARCH captures the propensity for the volatility to rise more subsequent to large negative shocks than to large positive shocks, known as the "leverage effect".

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \gamma_i u_{t-i}^2 d_{t-1} + \sum_{i=1}^{p} \beta_j h_{t-j} \tag{10}$$

Where

$$d_{t-1} = \begin{cases} 1 \text{ if } u_{t-1} < 0, & \text{bad news} \\ 0 \text{ if } u_{t-1} \geq 0, & \text{good news} \end{cases}$$

In the model, effect of good news shows their impact by α_i, while bad news shows their impact by $\alpha + \gamma$. In addition if $\gamma \neq 0$ news impact is asymmetric and $\gamma > 0$ leverage effect exists. To satisfy non-negativity condition coefficients would be $\alpha_0 > 0$, $\alpha_i > 0$, $\beta \geq 0$ and $\alpha_i + \gamma_i \geq 0$. The GARCH model is simply a restricted version of the GJR-GARCH, with $\gamma = 0$

2.7 Exponential GARCH

Exponential GARCH (EGARCH) proposed by Nelson (1991) which has form of leverage effects in its equation. The GARCH process fails in explaining the "leverage effects" which are observed in the financial time series. The leverage effects represent the tendency of variation in the prices of stocks to be negatively correlated with changes in the stock volatility. In other words, the effect of a shock upon the volatility is asymmetric, meaning that the impacts of "good news" (positive lagged residual) and of "bad news" (negative lagged residual) are different. The EGARCH) model accounts for such an asymmetric response to a shock.

In the EGARCH model the specification for the conditional covariance is given by the following form:

$$\log(h_t) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{u_{t=i}}{\sqrt{h_{t=i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}} \tag{11}$$

In the equation γ_k represent leverage effects which accounts for the asymmetry of the model. While the basic GARCH model requires the restrictions the EGARCH model allows unrestricted estimation of the variance.

If $\gamma_k < 0$ it indicates leverage effect exist and if $\gamma_k \neq 0$ impact is asymmetric. The meaning of leverage effect bad news increase volatility.

The EGARCH model does not require any restriction on the parameters because, since the equation is on log variance instead of variance itself, the positivity of the variance is automatically satisfied, and that is the main advantage of the EGARCH model.

2.8 Integrated GARCH

A number of authors have found parameter estimates in GARCH (1,1) models close to the unit root region, and have proposed using the integrated GARCH or IGARCH process which imposes this restriction, see for example Engle and Bollerslev (1986).

Thus, IGARCH models are unit-root GARCH models. Similar to ARIMA models, a key feature of IGARCH models is that the impact of past squared shocks is persistent.

An IGARCH (1,1) model can be written as

$$h_t = \alpha_0 + (1-\beta_1)u_{t-1}^2 + \beta_1 h_{t-1} \tag{12}$$

Where $1 > \beta_1 > 0$.

2.9 Asymmetric Power ARCH (APARCH) Model

The APARCH model also delivers the long-memory property of returns discussed in Ding et.al (1993). In the APARCH model, the standard deviation is modeled rather than the variance. It is a very changable ARCH model and the model is specified as follows:

$$h_t^{\delta} = \alpha_0 + \alpha_1 \left(\left|u_{t-1}\right| - \gamma u_{t-1}\right)^{\delta} + \beta h_{t-1}^{\delta} \tag{13}$$

Besides leptokurtic returns, the APARCH model, as the GARCH model, captures other stylized facts in financial time series, like volatility clustering. The volatility is more likely to be high at time *t* if it was also high at time *t*–1. The APARCH model, as the GJR-GARCH model, additionally captures asymmetry in return volatility. That is, volatility tends to increase more when returns are negative, as compared to positive returns of the same magnitude.

2.10 FIGARCH: A Long Memory Model for Volatility

Most financial time series have d = 1, d is the degree of integration, for the (raw or log) levels, for instance log of exchange rates. It is the volatility which typically has a fractional value of d. What is needed, then, is a long memory model for the volatility of returns which allows the returns themselves to be a Martingale Difference.

The Fractionally Integrated GARCH (FIGARCH) model of Baillie, Bollerslev, and Mikkelsen (1996), is written as: FIGARCH (p , d , q) for p ∈ {0, 1} and q ∈ {0, 1}. FIGARCH is a fractionally integrated version of GARCH, which is usually represented using its ARCH (∞) representation.

$$h_t = \alpha_0 + \sum_{i=1}^{\infty} \lambda_i u_{t-i}^2 \quad (14)$$

Where

$$\delta_1 = d$$

$$\lambda_1 = \phi - \beta + d \,.$$

$$\delta_1 = \frac{i-1-d}{i} \delta_{i-1}, i = 2,..$$

$$\lambda_1 = \beta\lambda_{i-1} + \delta_i - \phi\delta_{i-1,} i = 2,....$$

3.0 EMPIRICAL ANALYSIS OF EXCHANGE RATE SERIES

Our raw data represents 1000 observations of the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates both on the day of the announcement (**25th November 2014 and** 19 February, 2015) and two business days after. We therefore have 8 data series for the analysis. For the policy announcement of the **25th November 2014, data was downloaded from CBN website**[2] **covering** 10/28/2010 to 11/21/2014 and 11/01/2010 to 11/25/2014 for 2 days after the announcement. Similarly, the 19 February, 2015 policy decision had data downloaded covering 1/25/2011 to 2/18/2015 and from 1/27/2011 to 2/20/2015 for 2 days after the announcement.

Table 1 gives a selection of descriptive statistics for the daily raw of the four series and are plotted In Figure 1.

[2] www.cenbank.org

Let the daily return of Naira vs (USD, Euro, Pound or Yuan) exchange rate be calculated as follows:

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

Where P_t is the closing price on tth day and r_t is the continuously compounded return on tth day.

Table 1a: Descriptive Statistics of Nominal (Raw) Price for policy announcement of the **25th November 2014**

PRICE	MEAN	MEDIAN	MIN	MAX	STD	MODE	SKEWNESS	KURTOS
Naira/USD	154.18	155.24	148.00	157.91	2.216	155.25	-1.50	3.81
Naira/Yuan	236.57	237.41	225.44	246.71	3.90	231.62	-0.36	3.03
Naira/Euro	206.09	206.09	187.87	226.89	7.16	203.64	-0.04	2.70
Naira/Pound	246.70	246.21	228.70	266.51	8.00	240.11	0.33	2.66

Table 1b: Descriptive Statistics of Raw Price for policy announcement of the **25th November 2014 but** two days after the announcement

PRICE	MEAN	MEDIAN	MIN	MAX	STD	MODE	SKEWNESS	KURTOS
Naira/USD	154.21	155.24	148.00	162.00	2.23	155.25	-1.39	4.00
Naira/Yuan	236.56	237.41	225.44	246.71	3.91	231.61	-0.36	3.01
Naira/Euro	206.08	206.09	187.87	226.89	7.16	203.64	-0.04	2.69

Naira/Pound	246.73	246.28	228.70	266.51	8.00	240.11	0.32	2.65

Table 1c: Descriptive Statistics of Raw Price for policy announcement of the 19 February, 2015

PRICE	**MEAN**	**MEDIAN**	**MIN**	**MAX**	**STD**	**MODE**	**SKEWNESS**
Naira/USD	155.251	155.2500	149.4500	167.5000	3.4388	155.2500	2.0695
Naira/Yuan	237.1239	237.6916	226.7846	246.7062	3.5638	242.7450	-0.1659
Naira/Euro	206.0314	206.1997	187.3655	226.8884	7.3400	203.6414	-0.1555
Naira/Pound	248.1492	247.3569	230.8716	306.8215	8.1911	240.1097	0.9353

Table 1d: Descriptive Statistics of Raw Price for policy announcement of the 19 February, 2015 **but** 2 days after the announcement

PRICE	**MEAN**	**MEDIAN**	**MIN**	**MAX**	**STD**	**MODE**	**SKEWNESS**
Naira/USD	155.3486	155.2500	149.4500	198.5000	3.9374	155.2500	3.9640
Naira/Yuan	237.1802	237.7020	226.7846	280.9410	3.8129	242.7450	1.3495
Naira/Euro	206.0733	206.2674	187.3655	226.8884	7.3907	203.6414	-0.1330
Naira/Pound	248.1492	247.3569	230.8716	306.8215	8.1911	240.1097	0.9353

From Tables 1(a-d), the various exchange rates (USD, Euro, Pound and Yuan) against the Naira shows evidence of non-normality: not symmetric with skewness not equal to 0, have fat tails with kurtosis not equal to 3.

Figures 1a and 1b show that nominal exchange rates have stochastic trend, that is, they are nonstationary. Other nominal rates for Naira/Pound and Naira/Euro depicted similar characteristics. The absence of normality and stationarity observed in the nominal exchange rates of Naira vs other currencies is as observed in previous studies of exchange rates (Erdemlioglu et al, 2012).

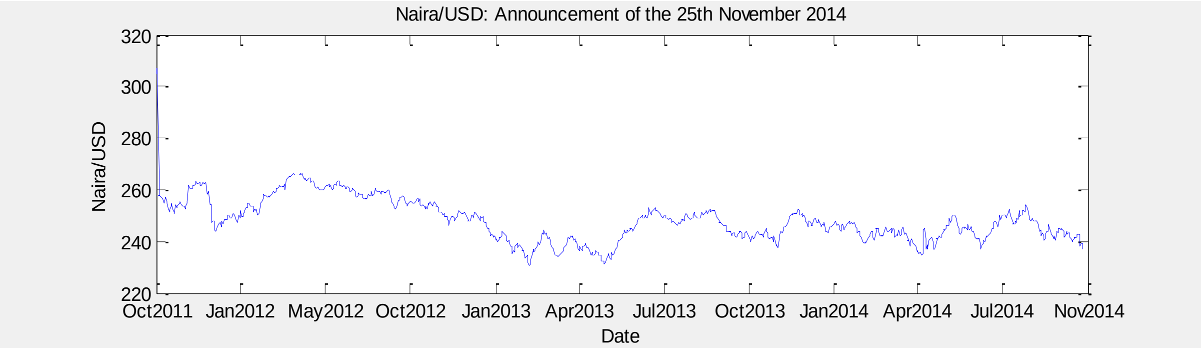


Figure 1a: Naira/USD Exchange Rate for policy announcement of the **25th November 2014**

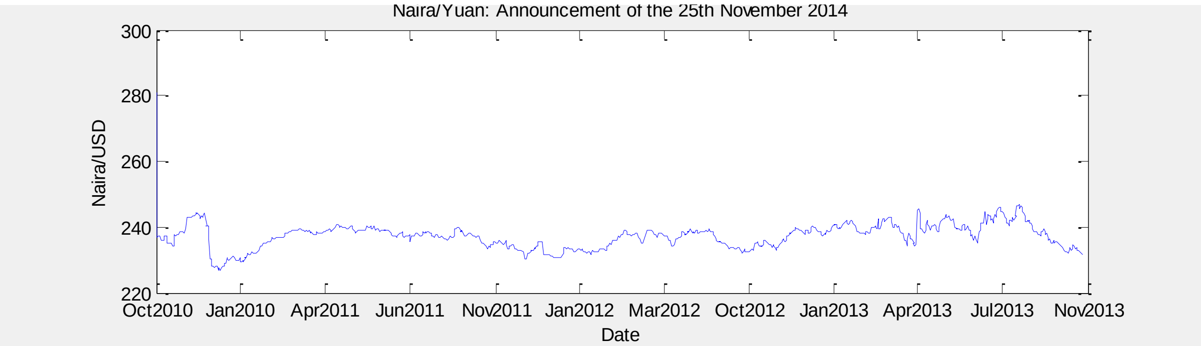


Figure 1b: Naira/Yuan Exchange Rate for policy announcement of the **25th November 2014.**

From Figure 1, we observe that the prices have been very volatile[3]. The trajectory of the exchange rates is visible at various times, which concide with

[3] Though there are 4 foreign exchange prices, we have only plotted two to save space. All the four series exhibited similar pattern because they are global currencies priced against the Naira.

policy decisions that affect the exchange rates. Nevertheless, its gains and losses in the second decade fall back into with other world markets.

We therefore consider a stationary series so as to carry out empirical analysis of the exchange rates with associated risk measure.

Tables and 2a and 2b gives a selection of descriptive statistics for the daily log returns of the four series of the **25th November 2014 announcement as well as announcement of two days later, respectively.**

3.1 Analysing Stylized Facts of Asset Returns of Foreign Exchange Return based on the policy announcement of the 25th November 2014[4] and 2 days later

Table 2a: Descriptive Statistics of Foreign Exchange Return based on the policy announcement of the **25th November 2014**

RETURN SERIES	**MEAN**	**MEDIAN**	**MIN**	**MAX**	**STD**	**MODE**	**SKEWNESS**	**KURTOSIS**
Naira/USD	0	0	-0.014	0.045	0.18 %	0	14.93	412.98
Naira/Yuan	0	0	-0.02	0.044	0.33 %	0	2.17	37.09

[4] To save space, not all plots of the four series will be shown as presented in the analysis of policy announcement of 24th November 2014. This is because the different exchange rates displayed similar characteristics. The reader can observe the characteristics of those not shown based on those plotted.

			0					
Naira/Euro	0	0	-0.087	0.086	0.69%	0	0.20	51.80
Naira/Pound	0	0	-0.020	0.040	0.47%	0	0.49	8.10

Table 2b: Descriptive Statistics of Foreign Exchange Return based on 2 days after the policy announcement of the **25th November 2014**

RETURN SERIES	**MEAN**	**MEDIAN**	**MIN**	**MAX**	**STD (%)**	**MODE**	**SKEWNESS**	**KURTOSIS**
Naira/USD	0	0	-0.0200	0.0389	0.47	0	0.4876	8.0996
Naira/Yuan	0	0	-0.0200	0.0438	0.33	0	2.1476	36.905
Naira/Euro	0	0	-0.0200	0.0389	0.47	0	0.4876	8.0996
Naira/Pou	0	0	-	0.086	0.6	0	0.1635	50.748

nd			0.086 7	3	9			

Nonnormality

Arithmetic mean and median as measures of central tendency, are very close to zero for both **25th November 2014 announcement (Table 2a) as well as announcement of 2 days later (Table 2b)**. Thus the standard assumption of the Random Walk model that the expected value of daily returns equals zero is met. In terms of daily standard deviation from Table 2a, the Naira/USD had the lowest (0.18%) and the Naira/Euro the highest (0.69%), more than triple the Naira/USD. However, for 2 days after the **25th November 2014 announcement,** the Naira/Yun had the lowest (0.33%), the Naira/Pound the highest (0.69%) value and both the Naira/USD as well as Naira/Euro had 0.47% as the standard deviation.

In terms of assessing the normality of logarithmic returns of the exchange rates, the results for the four pairs of returns series[5] all show strong departure from normality, as the coefficients of skewness (value not equal to zero) and kurtosis (greater than 3) are statistically different from those of a normal distribution. All the pairs of series[6] have asymmetric tails and clearly leptokurtic (the sample kurtosis is much greater than 3), which justifies the assumption of fat-tailed distributions. Because of the existence of asymmetry of the return distributions observed, it is necessary to model left and right tails separately in order to capture their distinct characteristics. In this case there is evidence of positive skewness, which means that the right tails are particularly extreme.

[5] both **25th November 2014 announcement (Table 2a) as well as announcement of 2 days later (Table 2b)**

[6] both **25th November 2014 announcement (Table 2a) as well as announcement of 2 days later (Table 2b)**

We now conduct formal tests of normality for the pairs of the return series based on the two policy announcements. The Jarque-Bera, Kolmogorov-Smirnov and Anderson-Darling normality tests and their p-values for each of the logarithmic daily returns both on **25th November 2014 announcement as well as announcement of 2 days later are shown in Tables 2c and 2d, respectively**. The Jarque-Bera test uses sample skewness and kurtosis to measure the deviation of a distribution from normality. Under the null hypothesis, both the skewness and excess kurtosis. The **Kolmogorov-Smirnov** (kstest) returns a test decision for the null hypothesis that the data in a vector comes from a standard normal distribution, against the alternative that it does not come from such a distribution. The Anderson-Darling test is commonly used to test whether a data sample comes from a normal distribution. However, it can be used to test for another hypothesized distribution, even if you do not fully specify the distribution parameters. Instead, the test estimates any unknown parameters from the data sample.

Table 2c: Jarque-Bera, Kolmogorov-Smirnov and Anderson-Darling normality tests for the foreign exchange return series based on the policy announcement of the **25th November 2014**

Return Series	**Jarque-Bera(5%)**	**p-value**	**Kolmogorov-Smirnov (5%)**	**p-value**	Anderson-Darling **(5%)**	**p-value**
Naira/USD	1	0.001	1	0.000	1	0.000
Naira/Yuan	1	0.001	1	0.000	1	0.005
Naira/Euro	1	0.020	1	0.000	1	0.008

Naira/Pound	1	0.010	1	0.000	1	0.000

Table 2d:Jarque-Bera, Kolmogorov-Smirnov and Anderson-Darling normality tests for the pairs of return series based on the policy announcement 2 days after the **25th November 2014**

Return Series	**Jarque-Bera(5%)**	**p-value**	**Kolmogorov-Smirnov (5%)**	**p-value**	Anderson-Darling **(5%)**	**p-value**
Naira/USD	1	0.001	1	0.000	1	0.0005
Naira/Yuan	1	0.001	1	0.000	1	0.0005
Naira/Euro	1	0.001	1	0.000	1	0.0005
Naira/Pound	1	0.001	1	0.000	1	0.0005

The Anderson-Darling, Jarque-Bera and Kolmogorov-Smirnov Normality tests from the two tables show that all the series strongly reject the null hypothesis of normality for all the series.

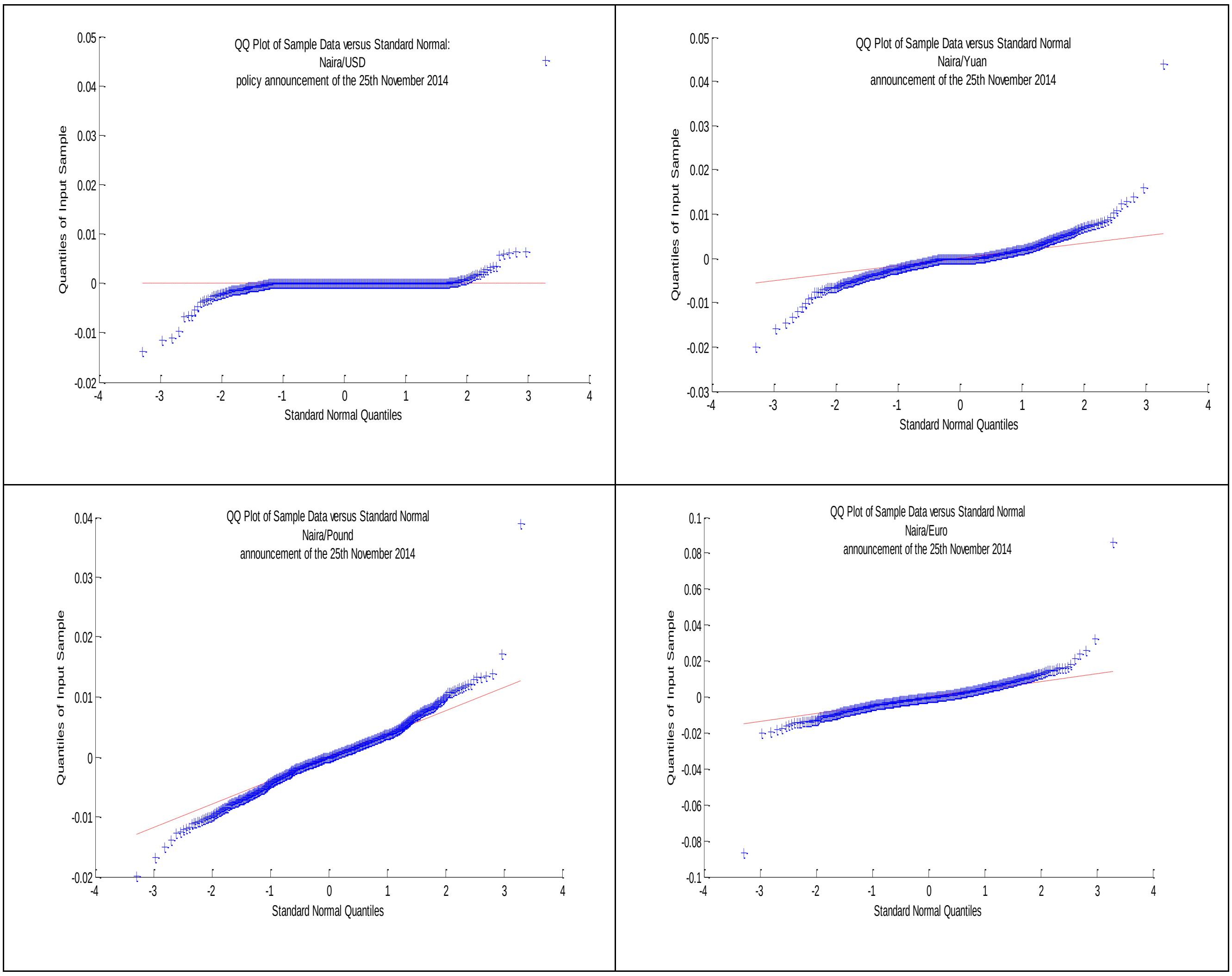
Quantile-Quantile Plot

Quantile-quantile plots (also called qq plot) are used to determine if two data sets come from populations with a common distribution (whether normally distributed or not). In such a plot, points are formed from the quantiles of the data. If the resulting points lie roughly on a line with the drawn slope, then the distributions are the same. The logarithmic daily returns on the four exchange rate series is normal, if the sample quantiles of the logarithmic daily returns on the four exchange rate series versus theoretical quantiles from a normal distribution is close to linear.

In particular, if the qq-plot is linear, then the specified distribution fits the data, and we have identified the distribution to which our data belongs. In addition, departures of the qq-plot from linearity in the tails can tell us whether the tails of our empirical distribution are fatter, or thinner, than the tails of the reference distribution to which it is being compared (Dowd, 2005).

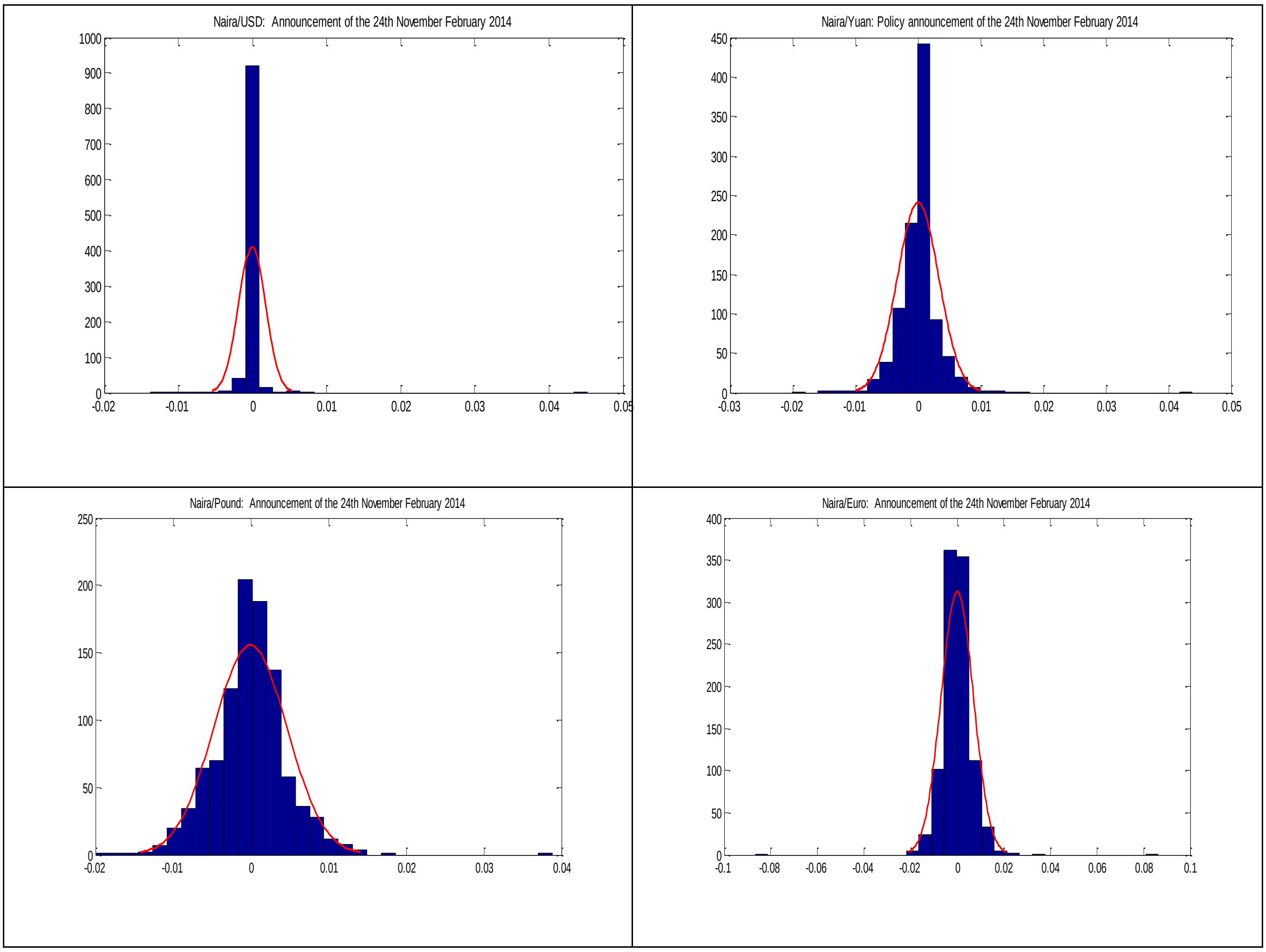
Figure 2 shows the qqplot of the logarithmic daily returns on the four exchange rate series (the empirical distributions) against standard normal quantiles. All the 4 qq-plots have steeper slopes at their tails while the central mass of the empirical observations are approximately linear, this suggests that empirical distributions have heavier tails than the reference distribution. A qq-plot where the tails have slopes different than the central mass is therefore suggestive of the empirical distribution having heavier, or thinner, tails than the reference standard normal distribution. In addition, outliers are visible in the upper right and lower left corners of all the plots. Fat tails mean that crashes and huge increases appear far more often than predicted by the normal law.

Figure 2: qqplot of the logarithmic daily returns of the four exchange rate series against standard normal quantiles for 25th November 2014 announcement



To further confirm the normality assumption for the four foreign exchange return series based on the policy announcement of the **25th November 2014, we consider how well these series individually fit a normal density function using a histogram, as plotted in Figure 3.** The histogram is a traditional way of displaying the shape of a group of data. It is well-known that the mathematical model of the normal distribution produces a perfectly smooth, symmetrical, bell-shaped curve. The mean and standard deviation of the data determine the shape of the bell. The mean locates the bell peak on the horizontal axis, and the standard deviation determines the width of the bell. The ideal shape to look for in the case of normality is a bell-shaped distribution. The red (solid) line with the bell shows a normal or Gaussian distribution.

Figure 3: Histogram of the logarithmic daily returns on the four exchange rate series for 25th November 2014 announcement



The empirical distributions are all more peaked than the normal density around the mean. Therefore, the logarithmic daily returns on the four exchange rate series exhibit fat tails (leptokurtic).

Figure 4 (upper row) shows the qqplot of the logarithmic daily returns of exchange rate series (the empirical distributions) against standard normal quantiles for 2 days after policy announcement of 25th November 2014. All the 4 qq-plots have steeper slopes at their tails while the central mass of the empirical observations are approximately linear, this suggests that empirical distributions have heavier tails than the normal distribution. The empirical distributions of the exchange rate superimposed on a histogram with normal density (lower row) shows that the exchange rates are all more peaked than the normal density around the mean. Therefore, the logarithmic daily returns on the four exchange rate series exhibit fat tails (leptokurtic).

Figure 4: qqplot and histogram of the logarithmic daily returns of the exchange rate series against standard normal quantiles (upper row) and fitted to a histogram (lower row) for 2 days after the 25th November 2014 announcement

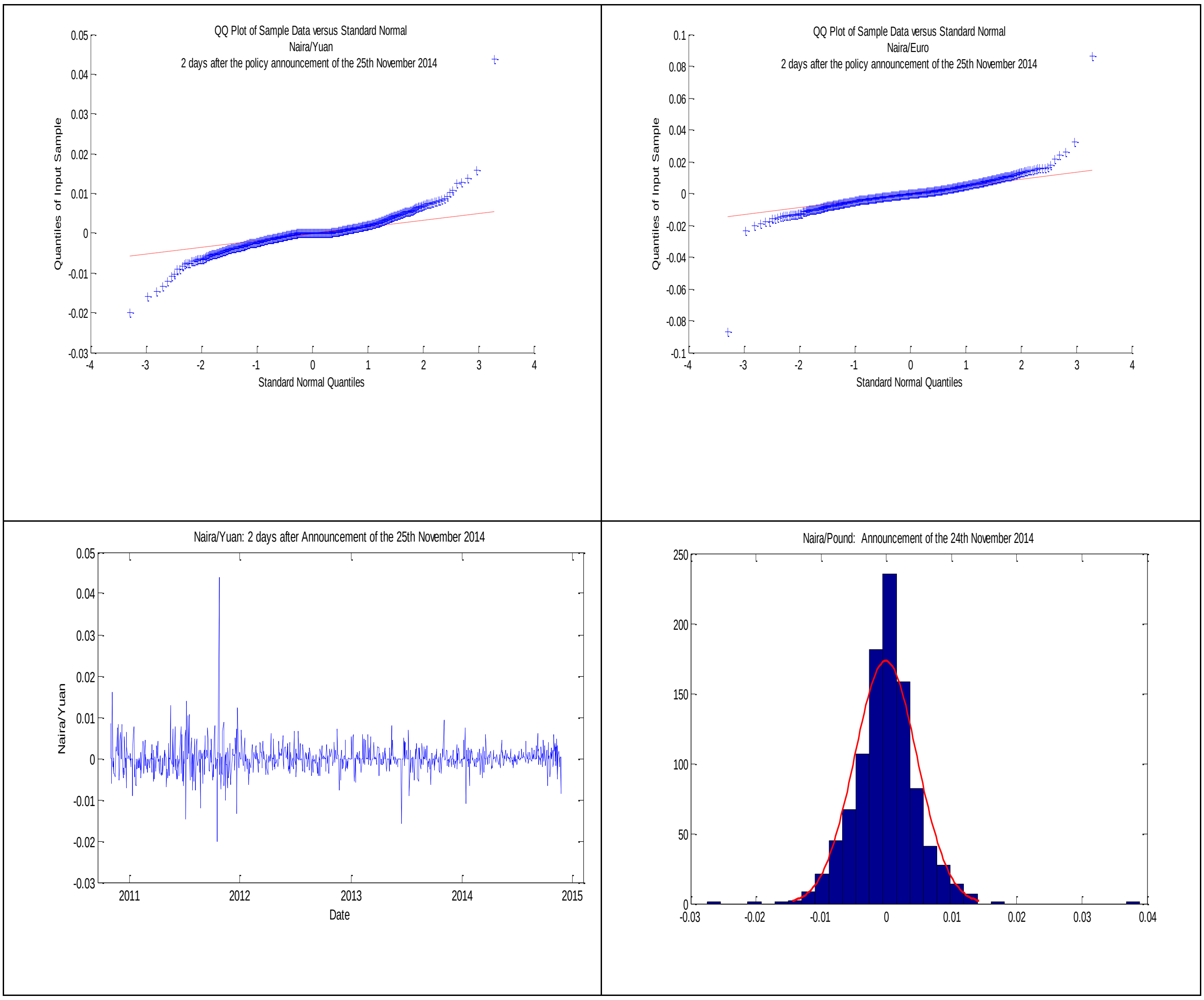


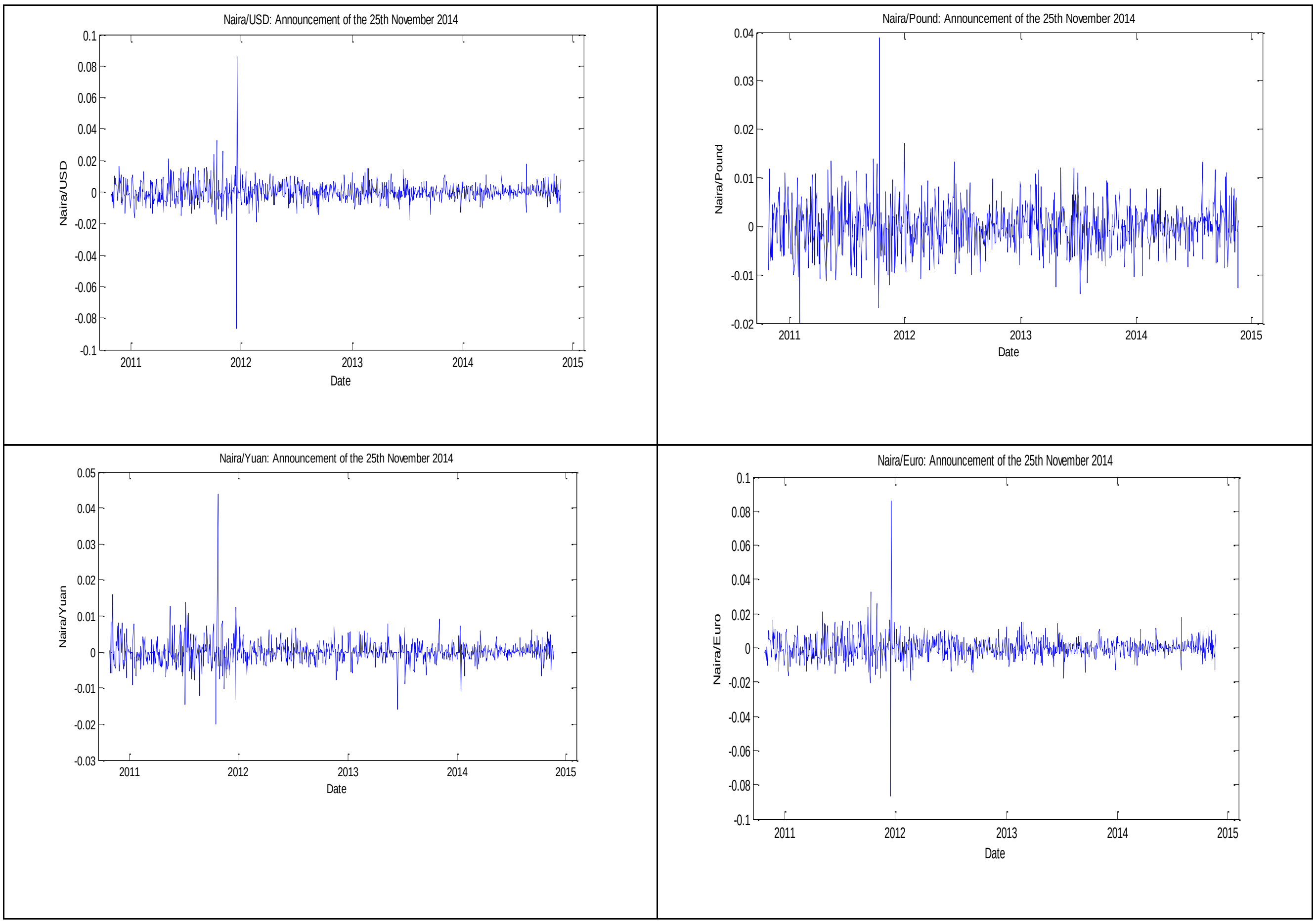
Figure 4 (lower left quadrant) shows the logarithmic daily returns of the Naira/Yuan exchange rate series with the returns fluctuating around a constant level, but exhibiting volatility clustering. The same characteristic was observed in the other 3 unreported series for 2 days after policy announcement of 25th November 2014.

Autocorrelation

Autocorrelation, "lagged correlation" or "serial correlation", is the linear dependence of a variable with itself at two points in time. For stationary processes, autocorrelation between any two observations only depends on the timelag between them. A well-known stylised fact is that exchange rates exhibit volatility clustering (that is, volatility shows positive autocorrelation) and the shocks to volatility can take some time to die out. We now investigate if there are autocorrelations in squared returns or "ARCH effects" in the daily returns on the four exchange rate series. Is there substantial evidence of ARCH effects based on the autocorrelations of the squared residuals of the daily returns on the four exchange rate series.

ARCH models are used to characterize and model time series. ARCH models assume that the variance of the current error term is related to the size of the previous periods' error terms, giving rise to volatility clustering. This phenomenon is widely observable in financial markets, where periods of low volatility are followed by periods of high volatility and vice versa. Figure 5 presents the logarithmic daily returns on the four exchange rate series for policy announcement of 25th November 2014.

Figure 5: Logarithmic daily returns of the four exchange rate series for 2 days after the 25th November 2014 announcement



The returns appear to fluctuate around a constant level, but exhibit volatility clustering. The bulges in the return plots are graphical evidence of time-varying volatility.

We therefore conducted both ARCH test of Engle (1988) and Ljung-Box Q-test on the squared residual series for the logarithmic daily returns on the four exchange rate series at lags 5, 10, 15 and 20. The null hypothesis is rejected for the two tests (h = 1) of the four exchange rate series. The p-value for all tests is 0. Thus, not all of the autocorrelations up to lag 5, 10, 15 or 20 are zero, indicating volatility clustering in the residual series.

To investigate autocorrelation for the pairs of exchange rate return series for 2 days after policy announcement of 25th November 2014, we conducted both

ARCH test of Engle (1988) and Ljung-Box Q-test on the squared residual series for the logarithmic daily returns on the four exchange rate series at lags 5, 10, 15 and 20. The null hypothesis is rejected for the two tests (h = 1) of the four exchange rate series. The p-value for all tests is 0. Thus, not all of the autocorrelations up to lag 5, 10, 15 or 20 are zero, indicating volatility clustering in the residual series.

These characteristics suggest that a good volatility model for the Naira vs other currencies return series of 25th November 2014 policy announcement and 2 days after are: i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails; should be captured .

3.2 Analysing Stylized Facts of Asset Returns of Foreign Exchange Return based the policy announcement of the 19th February 2015 as well as 2 days after the policy announcement of 19th February 2015

Tables 3a and 3b report descriptive statistics of foreign exchange return for policy announcement of the 19 february, 2015 and 2 days after, respectively.

Table 3a: Descriptive Statistics of Foreign Exchange Return for policy announcement of the 19 February, 2015

Return Series	**mean**	**median**	**min**	**max**	**Std (%)**	**mode**	**skewness**	**kurtosis**
Naira/USD	0	0	-0.0256	0.045	0.21	0	6.684	255.64
Naira/Yuan	0	0	-	0.044	0.34	0	1.321	36.895

			0.0263					
Naira/Euro	0	0	-0.0867	0.086	0.70	0	0.330	50.155
Naira/Pound	0	0	-0.0275	0.039	0.49	0	0.295	9.178

Table 3b: Descriptive Statistics of Foreign Exchange Return based on 2 days after the policy announcement of the 19 February, 2015

Return Series	**mean**	**median**	**min**	**max**	**Std (%)**	**mode**	**skewness**	**kurtosis**
Naira/USD	0	0	-0.170	0.045	0.58	0	-25.211	756.723
Naira/Yuan	0	0	-0.171	0.044	0.64	0	-18.779	510.251
Naira/Euro	0	0	-0.172	0.086	0.89	0	-7.051	159.880
Naira/Pound	0	0	-0.172	0.039	0.73	0	-12.961	309.948

From table 3, arithmetic mean and median as measures of central tendency, are very close to zero for both on and 2 days after the 19 February, 2015 policy announcement. Thus the standard assumption of the Random Walk model that the expected value of daily returns equals zero is met. In terms of daily standard deviation, the Naira/Euro had the highest value while Naira/USD had the lowest (0.33%) both on and 2 days after the 19 February, 2015 policy announcement.

The standard deviation is much higher for each foreign exchange rate 2 days after the 19 February, 2015 policy announcement than on the day of the announcement. This is expected as supported by empirical findings.

In terms of assessing the normality of logarithmic returns of the exchange rates, the results show that all four returns series show strong departure from normality, as the coefficients of skewness (value not equal to zero) and kurtosis (greater than 3) are statistically different from those of a normal distribution.

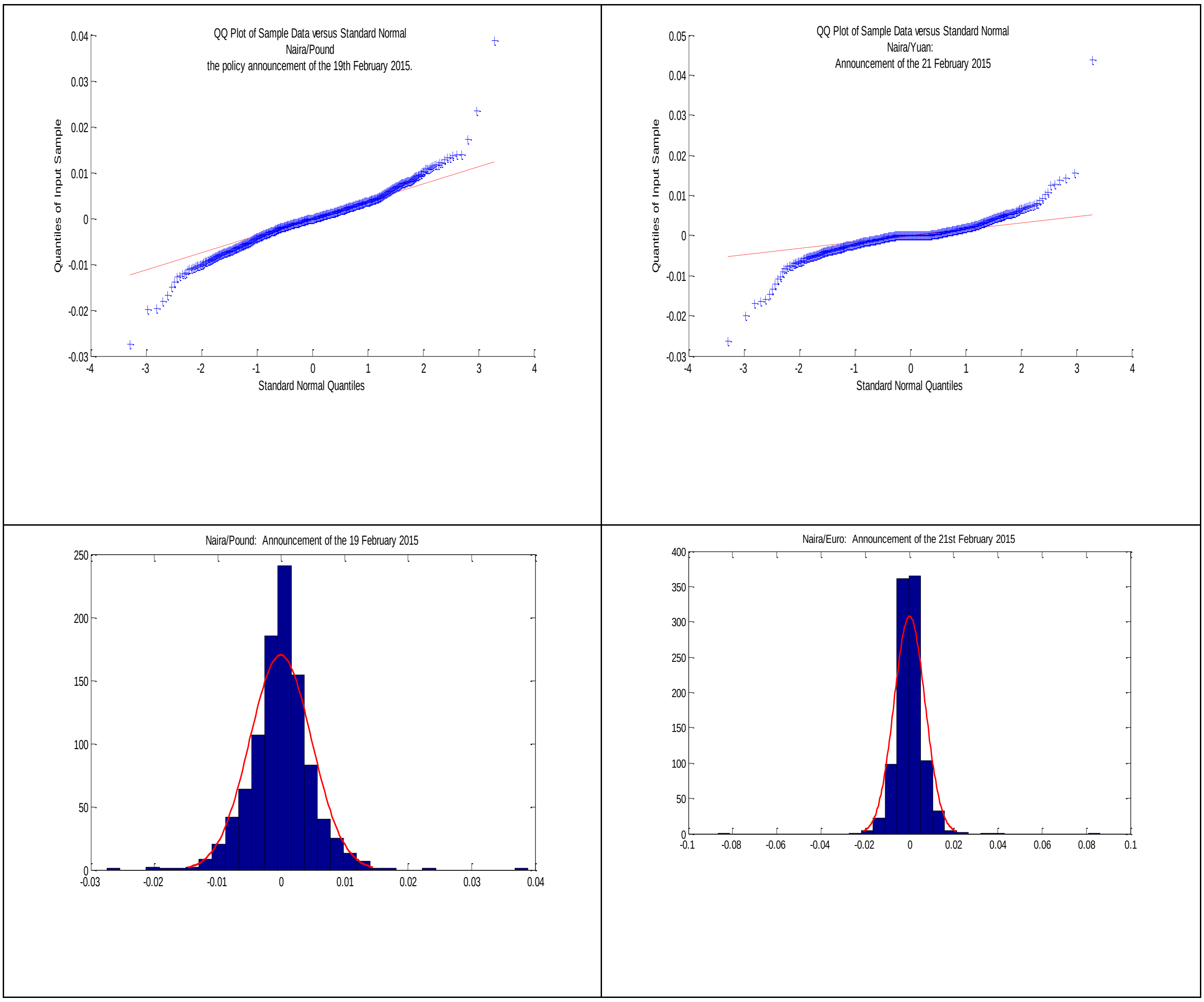
Formal tests of normality using the Anderson-Darling, Jarque-Bera and Kolmogorov-Smirnov Normality tests (not reported) strongly reject the null hypothesis of normality for the four foreign exchange return series based on and 2 days after the policy announcement of the **19th February 2015**.

Quantile-Quantile and Histogram Plots

Figure 5 (upper row) shows the qqplot of the logarithmic daily returns on exchange rate series (the empirical distributions) against standard normal quantiles. The left shows the Naira/Pound exchange rate based on 19 February, 2015 policy announcement while the right qqplot shows the Naira/Yuan exchange rate based on 21 February, 2015 policy announcement. The qpplots have steeper slopes at their tails while the central mass of the empirical observations are approximately linear, this suggests that empirical distributions have heavier tails than the normal distribution.

The empirical distributions of the exchange rate superimposed on a histogram with normal density (lower row) shows that the exchange rates are all more peaked than the normal density around the mean. Therefore, the logarithmic daily returns on the exchange rate series exhibit fat tails (leptokurtic). . The left shows the Naira/Pound exchange rate based on 19 February, 2015 policy announcement while the right histogram shows the Naira/Euro exchange rate based on 21 February, 2015 policy announcement.

Figure 5: qqplot and histogram of the logarithmic daily returns of the exchange rate series against standard normal quantiles (upper row) and fitted to a histogram (lower row)

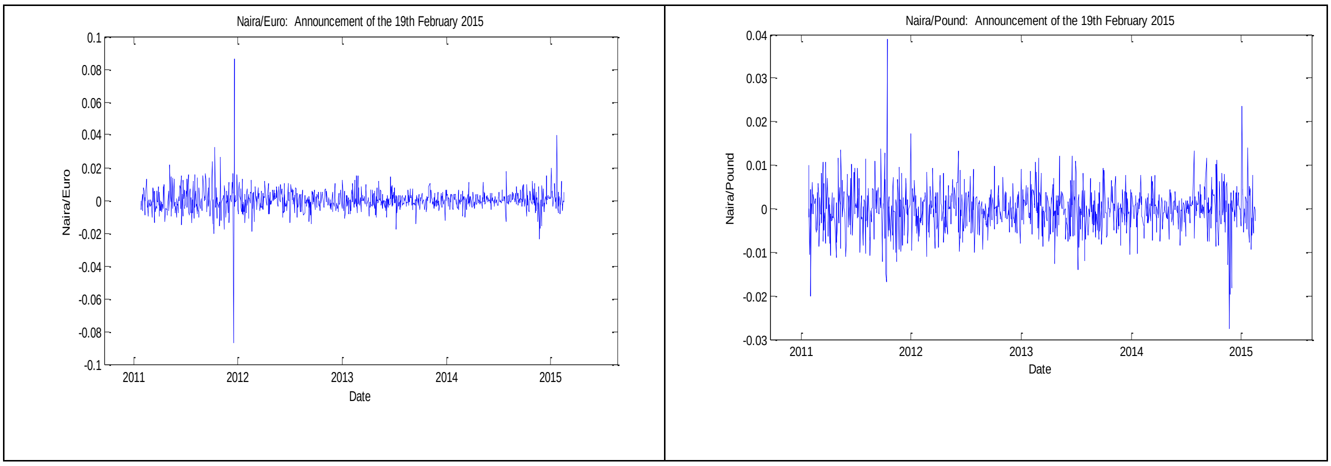


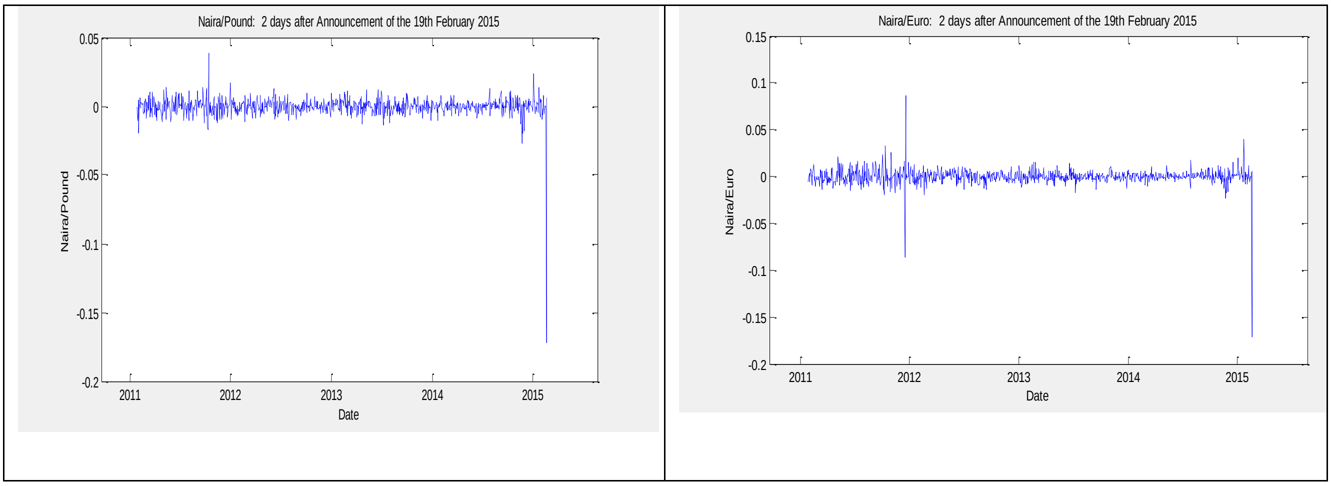
Autocorrelation

Figure 6 shows the logarithmic daily returns of exchange rate series with the returns fluctuating around a constant level, but exhibiting volatility clustering. The same characteristic was observed in the other unreported series. The top row shows the exchange rates based on 19 February, 2015 policy announcement while the right bottom shows exchange rates based on 21 February, 2015 policy announcement.

To investigate autocorrelation, we conducted both ARCH test of Engle (1988) and Ljung-Box Q-test on the squared residual series for the logarithmic daily returns on the four exchange rate series at lags 5, 10, 15 and 20. The null hypothesis is rejected for the two tests (h = 1) of the four exchange rate series. The p-value for all tests is 0. Thus, not all of the autocorrelations up to lag 5, 10, 15 or 20 are zero, indicating volatility clustering in the residual series.

Figure 6 shows the logarithmic daily returns of exchange rate series





These characteristics in Figure 6 and Table 4 suggest that a good model for the Naira vs other currencies return series should capture i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails.

3.3 Summary of Analysis of Stylized Facts of Asset Returns of Foreign Exchange Return Series and Lessons Learnt

Figure 7 shows a plot of the standard deviation of the logarithmic daily returns of the four exchange rate series on and 2 days after the 24 November 2014 policy announcement as well as on and 2 days after the 19 February, 2015 policy announcement. From the plot, the Naira/Euro has had the highest standard deviation value while the Naira/USD has had the lowest value of standard deviation. Furthermore, 2 days after the 19 February, 2015 policy announcement produced the highest value of standard deviation for each of the 4 exchange rates in comparison to the other periods used for the analysis.

Figure 7 shows a plot of the standard deviation of the pairs of the exchange rates

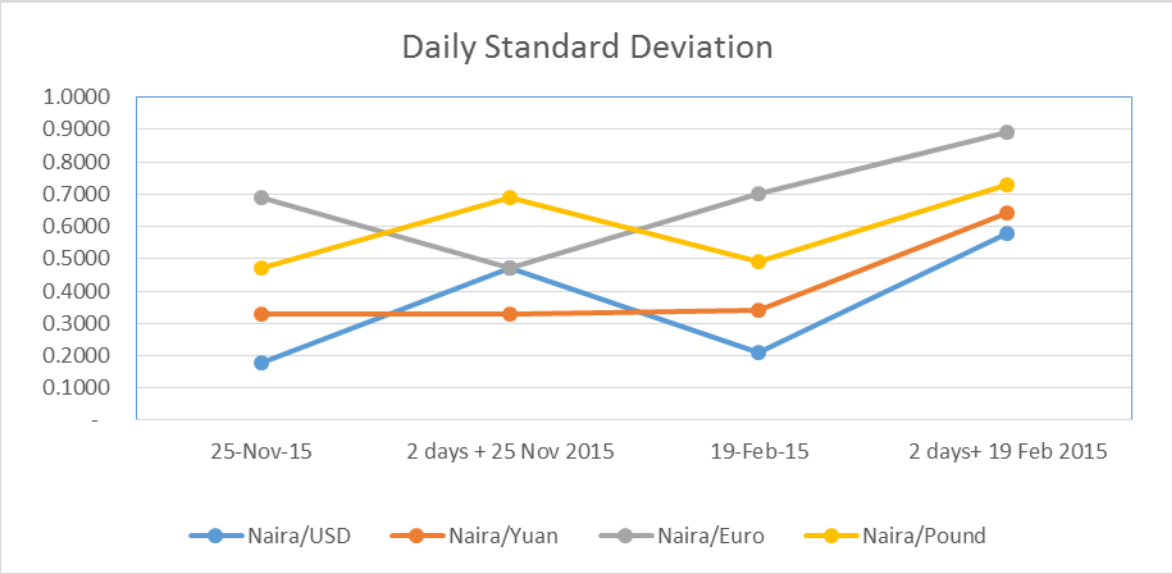
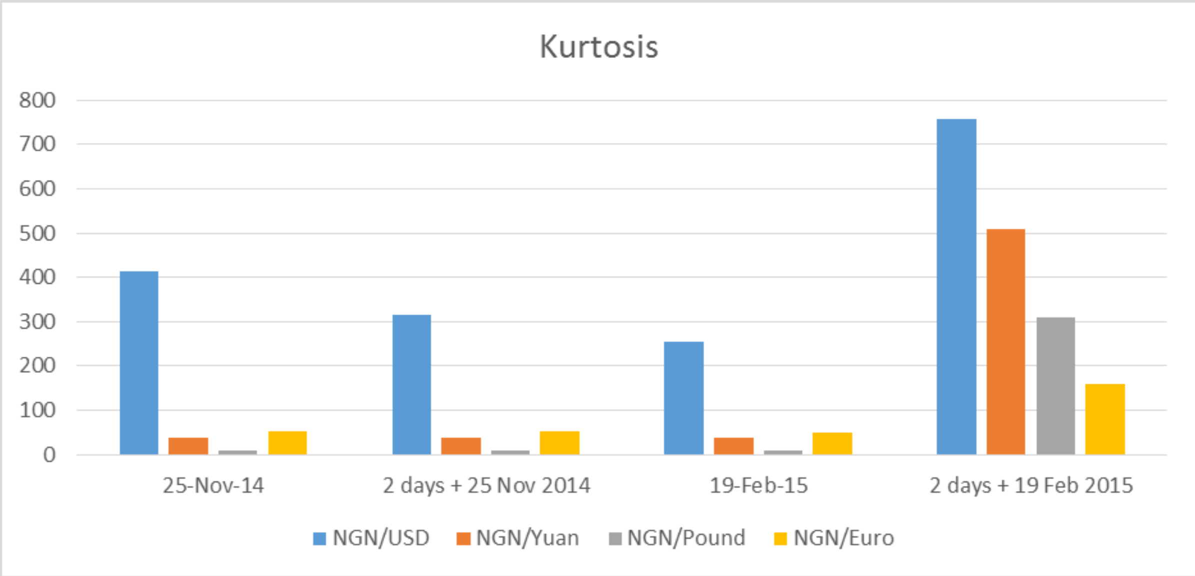


Figure 8 shows a plot of the kurtosis of the logarithmic daily returns of the four exchange rate series on and 2 days after the 24 November 2014 policy announcement as well as on and 2 days after the 19 February, 2015 policy announcement. The figure shows that the kurtosis of 2 days after the 19 February, 2015 policy announcement is the highest for each return series when compared to the kurtosis of other periods used for the analysis. The Naira/USD produced the highest kurtosis in 3 out of 4 analysis periods.

Figure 8 shows a plot of the kurtosis of the logarithmic daily returns



In terms of skewness, all exchange rates produced positive skewness except the data used for 2 days after the 19 February, 2015 policy announcement, where all the rates produced negative skewness. Furthermore, the period that produced the highest skewed values, in decreasing order, are 2 days after 19 February, 2015 policy announcement, on 25 November 2014 policy announcement, on 19 February, 2015 policy announcement and 2 days after November 2014 policy announcement.

Because of the existence of asymmetry of the return distributions observed, it is necessary to model left and right tails separately in order to capture their distinct characteristics. In the case there is evidence of positive (negative) skewness, which means that the right (left) tails are particularly extreme.

Several qq-plot where the tails have slopes different than the central mass is therefore suggestive of the empirical distribution having heavier, or thinner, tails than the reference standard normal distribution. None of the four series under four separate policy regimes studied here shows a normal distribution of returns. In addition, outliers are visible in the upper right and lower left corners of all the plots. Fat tails mean that crashes and huge increases appear far more often than predicted by the normal law.

These characteristics suggest that a good model for describing/forecasting volatility and risk measures of the Naira vs other currencies return series should capture i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails.

3.4 Fitting of GARCH-based Models

In the previous section, we discovered that a good model for modelling volatility and risk measures of the Naira vs other currencies return series should capture i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails. We therefore fit ARCH(1), GARCH(1,1), GJR-GARCH(1,1), EGARCH(1,1), APARCH(1,1) and FIGARCH to the for the four foreign exchange return series based on the day of the announcement (**25th November 2014 and** 19 February, 2015) and two business days after. The exchange rates are the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates.

Tables 5 and 6 report model estimates of log-likelihood for the 4 return series based on the day of the announcement of 24 November 2014 two days after the announcement of 24 November 2014 Announcement, respectively. Similarly, Tables 7 and 8 show model estimates for the four pairs of exchange rate return series based on the day of the announcement of 19 February 2015 Announcement and two days after, respectively.

All estimates were computed using maximum likelihood assuming the innovations are conditionally normally distributed. For many applications, the natural logarithm of the likelihood function, called the log-likelihood, is useful as the measure of fit. The log-likelihood is maximized to determine optimal values of the estimated coefficients, which are not reported until after the best fitting model is identified. Because we want to maximize the log-likelihood, the higher value signifies a better model fit.

Tables 5a and 6a show the ARCH log-likelihood estimates of the announcement of 24 November 2014 and two days after the Announcement for the four pairs of the Naira exchange rates. In both tables, the highest log-likelihood, as a measure of fit, is produced by the USD ARCH (5) model based on Skewed Student T error distribution. In all pairs of the exchange rate, ARCH (5) model with Normal errors returned a higher log-likelihood value than corresponding ARCH(1) model with Normal error distribution, implying better fit for the data. Moreover, the models with Student t and Skewed Student t distribution of residuals produced better fit for the exchange rate than those based on Normal distribution. These are the same findings obtained in the case of the announcement of 19 February 2015 and two days after the Announcement, as depicted in Tables 7a and 8a, respectively.

Tables 5b, 6b, 7b and 8b report the Naira/USD log-likelihood estimates for all GARCH models based on announcements of 24 Nov 2014 and two days after as well as 19 February 2015 and two days after, respectively. FIGARCH model with Student T error distribution produced the highest log-likelihood and hence the preferred model for the Naira/USD exchange rate based on the announcements of 24 Nov 2014 and two days after. In the case of two days after the 19 February 2015 announcement, FIGARCH model with skewed Student T error distribution produced the highest log-likelihood and hence the preferred model for the Naira/USD exchange. Based on announcements of 24 November 2014 and 19 February 2015 and their two days after, the two next best fitting models are the APARCH model with student t and APARCH with skewed student t errors. Moreover, all the GARCH models with normal error distribution gave lower values of log-likelihood than their corresponding counterparts with student t and skewed student t distributions.

The log-likelihood estimates for all the Naira/Yuan return series using GARCH models based on announcements of 24 Nov 2014 and two days after as well as 19 February 2015 and two days after, are reported in Tables 5c, 6c, 7c and 8c, respectively.

For 24 Nov 2014 announcement, APARCH model with Student T error distribution produced the highest log-likelihood while for 26 Nov 2014 as well as 19 February2015 announcements and its two days after, APARCH model with Skewed Student t and Student t error distributions (both reported the same value) produced the highest log-likelihood. In the case of announcement of 24 Nov 2014, the next models with higher values of log-likelihood are APARCH with Student T error distribution and GJR-GARCH with Skewed Student T error distribution.

Tables 5d, 6d, 7d and 8d report the Naira/Pound log-likelihood estimates for all GARCH models based on announcements of 24 Nov 2014 and two days after as well as 19 February 2015 and two days after, respectively. In all the announcement dates, APARCH model with Skewed Student T error distribution produced the highest log-likelihood. The next best fitting model in most dates is EGARCH.

Similarly, Tables 5e, 6e, 7e and 8e report the Naira/Euro log-likelihood estimates for all GARCH models based on announcements of 24 Nov 2014 and two days after as well as 19 February 2015 and two days after, respectively. In the announcement dates, APARCH model with Skewed Student T error distribution is the preferred model when modelling Naira/Euro exchange rate. The next preferred model is APARCH model with Student T error distribution in the case of 24 Nov 2014 and two days after and GJR-GARCH model with Skewed Student T error distribution for 19 February 2015 and two days after.

Generally, modelling volatility of the four pairs of the exchange rate based on the announcements, the ARCH models produced lowest log-likelihood values compared to the GARCH-based models. The GARCH models are therefore preferred. In the GARCH models, APARCH models with skewed student t distribution is preferred for modelling volatility in all currency pairs except in the case of Naira/USD that portrayed FIGARCH as the best model. Also, the Naira/USD exchange rate produced the highest log-likelihood values while the Naira/Euro exchange rate produced the lowest fit in terms of the log-likelihood values.

Furthermore, the result of the best fitting model for a particular pair of exchange rate obtained for the announcement of 24 Nov 2014 is the same as the result for the same pair for announcement of 26 Nov 2014. The same applies to 19 February 2015 and its two days after.

Table 9 shows the parameter estimates, p-values and log-likelihoods from the selected models for the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates based on the day of the announcement (**25th November 2014 and** 19 February, 2015) and two business days after.

The GARCH (1, 1) and other asymmetric GARCH models (EGARCH, GJR-GARCH and APARCH) clearly improve upon the ARCH models because they have a much higher log likelihood and no serial correlation. As seen in the table, the log-likelihood estimate of the IGARCH (1,1) model is not far away from those of the

GARCH(1,1) model, but there is a major difference between the two models. The unconditional variance of is not defined under the above IGARCH (1,1) model.

The asymmetric EGARCH, GJR-GARCH and APARCH, in all cases provide superior fit when compared to standard GARCH models. This suggests the presence of asymmetry, which is largely responsible for the superior fit since the pairs of the exchange rate asset return series have been found to exhibit a "leverage" effect. Specifically, in most cases, the APARCH (1,1) model had the highest log-likelihood than other corresponding asymmetric models.

Besides leptokurtic returns, the APARCH(1,1) model, as the best fitting GARCH model, captures other stylized facts in financial time series, like volatility clustering. The APARCH model, as the EGARCH and GJR-GARCH model, additionally captures asymmetry in return volatility. That is, volatility tends to increase more when returns are negative, as compared to positive returns of the same magnitude.

To investigate the stability of the estimates, we compare the log-likelihood of fitting the models to the return pairs of Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro on the day of the announcement **25th November 2014** and two business days after. The same analysis is carried out for the announcement of 19 February, 2015 and two business days after.

Recall that we also estimated a FIGARCH (1, d, 1) model to account for the potential presence of long-memory in volatility. FIGARCH model with Student T error distribution produced the highest log-likelihood and hence the preferred model for the Naira/USD exchange rate based on the announcements of 24 Nov 2014 and two days after. In the case of two days after the 19 February 2015 announcement, FIGARCH model with skewed Student T error distribution produced the highest log-likelihood and hence the preferred model for the

Naira/USD exchange. The Naira/USD exchange in this case accepted the additional flexibility of the FIGARCH model.

For the Naira/Yuan, the APARCH model, the log-likelihood on the announcements of 24 Nov 2014 and two days after are the same. In the Naira/Pound and Naira/Euro, the 24 Nov 2014 announcement period is much higher than the estimate of two days after the announcement. However, the 19 February 2015 announcement period is much higher than the estimate of two days after the announcement. This implies there is more in the Naira/Yuan, Naira/Pounds and Naira/Euro exchange rates before the 19 February 2015 announcement, which has been captured by the APARCH model.

In summary, our empirical results show that FIGARCH models with fat-tailed distributions are capable of capturing serial correlation, time-varying variance, long-memory, peakedness as well as fat tails for the Naira/USD. For the Naira/Yuan, Naira/Pound and Naira/Euro, the APARCH(1,1) model with student t or skewed student t error disrtibutions are able to capture i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails as discovered in the previous section.

4.0 SELECTING THE BEST VOLATILITY MODEL

This paper analyses the stylized facts of asset returns of the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates both on **25th November 2014 and** 19 February, 2015 announcement dates and two business days after. The paper also demonstrates empirical analysis of GARCH processes, compares different GARCH models, and explores the role of alternative distributional assumptions in the estimation of GARCH models using the conditional normal, the Student t and the Student skewed t.

The logarithmic daily returns of the four exchange rate series shows that the Naira/Euro had the highest standard deviation value while the Naira/USD had the lowest value of standard deviation. Furthermore, 2 days after the 19 February, 2015 policy announcement produced the highest value of standard deviation for each of the 4 exchange rates in comparison to the other periods used for the analysis.

This paper therefore also applies ARCH, symmetric GARCH and three asymmetric GARCH models (which are EGARCH, GJRGARCH and APARCH), unit-root GARCH models (IGARCH) and long memory in volatility, that is FIGARCH with variations in the distribution of the errors to be normal, student t and skewed student t that capture most stylized acts about exchange rate returns such as volatility clustering and leverage effect to the four pairs of Nigerian foreign exchange data. The question asked in this regard is 'Which volatility model best fits each of the four pairs of Nigerian foreign exchange data?'

Because of the existence of asymmetry of the return distributions observed, we find that it is necessary to model left and right tails separately in order to capture their distinct characteristics. In the case there is evidence of positive (negative) skewness, which means that the right (left) tails are particularly extreme.

The Nigerian exchange rate (Naira/USD, Naira/Pound, Naira/Euro and Naira/Yuan) exhibited the widely observed stylised facts of asset returns based on CBN policy announcements of the two dates. These characteristics suggest that a good model for describing/forecasting volatility and risk measures of the Naira vs other currencies return series should capture are: i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails.

The asymmetric EGARCH, GJR-GARCH and APARCH, in all cases provide superior fit when compared to standard GARCH models. This suggests the presence of asymmetry, which is largely responsible for the superior fit since the pairs of the exchange rate asset return series have been found to exhibit a "leverage" effect. That is, volatility tends to increase more when returns are negative, as compared to positive returns of the same magnitude. Specifically, in most cases, the APARCH (1,1) model had the highest log-likelihood than other corresponding asymmetric models.

4.1 FINDINGS AND POLICY IMPLICATIONS

FINDINGS

i. Volatility is very dynamic as it continuously changes over time. In this paper, we observe that the change in volatility is due to policy announcements by the CBN with respect to the exchange rates.
ii. A good model for describing/forecasting volatility and risk measures of the Naira vs other currencies return series should capture are: i) serial correlation, ii) time-varying variance, iii) peakedness as well as iv) fat tails. Furthermore, due to the existence of asymmetry of the return distributions observed, it is necessary to model left and right tails separately in order to capture their distinct characteristics. In the case there is evidence of positive (negative) skewness, which means that the right (left) tails are particularly extreme.
iii. We also find that FIGARCH models with fat-tailed distributions are capable of capturing serial correlation, time-varying variance, long-memory, peakedness as well as fat tails for the Naira/USD. For the Naira/Yuan, Naira/Pound and Naira/Euro, the APARCH (1,1) model with student t or skewed student t error distributions are able to capture serial correlation,

time-varying variance, peakedness as well as fat tails as discovered in the data.

iv. Generally, modelling volatility of the four pairs of the exchange rate based on the announcements, the ARCH models produced lowest log-likelihood values compared to the GARCH-based models. The GARCH models are therefore preferred. In the GARCH models, APARCH models with skewed student t distribution is preferred for modelling volatility in all currency pairs except in the case of Naira/USD that portrayed FIGARCH as the best model. Also, the Naira/USD exchange rate produced the highest log-likelihood values while the Naira/Euro exchange rate produced the lowest fit in terms of the log-likelihood values. Moreover, the models with Student t and Skewed Student t distribution of residuals produced better fit for the exchange rate than those based on Normal distribution.

POLICY IMPLICATIONS

i. The choice of the model for calculating value-at-risk based on volatility forecast should be as dictated by the stylised facts of the underlying data and according to the model's assumption in order to avoid model risk or inaccurate risk forecast.

ii. Accurate forecast of volatility by regulators is not only useful for estimating risk measures, it can also indicate the possible directions that banks will take in the future. As discussed by Gerlach et al (2006), shifts in volatility affect investors' willingness to hold risky assets and their prices. Banks' willingness and ability to extend credit can be influenced by the level of volatility in financial markets. A quick surge in volatility might deter major market participants from being involved in a price quotation system like Nigeria's FMDQ. This can in turn reduce liquidity and lead to low activity in the Forex market. Sudden changes in the level of financial market volatility, when accurately forecasted, should be of concern to policymakers.

iii. Poon and Granger (2003) stated that Federal Reserve as well as Bank of England utilise the volatility estimates of bonds, stocks and other parameters in policy-making. CBN should also do the same and NDIC should assist the monetary authority in this regard through regular estimation and analysis of this risk forecast.

iv. For bank regulators, the choice of the wrong VaR estimate, which in most cases rely on the particular volatility model, can make a great deal of difference in the actual capital to be set aside by the bank. Similarly, the bank risk managers can set the wrong or inappropriate limit for trading based on the wrong choice of volatility model.

v. Modern financial regulations are increasingly dependent on statistical risk models. Similarly, financial institutions use the same models for both regulatory and economic capital decisions. Volatility models are among the most prominent statistical risk forecasting models and commonly used in computing value-at-risk and in derivatives pricing. However, in practice, as argued by Danielsson (2015), most risk modelling approaches can highly inaccurate. A simple reason for the inaccuracy can be narrowed down to the choice of the right model. No matter how simple or sophisticated the risk model is, it must be applied in the problem based on the stylised facts of the underlying data and according to the model's assumption.

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Appendix

Table 5a: ARCH log-likelihood (LL) Estimates of 24 Nov 2014 Announcement

	ARCH (1), Normal Errors	ARCH(5), Normal Errors	ARCH(5), Student t Errors	ARCH(5), Skewed ST
USD	298	365	2642	3318
Yuan	-303	-180	-35	-35
Pound	-668	-654	-617	-617
Euro	-968	-964	-824	-822

Table 5b: Naira/USD log-likelihood (LL) Estimates for all GARCH models of 24 Nov 2014

	Normal Errors	Student t Errors	Skewed ST
GARCH	1,260	2,471	3,185
EGARCH	1,152	2,741	
GJR-GARCH	1,324	2,484	3,185
APARCH	1,384	8,423	8,443
IGARCH	1,260	2,473	3,113
FIGARCH	1,260	8,532	3,113

Table 5c: Naira/Yuan LL Estimates for all GARCH models of 24 Nov 2014 Announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	-178	-23	-23
EGARCH	-166	-70	
GJR-GARCH	-170	-22	-21
APARCH	-166	-21	-20
IGARCH	-178	-23	-23
FIGARCH	-171	-23	-23

Table 5d: Naira/Pound LL Estimates for all GARCH models of 24 Nov 2014 Announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	-640	-608	-608
EGARCH	-623	-600	
GJR-GARCH	-628	-602	-602

APARCH	-626	-600	-599
IGARCH	-641	-609	-608
FIGARCH	-645	**-609**	-608

Table 5e: Naira/Euro LL Estimates for all GARCH models of 24 Nov 2014 Announcement

	Normal	Student t	Skewed ST
GARCH	-910	-804	-801
EGARCH	-902	-807	
GJR-GARCH	-908	-801	-799
APARCH	-906	-792	790
IGARCH	-910	-805	-802
FIGARCH	-909	**-806**	-803

Table 6a: ARCH log-likelihood (LL) Estimates of two days after the announcement of **24 November 2014**

	ARCH (1), Normal Errors	ARCH(5), Normal Errors	ARCH(5), Student t Errors	ARCH, Skewed ST
USD	206	320	2,410	3,106
Yuan	-	-	-	-

	305	183	37	37
Pound	- 680	- 619	- 619	- 618
Euro	- 975	- 972	- 829	- 827

Table 6b: Naira/USD log-likelihood (LL) Estimates for all GARCH models of two days after the announcement of **24 November 2014**

	Normal Errors	Student t Errors	Skewed ST
GARCH	1,209	2,264	3,009
EGARCH	1,047	2,711	
GJR-GARCH	1,276	2,267	2,978
APARCH	1,346	8,299	8,271
IGARCH	1,209	2,264	2,953
FIGARCH	1,209	8,591	2,953

Table 6c: Naira/Yuan LL Estimates for all GARCH models of two days after the announcement of **24 November 2014**

	Normal Errors	Student t Errors	Skewed ST
GARCH	-181	-26	-25
EGARCH	-169	-73	
GJR-GARCH	-175	-24	-24
APARCH	-171	-20	-20
IGARCH	-181	-26	-25
FIGARCH	-175	-24	-24

Table 6d: Naira/Pound LL Estimates for all GARCH models of two days after the announcement of **24 November 2014**

	Normal Errors	Student t Errors	Skewed ST
GARCH	-650	-613	-612
EGARCH	-638	-607	
GJR-GARCH	-643	-612	-611
APARCH	-636	-605	-604
IGARCH	-653	-615	-614
FIGARCH	-613	-614	-651

Table 6e: Naira/Euro LL Estimates for all GARCH models of two days after the announcement of **24 November 2014**

	Normal Errors	Student t Errors	Skewed ST
GARCH	-917	-812	-810
EGARCH	-908	-813	
GJR-GARCH	-915	-812	-809
APARCH	-912	-800	-798
IGARCH	-917	-813	-811
FIGARCH	-917	-813	-811

19 February 2015

Table 7a: ARCH log-likelihood (LL) Estimates of **19 February 2015** Announcement

	ARCH (1), Normal Errors	ARCH(5), Normal Errors	ARCH(5), Student t Errors	ARCH, Skewed ST
USD	145	310	2,318	3,079
Yuan	- 323	- 215	- 20	- 20
Pound	-	-	- 618	-

	697	669		618
Euro	- 988	- 984	- 819	- 817

Table 7b: Naira/USD log-likelihood (LL) Estimates for all GARCH models of **19 February 2015** Announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	794	2,190	3,003
EGARCH	839	2,740	
GJR-GARCH	835	2,214	2,986
APARCH	1,105	8,774	9,099
IGARCH	794	2,190	2,953
FIGARCH	799	9,953	7,965

Table 7c: Naira/Yuan LL Estimates for all GARCH models of 19 February **2015** announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	-208	-7	-7
EGARCH	-201	-80	
GJR-GARCH	-205	-3	-3
APARCH	-204	-2	-2
IGARCH	-208	-7	-7
FIGARCH	-205	-4	-3

Table 7d: Naira/Pound LL Estimates for all GARCH models of 19 February 2015 announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	-668	-616	-615
EGARCH	-691	-641	
GJR-GARCH	-660	-613	-613
APARCH	-656	-614	-608
IGARCH	-669	-617	-617
FIGARCH	-667	**-615**	-614

Table 7e: Naira/Euro LL Estimates for all GARCH models of 19 February 2015 announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	-932.0225	-801.5961	-798.9906
EGARCH	-919.3107	-811.2554	
GJR-GARCH	-931.4421	-800.4942	-798.1158
APARCH	-929.6136	-793.4606	-791.0954
IGARCH	-932.0238	-804.0744	-801.3749
FIGARCH	-931.3422	**-806.0238**	-803.3709

Table 7g: Parameter Estimates based on 'Normal' distribution of errors of Naira/USD

	GARCH	**GJR-GARCH**	**APARCH**
AIC	-1.436	-1.51774	-1.515
Q(20)	17.37	0.100	17.2646
$Q^2(20)$	0.268	0.164	0.164

Table 7h: Parameter Estimates based on 'Student t' distribution of errors of Naira/USD

	GARCH	GJR-GARCH	APARCH
AIC	-20.186	-17.58	-14.617
Q(20)	0.2367	25.42	0.0282
$Q^2(20)$	0.0838	0.232	0.02141

Table 7i: Parameter Estimates based on 'Skewed Student t' distribution of errors of Naira/USD

	GARCH	GJR-GARCH	APARCH
AIC	-22.802	-19.89	-13.63
Q(20)	116.74	0.041	0.0275
$Q^2(20)$	11.447	0.0415	0.021

21 Feb 2015: Tables 8 reports model estimates for the 4 return series based on two days after the announcement of **19 February 2015.**

Table 8a: ARCH log-likelihood (LL) Estimates of two days after **19 February 2015** Announcement

	ARCH (1), Normal Errors	ARCH(5), Normal Errors	ARCH(5), Student t Errors	ARCH, Skewed ST

USD	- 868	- 115	1,620	2,467
Yuan	- 651	- 554	- 36	- 36
Pound	- 1,044	- 927	- 637	- 637
Euro	- 1,228	- 1,182	- 838	- 837

Table 8b: Naira/USD log-likelihood (LL) Estimates for all GARCH models of two days after **19 February 2015** Announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	1,064	1,534	2,445
EGARCH	1,088	2,691	
GJR-GARCH	1,118	1,536	2,414
APARCH	1,174	7,078	7,899
IGARCH	1,064	1,526	2,412
FIGARCH	1,064	6,799	

			8,730

Table 8c: Naira/Yuan LL Estimates for all GARCH models of two days after 19 February **2015 announcement**

	Normal Errors	Student t Errors	Skewed ST
GARCH	-260	-44	-44
EGARCH	-575	-119	
GJR-GARCH	-260	-43	-43
APARCH	-248	-12	-12
IGARCH	-261	-47	-47
FIGARCH	-261	-47	-47

Table 8d: Naira/Pound LL Estimates for all GARCH models of two days after the 19 February 2015 announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	-709	-639	-639
EGARCH	-951	-664	
GJR-GARCH	-707	-638	-637
APARCH	-708	-626	-625

IGARCH	-731	-650	-650
FIGARCH	-731	-650	-650

Table 8e: Naira/Euro LL Estimates for all GARCH models of two days after 19 February 2015 announcement

	Normal Errors	Student t Errors	Skewed ST
GARCH	- 967	- 838	- 837
EGARCH	- 1,099	- 840	
GJR-GARCH	- 957	- 837	- 837
APARCH	- 953	- 806	- 804
IGARCH	- 968	- 843	- 840
FIGARCH	- 968	- 843	- 840