Measuring the Risk in Risk Measures: The Case of the Nigerian Foreign Exchange Market

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Abstract
As part of its mandate, the Central Bank of Nigeria (CBN) carried out a series of foreign exchange policy decisions from 2014 to 2016. This paper, therefore, evaluated model risk of two key risk measures, expected shortfall (ES) and value-at-risk (VaR), due to the CBN's policy decisions using daily data for the naira exchange rates covering 2010 to 2014, as well as, 2011 to 2015 for the respective policy resolutions. The risk measures were implemented using 6 different models, as the most common techniques used by regulators and practitioners. The implementation of Basel III recommends the switchover from VaR to ES and a reduction in confidence levels from 99 per cent to 97.5 per cent. The paper estimated VaR and ES at 97.5 per cent and 99 per cent levels and assessed their accuracy using risk ratios methodology. The results indicated that VaR 99 per cent per cent measure produced higher model risk than ES 97.5 per cent. Therefore, ES 97.5 per cent per cent should be preferred to VaR 99 per cent per cent for naira exchange rate risk forecasting and capital allocation. The study also recommends that regulators, banks and other participants should seriously consider model risk analysis and make it part of the regulatory and operational design process.

Keywords: Expected Shortfall, Model Risk, Risk Ratios, Value-at-Risk
JEL Classification: *C52, G12, G21, G28, G32*

I. Introduction

After the CBN Monetary Policy Committee meeting of November 24th and 25th, 2014, the midpoint of the official window of the currency market was moved from ₦155/US$ to ₦168/US$. In effect, the CBN devalued the currency by ₦13. In addition, on 19th February 2015, the CBN closed the Retail and Wholesale Dutch Auction System (RDAS/WDAS) of the foreign exchange market, signaling a further devaluation of the exchange rate from ₦168/US$ to ₦198/US$. Furthermore, 20th June 2016, was the commencement date of the new flexible exchange rate policy by the CBN which allowed market forces determine the rate of naira[1].

Naturally, these announcements had significant effect on the portfolio, risk management and capital adequacy decisions of banks and other related financial sector participants. This is because risk management and forecasting

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[1]The reader is referred to Katata (2016) for a review of stylised facts of naira exchange rate data, based on the CBN policy decisions of 2014 and 2015.

are central to bank's minimum capital requirements, setting risk limits as well as portfolio decisions. Banks' profits are based on how financial time series, such as interest rates, exchange rates and stock prices, behave. The exposure of banks to these factors is referred to as 'market risk'.

Instead of gut feeling and 'expert judgement', models are used to describe the markets factors, risks, their complex relationships and several other financial products and services. Naturally, in an important regulatory innovation, the Basel Committee on Banking Supervision (BCBS) proposed that VaR models be used in the determination of the capital for banks' minimum capital requirements (BCBS, 2006 and Berkowitz & O'Brien, 2002). Generally, VaR value can be calculated using three main methodologies: the Analytical method (co-variation- variation method or delta-normal), historical simulation method and Monte Carlo simulation technique (Hull, 2011). The issue here is that each of these methods can produce different estimates from one another and could therefore present a problem for the regulator over which model to pick as the ideal one thereby leading to model risk. Model risk has been loosely defined as the risk of error in risk estimates due to inadequacies in risk measurement models (Dowd, 2005).

Furthermore, VaR as a risk measure has been widely criticised, principally due to its lack of sub-additivity property, amongst others (Artzner, Delbaen, Eber and Heath,1997 & 1999). The Expected Shortfall was proposed as a better risk estimate, which measures the expected value of portfolio returns given that some threshold (usually the VaR) has been exceeded (Dowd, 2005). Consequently, in 2013, the BCBS introduced three main modifications to the then regulatory regime to be added into Basel III: the substitution of 99 per cent VaR with 97.5 per cent ES, utilisation of overlapping estimation windows, and the setting of a risk forecast to its worst outcome based on past history (Danielsson, 2013). Despite the fallacy of VaR as a risk measure, it is still heavily used by the industry. Also, VaR is considered as the first fundamental stage in both the implementation of systemic risk measures and other risk measures such as ES (Danielsson et al., 2017).

The BCBS, European Banking Authority, Federal Reserve, and most financial sector regulators and standard setters are concerned with the impact of model risk in banking and financial systems (Brown, McGourty & Schuermann, 2015). Moreover, given the importance of VaR risk estimates to banks and their regulators, evaluating model risk of risk measures is necessary (Lopez, 1999). It is important to study model risk because vastly different outcomes are produced by different risk models and identifying the best model is not a trivial task

(Danielsson et al., 2017). In addition, risk models have been blamed for several catastrophic financial losses. For instance, Deloitte (2017) discussed JP Morgan's London Whale model risk loss that cost the bank losses of £6bn and was fined £1bn because the bank changed its VaR metric in early 2012 and there was an error in the spreadsheet used for that purpose where the risk was understated by 50 per cent. Deloitte (2017) also stated that model risk was one of the main causes of losses in the 2007 financial crisis whereas of September 2008, bank write downs and losses totaled $523bn. The report further cites the US Financial Crisis Inquiry Commission as stating that agencies' credit ratings were influenced by “flawed computer models…”.

Several authors have studied model risk (Lopez, 1999; Danielsson, 2008; Danielsson, 2009; Danielsson, 2015; Danielsson et al., 2015 and Danielsson et al., 2017), to mention a few. Some discussed the negative impact of models on 2007 financial crisis (Jorion, 2009; Persaud, 2008; Danielsson & Macrae, 2011, Danielsson et al., 2017). Others studied model risk due to the 2015 Swiss National Bank (SNB) decision that it would no longer intervene to keep the franc/euro exchange rate at 1.20 (Danielsson, 2015b).

Consequently, numerous approaches have been proposed to understand, quantify and possibly limit the disastrous impact of model risk to financial institutions, especially through back testing (Dowd, 2015 and Alexander, 2008). It should be noted that model risk may be particularly high, especially under stressed conditions or combined with other interrelated trigger events (Boucher et al., 2013; Danielsson et al., 2017). Indeed, the 2014 and 2015 exchange rate policy decisions by the CBN were periods of significant stress to the Nigerian financial system. Given the roles played by risk forecasts and capital adequacy decision based on model estimates, an understanding of model risk and impact of Basel III on model risk in Nigeria is very important.

Adeoye and Atanda (2011) examined the reliability, perseverance, and degree of volatility in naira exchange, while Katata (2016) carried out statistical study of Nigerian exchange rate (Naira/USD, Naira/Pound, Naira/Euro and Naira/Yuan). Aliyu (2010), Isaac (2015) and Yakub et al. (2019) study Nigerian exchange rate risk as it relates to trade and performance of banks. However, literature on model risk based on naira exchange rate or due to CBN's policy decision does not exist, which this paper considered a major gap.

The main contributions of this study are four-fold. First, the study applies a range of VaR, and ES forecasts estimated using various methods to returns on

Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates. The methods used are generalised autoregressive conditional heteroskedasticity (GARCH), Historical Simulation, Normal, Student t and Extreme Value Theory (EVT) as suggested by Danielsson et al., (2017), being the most common techniques utilised by regulators and practitioners. The paper also estimates risk measures using asymmetric power autoregressive conditional heteroskedasticity (APARCH) due to the findings of Katata (2016), which show that it captures the stylised facts observed in most of the naira exchange rate series. The analysis adds to the literature on comparison of risk measures. Second, the paper also evaluates which of the confidence levels suggested by Basel II and III result in lower model risk using the naira exchange rate pairs. The study therefore estimates VaR and ES at 97.5 per cent and 99 per cent levels using the 6 techniques and evaluates model risk as a result of the two CBN policy decisions of 2014 and 2015. Third, model risk as measured by the risk ratios methodology of Danielsson et al. (2017) is used in evaluating the risk measures due to the CBN decisions. The study therefore contributes to the evaluation of model risk in the Nigerian banking system and provides further empirical literature on state-of-the-art models for risk forecasting. Fourth, specific policy implications for the Nigerian financial system regulators are provided to aid in model risk management in the Nigerian banking system.

The paper is organised in to five sections. Section 2, which follows the introduction, presents a review of empirical and theoretical literature. Section 3 highlights the methodology. Section 4 discusses the results of estimated risk forecasts and model risks and interprets the findings. Section 5 concludes.

II. Brief Review of Current Theoretical and Empirical Literature

II.1 A Theoretical Review of VaR & ES Risk Measures

II.1.1 VaR Risk Measure

Adamko et al. (2015) discuss the history and concepts behind VaR. The authors traced the origin of VaR to the need for a risk measure that could handle the complexities of financial market not adequately captured by Markowitz (1952) standard deviation measure of portfolio risk. As corroborated by Allen et. al., (2004) but differs slightly, the Nobel Prize-winning theory of Markowitz portfolio risk theory was not accepted by practitioners due to its arduous data requirements until Bill Sharpe's Nobel Prize winning Capital Asset Pricing Model was introduced.

The search for a better risk measure continued until VaR was adopted as the standard financial risk measure largely due to the decision by J. P. Morgan investment bank in 1994 to release a transparent VaR measurement model, called Risk Metrics (Dowd, 2005; Allen et al., 2004). Indeed, from the time of the 1996 amendment to Basel I, market risk regulations have been based on daily 99 per cent VaR and VaR had become the standard measure that financial analysts use to measure financial risk (Danielsson et al., 2017; Berkowitz and O'Brien, 2002 and Jorion, 2006).

VaR is a lower tail percentile for the distribution of profit and loss (P&L). VaR gives an idea of what one expects to potentially lose in each time interval, assuming "normal" market conditions. It summarises the worst loss over a target horizon that will not be exceeded with a given level of confidence. VaR summarises in a single number the total exposure to not only foreign exchange risk but all market risks, and also the probability of adverse movement in the relevant financial variables. The unit of measurement of VaR is in the same unit as the variable of interest in the analysis. It is a summary measure of downside risk expressed in naira or in the reference currency (Jorion, 2007).

VaR as a risk measure is useful to financial sector players and regulator for many reasons. After a VaR value has been estimated based on daily, weekly, monthly or yearly data, the Management of a bank or regulators can then decide whether the level of risk is acceptable. If it's not, then the factors or positions taken that led to such a risk can be changed in order to trim the risk (Dowd, 2005).

VaR is an essential risk management tool that enables the aggregation or disaggregation of risks to different activities, risk types or asset classes. This risk budgeting process enables the allocation of economic capital to activities, the allocation of (VaR-based) limits for traders, and the estimation of the size of the regulatory capital requirement for market, credit and operational risks. Similarly, the disaggregation of VaR helps the analyst to understand the main sources of risk in a portfolio. Drilling down further, market risk can be split into the risk associated with a particular asset classes: equity VaR, interest rate VaR, forex VaR and commodity VaR (Alexander, 2008).

Basel II Accord further allows banks to use internal VaR models to assess their market risk capital requirement and VaR should be measured at the 1 per cent significance level, which is equivalent to 99 per cent confidence level (Alexander, 2008). VaR models have therefore been approved as the risk measure for calculating capital requirements for market risk. Consequently, VaR became the standard measure of financial market risk that is increasingly used by banking, other financial and nonfinancial firms as well (Berkowitz & O'Brien, 2002 and Jorion, 2003).

However, VaR has been proven not to be an ideal standard risk measure due to its shortcomings of not being sub-additive and therefore not coherent (Artzner et al., 1997). VaR is also only an estimate and a first-order approximation to possible losses due to movements of financial variables (Jorion, 1996) and therefore suffers from estimation risks. Also, VaR does not estimate the worst loss because it is not designed to measure it (Jorion, 2007). VaR disregards loss beyond the percentile and is not sub-additive (Yamai and Yoshiba, 2002). Furthermore, another major disadvantage of VaR is that it is easier for financial institutions to manipulate it than ES (Danielsson and Zhou, 2015). Consequently, ES has been suggested as a better risk measure (Artzner et al., 1997; Dowd, 2005).

II.1.2 ES Risk Measure

Artzner et al. (1997) and Yamai and Yoshiba (2002) suggest Expected Shortfall (ES) as a better substitute risk measure due to the problems inherent in VaR. A risk measure is sub-additive when the sum of its risk is less than or equal to the totality of the risk of the individual unit that make up the portfolio. This implies that risk measures should not violate the risk reduction characteristics of portfolio diversification effects, which VaR does.

ES describes loss beyond the level of VaR (Yamai and Yoshiba, 2002). It is the conditional expectation of loss given that the loss is beyond the VaR level. It measures the expected value of portfolio returns given that some threshold (usually the VaR) has been exceeded (Dowd, 2005).

It is worthy of note, as described by Dowd (2005), that the ES belongs to a closely related risk measures family that have been referred to as the tail VaR, worst conditional expectation, expected tail loss, tail conditional expectation (TCE), tail conditional VaR, conditional VaR as well as worst conditional expectation. However, ES and TCE are the two distinct members of this family of risk measures. The ES is basically a probability threshold, while the TCE is the average of losses exceeding VaR. These two risk measures will always coincide when the loss distribution is continuous, whereas the TCE can be ambiguous when the distribution is discrete.

A major benefit of ES in addition to being sub-additive is that, as stated by Yamai and Yoshiba (2002), it is easily decomposed and optimised than VaR. However, ES, like VaR and all other risk measures, are subjects of implementation and model risk if based on wrong assumptions or incorrectly implemented (Dowd, 2005). Also, Dowd (2005) stated that VaR is simply a quantile and can therefore be estimated much more easily than ES. Also, ES requires a bigger sample size than VaR for the same confidence level (Yamai and Yoshiba, 2002).

Furthermore, according to Danielsson and Zhou (2015), the estimation of ES requires more steps and more assumptions than that of VaR hence leading to more estimation risk.

II.1.3 Methods of Estimating ES and VaR

Kuester, Mittnik and Paolella (2006) use GARCH, mixed normal-GARCH, EVT, and conditional autoregressive VaR (CAViaR) to associate the performance (out-of-sample) of present methods and some different ones for forecasting VaR in a univariate setting. According to Danielsson et al. (2017), "by far the most common in practical use" for forecasting VaR risk measures are historical simulation, moving average, exponentially weighted moving average (EWMA), normal GARCH, student t GARCH, and EVT.

There are several methods of estimating VaR but Allen *et. al.,* (2014) categorised them into historical and implied volatility-based approaches. The historical-based makes use of historical time series data in order to determine the shape of the conditional distribution and can be parametric approach which enforces a precise distributional assumption on conditional asset returns, nonparametric approach that utilises historical data directly, without setting a precise set of assumptions and a hybrid approach that combines the two approaches. The implied volatility-based approach is based on derivative pricing models and prices so as to assign an implied volatility while historical data is not required.

Alexander (2008) discuss three basic methods of estimating VaR: the normal linear VaR model, in which it is assumed that the distribution of risk factor returns is multivariate normal and the portfolio is required to be linear; the historical simulation model, which uses a large quantity of historical data to estimate VaR but makes marginal assumptions of the risk factor return distribution; and the Monte Carlo VaR model, which in its most basic form makes similar assumptions to the normal linear VaR model.

Dowd (2005) however, present historical simulation and parametric approaches. The historical simulation consists of basic historical simulation, bootstrapped historical simulation, historical simulation using non-parametric density estimation and weighted historical simulation approaches. The parametric approaches require the explicitly specification of the statistical distribution from which the data observations are drawn. Some of which are: Normally, t- and Lognormally Distributed as well as Extreme Value Theory

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[2]Refer to Allen et. al., (2004) for detailed discussions on VaR, Jorion (2006) and Dowd (2005) for detailed exposition on VaR and ES.

approaches. Dowd (2005) also state other methods as miscellaneous ways of estimating VaR: L'evy processes (sometimes also known as stable Paretian processes), Elliptical and Hyperbolic, Normal Mixture, Jump Diffusion, Stochastic Volatility and Cornish–Fisher approximation approaches.

Manganelli and Engle (2001) organise the current models into three main categories: Parametric (Risk Metrics and GARCH), Nonparametric (Historical Simulation) and Semiparametric (Extreme Value Theory, CAViaR and quasi-maximum likelihood GARCH).

II.1.4 Risk Measures in Basel II and Basel III

There are several weaknesses with the VaR-based framework used in the Basel II Accord (BCBS, 2016a). Some of the weaknesses include the inability to adequately capture credit risk inherent in trading exposures as experienced in the fast development in the market for traded credit in the early 2000s implied that banks were exposed to huge undercapitalised credit-related instruments in their trading book. Another major weakness is that banks found it rewarding to be exposed to tail risk by not looking beyond the 99th percentile, the Basel II VaR metric – and hence regulatory capital requirements – fail to capture "tail risks" which exposes the banking system to perverse incentives.

Danielsson et al. (2001) view the Basel II accord as having key deficiencies in several areas and could enable the proliferation of new sources of instability. The authors' reason that Basel II fails to accept the idea that risk is endogenous and that VaR can have a devastating impact on an economy and cause financial crashes that will otherwise not occur. On VaR, the authors state that all statistical models used in risk forecasting produces are unreliable and subjective predictions especially by under-forecasting the joint downside risk of dissimilar assets. They further state that the risk measure selected by the Basel Committee is of poor quality and better options exist.

In the 2016 revision for market risk charge using the internal model approach, BCBS (2016) directed for a shift from VaR to an ES risk measure under stress in order to ensure a better measure of "tail risk" and more reliable capital adequacy estimates when the system is under substantial stress. Basel III therefore directed for a shift from 99 per cent VaR to 97.5 per cent ES, utilisation of overlapping estimation windows, and the setting of a risk forecast to its worst outcome based on history.

II.1.5 Model Risk

Model risk can also arise due to a complexity of factors, needs or offerings in financial and banking systems (Brown, McGourty & Schuermann, 2015). It should be noted that model risk is a natural consequence of using models and risk models should only be used after a thorough understanding of their assumptions and their limitations. While model risk has no single definition, it is related to the ambiguity due to not precisely knowing the true data generating process (Boucher et. al., 2013); or due to incorrect model or application specification of a model or as a result of wrong data used in risk models (Dowd, 2005). Model risk can simply be viewed as the potential for different models to provide inconsistent result or output.

Alexander and Sarabia (2012) distinguish two sources of model risk: due to inappropriate assumptions about the form of the statistical model for the random variable; and parameter uncertainty that arises because of estimation error in the parameters of the chosen model. Brown, McGourty & Schuermann (2015) discuss the development of model risk management (MRM) in the US banking system, while recognising the increasing role of model validation amidst complex financial products and due to the advent of the 2007-08 financial crisis. According to the authors, 1996-2000 was a period for expansion of model use and recognition of model risk, 2000-2011 was a period characterised by focus on model validation with emerging recognition of need for MRM. Post 2011 period was for greater reliance on models for capital-based regulation with special weight placed on MRM in supervisory review.

According to Boucher et al. (2013), the 2007-09 financial crisis has caused model risk to inaccurately forecast risk prior to it, the models were slow to react as a crisis unfolds as well as slow to reduce risk levels post–crisis. As stated by Boucher et al. (2013), “It is as if the risk models got it wrong in all states of the world”. In an earlier study, Berkowitz & O'Brien (2002) examined the VaR models used by six leading US financial institutions and their results indicate that these models tend to be too conservative and, in some cases, highly inaccurate. It was known right from the early days of financial risk forecasting that different models produced different forecasts, with an equivalent difficulty in selecting the best one out of several candidate models (Danielsson et al., 2017).

Dowd (2005) states that model risk can arise from many different sources such as stochastic processes that might be mis specified, missing risk factors, mis specified relationships and Ignoring of transactions costs, crisis and liquidity factors.

Greg et al. (2010) edited a theoretically thorough book with a very high level of practicality for risk modelling. The book provides a very useful and extremely timely guide to the delicate and frequently hard issues concerned with model risk. The Handbook is a very good guide for refining approaches to model risk management.

In his book on MRM, Morini (2011) describes mathematical models as superb tools that can take further our understanding of the mechanics and interaction with financial markets which could not be possible without quantitative models. According to Morini, MRM requires the understanding of the dynamics between mathematics and data, regulations as well as markets together with human behaviour.

II.1.6 Main Regulatory References on MRM

Models are used by financial firms including banks for several tasks that include valuing positions and instruments; credit underwriting; derivatives pricing, measuring & hedging risk and for calculating capital charges as well as reserve adequacy.

Several financial sector regulators and standard setters have recommended or mandated measuring and, in some cases, accounting for model risk. Basel II Accord suggests further market risk capital to account for all sources of 'model risk' in the calculation risk measures (BCBS, 2006). The European Banking Authority (EBA) also issued Guidelines and standards for the management of model risk[3]. The Canadian Office of the Superintendent of Financial Institutions has also issued policies for model risk management that applies to bank and other financial institutions[4]. The UK PRA has also issued guidance on model risk[5].

In 2011, the Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency outlines effective management of risks for banks using quantitative models including model risk identification and management[6]. The US Federal Deposit Insurance Corporation (FDIC), together with The FDIC, the Federal Reserve Board and the Office of the Comptroller of the Currency have jointly issued several guidance to banks on several aspects of model risk management, like regulatory notes identified as FIL-52-96[7], FIL-2-2010[8],

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[3]https://eba.europa.eu/regulation-and-policy/model-validation

[4]http://www.osfi-bsif.gc.ca/eng/fi-if/rg-ro/gdn-ort/gl-ld/pages/e23.aspx accessed 20th August, 2019
Bank of England PRA letterhttp://www.bankofengland.co.uk/pra/Documents/about/letter270317.pdf

[5]https://www.occ.treas.gov/news-issuances/bulletins/2011/bulletin-2011-12a.pdf

[6]https://www.fdic.gov/news/news/financial/1996/fil9652.html

[7]https://www.fdic.gov/news/news/financial/2010/fil10002.html

[8]https://www.google.com/search?client=firefox-b-d&q=FIL-2-2012

FIL-2-2012[9]. For further discussion on MRM by the US and Canadian banking system regulators see Kiritz & Sarfati (2018).

II.1.7 Evaluating Model Risk

According to Danielsson et al. (2017), risk ratios methodology uses the ratio of the highest to the lowest risk forecasts across the range of these candidate models on a given horizon. The authors contend that their proposed methodology is a simple way of assessing the model risk by examining the level of difference amongst the candidate models while ignoring statistical issues and complications. They call their methodology *risk ratios.*

II.2 Review of Related Empirical Literature on VaR and ES Risk Measures

Jorion (1996) studied the estimation error in VaR risk measure and suggested how the accuracy of the measures can be improved. The data used for the study consist of exchange rate, equity and bond prices. Jorion concluded that recognising and accounting for estimation error in VaR measures could lead to better risk management practices.

Using a sample from equities, bonds, foreign ex-change, and commodities based on daily observations of 15 years, Danıelsson (2002) investigated the properties of risk measures, primarily VaR. Risk was forecasted on a one-day-ahead basis with 300, 1000, and 2000-day estimation windows. The risk measures were implemented using HS, EVT, Normal GARCH, and student-t GARCH models. The study concluded that VaR used for regulatory purposes has several shortcomings as detailed by Artzner (1997).

Danielsson and Zhou (2015) examined the similarities and deviations between ES and VaR using daily returns on all stock prices traded on NASDAQ, NYSE or AMSE from 1926 to 2014, The results indicated that risk forecasts can be extremely uncertain when the size of the sample is low and about half a century of daily data for the estimators to reach their asymptotic properties. The results also suggest that common trends and practices in risk management were wrong.

Rejeb et al. (2012) examined the empirical performance of four VaR simulation methods, which were used to forecast the VaR risk measure of three currencies and four currency portfolios in the Tunisian foreign exchange market. The study used data covering 01-01-1999 and 31-12-2007 at 95 per cent, 97.5 per cent and 99 per cent confidence levels with a rolling window of 250 days. The authors

[9] https://www.google.com/search?client=firefox-b-d&q=FIL-2-2012

reported that the Japanese Yen was the riskiest currency irrespective of the VaR method used; and that portfolio diversification decreases the foreign exchange rate risk, as expected.

Danielsson (2015b) investigated the impact of Swiss National Bank (SNB) exchange rate policy announcement on risk forecasting using historical, MA, EWMA, GARCH, t-GARCH and EVT and evaluated the model risk of ES and VaR risk measures using risk ratios methodology. The study used estimation window of 1000 days using the Swiss franc/euro exchange rate. The study concluded that the risk models significantly underappreciated the risk before the announcement and vastly overstated the risk after it.

Danielsson et al. (2017) studied the model risk of models using the risk ratio methodology on ES and VaR market risk measures. The authors used returns of large financial institutions traded on the NYSE, AMEX, and NASDAQ exchanges from the banking, insurance, real estate, and trading sectors for a period covering 1970 to 2012 with estimation window size of 1,000. The study used 11 different models, including five mainstream models historical simulation (HS), exponentially weighted moving average (EW), normal GARCH (G), student-*t* GARCH (tG), and extreme value theory (EVT) and six mixed models HS and EVT applied to a GARCH filtered data under the assumption of normal, student-*t*, and skewed-*t* distributions. The authors find that during calm periods, the underlying risk forecast models produce similar risk readings resulting in negligible model risk. However, the disagreement between the various risk measures and models increases significantly during market distress. The authors find that switching to ES from VaR does not overcome the model disagreement. They concluded that model risk is always present, regardless of the asset.

III. Methodology

III.1 Value-at-Risk

The VaR of a portfolio given confidence level $a \in (0,1)$, over the time period t is given by the smallest number such that the probability of a loss over a time interval t greater than k is a. For p=1- a, the VaR is simply the p-quantile of the loss distribution over some time period. In this paper, a is assumed to be 0.975 and 0.99. The time period/horizon used to estimate VaR is 1 or 10 days in market risk management applications but usually 1 year in credit risk management and operational risk management cases.

III.2 Expected Shortfall

Suppose X is a random variable denoting the loss of a given portfolio and VaR α(X) is the VaR at the 100(1– α) per cent confidence level. ES α(X) is defined by the following equation.

$$ES\alpha(X) = E\left[X \middle| X \geq VaR\alpha(X)\right] \quad (1)$$

III.3 Approaches of Implementing VaR and ES

Historical simulation (HS) provides the simplest way to estimate VaR by means of ordered loss observations[10]. More generally, where there are *n* observations, and the confidence level is α, the VaR is the (1−α), *n+1th* highest observation. The ES is simply the average of the *n*th highest observations.

The weighted historical simulation approach can be regarded as semi-parametric method because it combines features of both parametric and non-parametric methods. Volatility or Age-weighted Historical Simulation is one such approach which assigns weights based on the relative importance of the observations by their age or volatility. The exponential weighted moving average approach (EWMA) is a well-known example.

Estimating VaR at a confidence level with Normally Distributed data can be done as follows:

$$\alpha VaR = -\mu + \sigma Z_{\alpha} \quad (2)$$

Where *Z* is the standard normal variate corresponding to *α*, *μ* is the mean and *σ* is the standard deviation of the profit/loss of the data.

Since VaR is a loss (which is the difference between price at time *t*, P_t and P_{t-1}), then the Lognormally Distributed VaR is given as:

$$P_{t-1}(1 - e^{\mu + \sigma Z}) \quad (3)$$

It should be noted that the normally distributed geometric returns simply imply that the VaR is lognormally distributed.

It is relatively easy to estimate time-varying volatility such as the moving average models. Assuming returns are conditionally normally distributed, the volatility *σ* is calculated as:

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[10] The following description of the approaches implemented in this paper is largely from Dowd (2005).

$$\sigma^2_{MA,t+1} = \frac{1}{E_W}\sum_{i=1}^{E_W} u^2_{t-i+1} \tag{4}$$

where E_w is the estimation window size.

Let λ be the decay factor as set to 0.94 by J.P. Morgan for daily returns (Dowd, 2005). The EWMA model is similar to the above model but has exponentially decaying weights into the past as follows:

$$\sigma^2_{EWMA,t+1} = (1-\lambda)u_t^2 + \lambda u^2_{EWMA,t} \tag{5}$$

The most widely used specification is the GARCH (1,1) model introduced by Bollerslev (1986). Let a return time series $r_t=\mu+\varepsilon_t$, where μ is the expected return and zero-mean r white noise $t\varepsilon$is given as $\varepsilon_t=\sigma_t z_t$, where z_t is assumed to follow a standard Gaussian distribution the model is given as:

$$\sigma^2_{t+1} = \omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2 \tag{6}$$

This model forecasts the variance of date *t* return as a weighted average of a constant, yesterday's forecast, and yesterday's squared error. The parameters (ω, α, and β) can be simultaneously estimated by maximising the log-likelihood. The Asymmetric Power ARCH Model (APARCH) model also delivers the long-memory property of returns discussed in Ding, Granger, and Engle (1993). $|\varepsilon_t|^d$ often displays strong and persistent autocorrelation for various values of *d*. It is a very changeable ARCH model and the model is specified as follows:

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma^\delta_{t-1} \tag{7}$$

Again, the parameters (δ, ω, α, γ, and β) can be simultaneously estimated by maximising the log-likelihood. The APARCH model, as the GJR-GARCH model (Ding et al., 1993 and Sheppard, 2013), 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. From APARCH, GARCH (1,1) model is obtained by setting δ=2, γ=0.

Let the normal distribution be indicated by $\Phi(.)$. The VaR for volatility estimates using EWMA, GARCH and APARCH, for confidence level α and volatility σ, is given as

$$VaR = \alpha\sigma\phi^{-1} \tag{8}$$

The corresponding ES is also estimated as

$$ES = -\left[VaR(\alpha)\phi\sigma^2\right]/\alpha \quad (9)$$

Let υ be the degrees of freedom, confidence level term be $t_{\alpha,\upsilon}$, and h is the holding period, the t-VaR is given as:

$$t\text{-VaR} = -h\mu + \sigma\, t_{\alpha,\upsilon}\, \surd h\, \surd(\tfrac{\nu-2}{\nu}) \quad (10)$$

The t distribution is a generalisation of the normal distribution that produces higher than normal kurtosis when υ is finite. Generally, let $\varphi(.)$ be the value of the standard normal density function and h is time period-ahead. Estimating VaR and ES at a confidence level with Normally Distributed data can be done as follows:

$$VaR(h,\alpha) = -h\mu + \surd h\, \sigma Z_\alpha \quad (11)$$

$$ES(h,\alpha) = -h\mu + \surd h\, (Z_\alpha)/(1-\alpha) \quad (12)$$

where Z_α is the standard normal variate corresponding to α, μ is the mean and σ is the estimated volatility of the data[11].

III.4 Estimating VaR and ES using Extreme Value Theory

Extreme Value Theory (EVT) is an established field of statistics and based on rigorous mathematical methods (McNeil and Frey 2000). The approach is tailor-made to describe extreme events. Extreme events are defined as low-probability and high-impact events and are based on few observations. EVT provides a good fit for the tails of distributions.

The two approaches of modeling using EVT are the Fisher-Tippet-Gnedenko Theorem; concerned with modeling the distribution of minimum or maximum realisations and the Picklands-Dalkema-de Hann theorem that models the exceedances of a particular threshold.

<u>Fisher-Tippet-Gnedenko Theorem</u>

The Fisher-Tippet-Gnedenko Theorem (also called Block Maxima/Minima, BM) simply states that a sample of *iid* observations from an unknown distribution of extremes converges to the following generalised extreme-value (GEV) distribution:

Let $x = x_1, x_2 \ldots x_n$ be a sequence of iid random variables, μ is the location parameter, σ is the scale parameter and ξ is the tail index parameter of the distribution.

[11]Refer to Engle (1993), Engle (2001) and Sheppard (2013) for discussions on GARCH, its variants and specifications.

The CDF of the above GEV is rewritten as:

$$F(x) = \exp \{ -(1+\xi[(x-\mu)/\sigma]^{-1/\xi} \} \quad \text{if } \xi \neq 0,\ \xi[(x-\mu)/\sigma] > 0 \tag{13}$$

$$F(x) = \exp \{ -(\exp-[(x-\mu)/\sigma]\} \quad \text{if } \xi = 0 \tag{14}$$

If $\xi > 0$, the GEV becomes the Fretchet and the distribution therefore has heavy tails. Typical distributions include Levy, t- and Pareto distributions.

If $\xi = 0$, the GEV becomes the Gumbel and the distribution therefore has light tails. Normal and lognormal belong here.

If $\xi < 0$, the GEV becomes the Weibull and the distribution therefore has lighter tails than normal.

The quantiles and hence the VaR is,

$$= \mu -(\sigma/\xi)[1-(-\log(1-1/k))]^{-\xi} \} \quad \text{for Fretchet and } \xi \neq 0 \tag{15}$$

$$= \mu - \sigma\ln[-\log(p)] \text{for Gumbel and } \xi = 0 \tag{16}$$

The return level, RL

$$= \mu -(\sigma/\xi)\ [1-(-\log(1-1/k)\ )^{-\xi}\ ] \} \quad \text{for } \xi \neq 0 \tag{17}$$

$$= \mu - \sigma\log[-\log(1-1/k)] \quad \text{for } \xi = 0 \tag{18}$$

RL is a rather more conservative measure than the VaR and can be used as the maximum loss of a portfolio. A 10-year RL is a level, which on average, should only be exceeded in one year every 10 years. This level may or may not be exceeded more than once in the year, depending on data dependencies, clustering etc.

The Picklands-Dalkema-de Hann Theorem

The Picklands-Dalkema-de Hann Theorem deals with the behaviour of observations that exceed a certain threshold. It is therefore known as Peak-Over-Threshold (POT) method.

The conditional excess distribution function (the distribution function),

$$F_U = \text{Prob}(X- \mu= y \mid X > \mu), \tag{19}$$

where X is the values of ordered distribution and μ is the threshold to be exceeded According to this theorem, the limiting distribution of F_u as $\mu \rightarrow \infty$, is a generalised

Pareto distribution (GPD), whose CDF is:

$$F(x) = 1- (1+\xi(x/\sigma)^{-1/\xi} \} \quad \text{if } \xi \ ?0 \qquad (20)$$

$$F(x) = 1 - \exp(-x/\sigma) \quad \text{if } \xi = 0 \qquad (21)$$

This distribution has only two parameters; a positive scale parameter σ and the tail index ξ. Maximum likelihood (ML), method of moments and hill estimator are used to estimate the parameters.

III.5 Market Risk VaR Estimation in Basel II/III Accord

The two basic parameters of VaR are the significance level, *a* (or confidence level *1−a*) and the risk horizon, which is the period of time measured in trading days instead of calendar days. For banks, the significance level is set by a banking regulator such that under the Basel II Accord, banks using internal VaR models to assess their market risk capital requirement should measure VaR at the 1 per cent significance level, which is equivalent to 99 per cent confidence level (Alexander, 2008). The VaR significance or confidence level depends on the risk appetite of the user. The lower the appetite for risk of the user, the lower the value of *a*, which implies the higher the confidence level applied.

Market risk VaR is measured over a short-term risk horizon such as 1 day and then scaled up to represent VaR over a longer risk horizon. This is usually done under the assumption that the returns are independent and identically normally distributed, and that the portfolio is rebalanced daily to keep the portfolio weights constant (Jorion, 2006).

Generally, the BCBS requires market risk charge VaR to be computed with a horizon of 10 trading days or two calendar weeks, 99 per cent confidence interval and an observation period based on at least a year of historical data that is updated at least once a quarter (BCBS, 2006). Under the internal models approach (IMA) of the BCBS, the market risk charge (MRC) is measured to be the larger of the previous day's VaR or the average daily VaR over the previous 60 days times a multiplicative factor of 'k' that has a minimum value of 3 (i.e., average bank's daily earnings at risk $\times \sqrt{10} \times 3$). The Basel Committee allows the 10-day VaR to be obtained from an extrapolation of one-day VaR values.

III.6 Measuring Foreign Exchange Rate Risk

According to BCBS (2006), the standardised framework of measuring market risk capital charge requires the bank to calculate its net exposure in each foreign currency, which is then converted into home currency at the current spot exchange rate. All net long positions across all foreign currencies are then summed separately from all net short currency positions. The capital charge is then calculated as 8 per cent of the higher of the aggregate long positions or the aggregate short positions. The IMA for foreign exchange risk is estimated as described above.

The 2016 Standardised Approach for Market Risk requires sensitivities-based method of Capital charges for delta, vega and curvature risk factor sensitivities within a prescribed set of Foreign exchange and other risk classes.

In the 2016 revision for market risk charge using the internal model approach, BCBS, (2016) has directed for a shift from VaR to an ES measure of risk during stress so as to certify a more judicious capture of "tail risk" and capital adequacy when the financial market is under serious stress. Banks will have the right to choose their risk models, but "Expected shortfall" must be estimated on a daily basis for the whole bank for its regulatory capital calculation. ES must also be calculated daily for every trading desk that a bank is considering for inclusion within the scope for the internal model for its regulatory capital calculation. To compute the ES, a 97.5th percentile, one-tailed confidence level is to be used.

Each bank must meet, daily, a capital obligation expressed as the higher of its previous day's aggregate capital charge for market risk or an average of the daily capital measures in the preceding 60 business days according to the specified parameters. BCBS (2016a) requires testing to be carried out using the entire forecasting distribution using the p-value of the bank's profit or loss on each day. For example the bank could be required to use in validation and make available to the supervisor the following information for each desk for each business day over the previous three years, with no more than a 60-day lag: Two daily VaR's for the desk calibrated to a one -tail 99.0 and 97.5 percent confidence level, and a daily ES calibrated to 97.5.

III.7 The Risk Ratios Methodology

This paper evaluates the accuracy of the VaR and ES risk models using the risk ratios methodology. In the risk ratios methodology, the ratio of the maximum to the minimum forecasted risk by common risk models is calculated. 1 is the baseline risk ratio estimate such that when risk is forecasted by some candidate models, then the risk ratio should be close to 1. Estimation risk accounts for the small deviation in the risk models and if the risk ratio is very different from 1, it therefore captures the degree to which different models disagree (Danielsson et al., 2014).

The following algorithm illustrates the main steps of Danielsson et al. (2014) risk ratios methodology:

i. Select the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates and obtain the daily holding period return for each stock.
ii. Estimate the daily VaR and ES at both 97.5 per cent as well as 99 per cent using the selected candidate risk models for the exchange rates with an estimation window size of 1,000.
iii. For each day, estimate the ratio of the highest to the lowest VaR and ES at both 97.5 per cent as well as 99 per cent (VaR and ES risk ratios) across all models.

III.8 Data Description

The data represents 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 19th February, 2015) and two business days after each one. Therefore, there are 16 data series for the analysis. For the policy announcement of the 25th November 2014, we collect 1001 daily observations from CBN website covering 28th October, 2010 to 24th November, 2014 and 1st November, 2010 to 26th November, 2014 for 2 days after the announcement. Similarly, for the 19th February, 2015 policy decision, we collected daily data covering 24th January, 2011 to 18th February, 2015 and from 26th January, 2011 to 20th February, 2015 for 2 days after the announcement. The total data points downloaded were 1001 out of which 1000 is the estimation window for the four exchange rate series. That corresponds to roughly four years of trading data.

In this paper, simple data analyses are carried out using Microsoft Excel, while the main estimations and simulations are performed with Matlab package.

IV. Empirical Analysis and Discussion of Results

IV.1 Empirical Analysis

In carrying out the empirical analysis, we first estimate the returns of the exchange rate series. Figure 1 presents the plot of returns of the raw exchange rates, p_t. The analysis of the paper is carried out using returns, y_t, of each of the 16

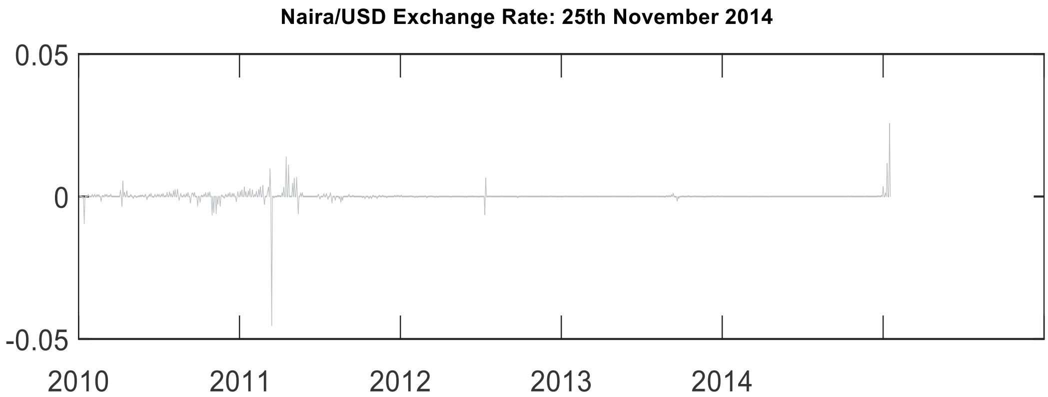
[12] www.cenbank.org

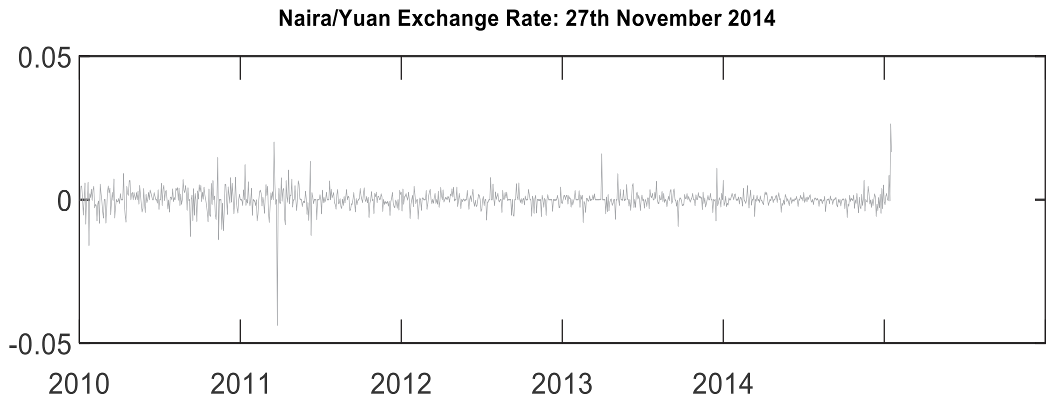
series:

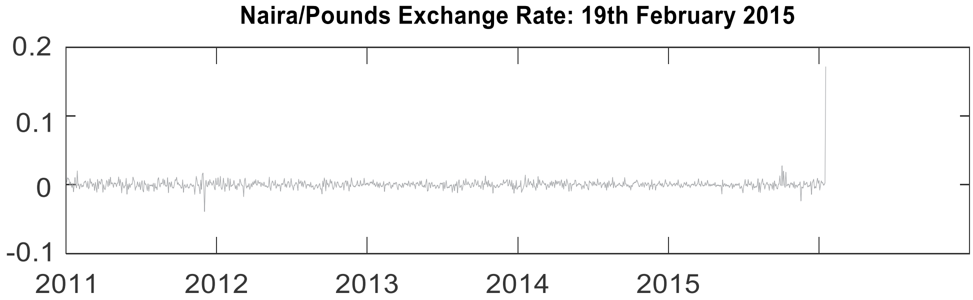
$$y_t = 100 \ \log(p_t/p_{t-1})$$

Instead of plotting 16 series, to save space, only 4 are plotted one from each date (25th November 2014 and two business days after as well as 19 February, 2015 and two business days after). Therefore, for 25th November, 2014, the Naira/USD exchange rate is plotted, and the Naira/Yuan exchange rate is plotted for 27th November, 2014. For 19th February, 2015, the Naira/Pound is plotted while the Naira/Euro exchange rate is presented for 21st February, 2015. As expected, all series of the returns appear to be mean reverting and exhibit periods of low volatility followed by periods of much higher volatility.

Figure 1: Daily Logarithmic Returns of Naira Exchange Rates







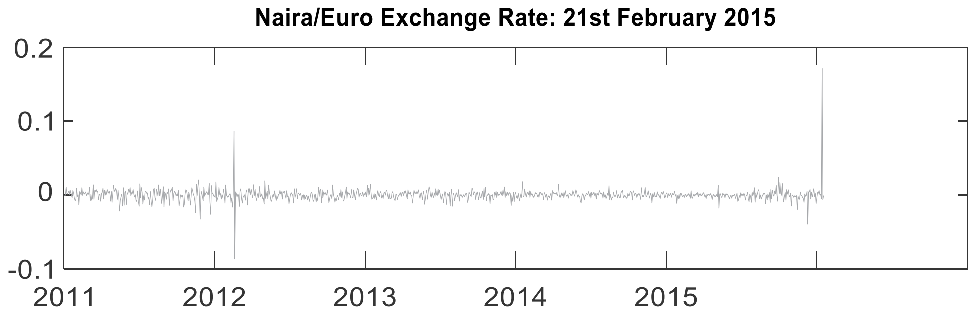


Table 1 presents the summary statistics of the unconditional returns of the four pairs of the naira exchange rates. From the Table, the sample skewness is not equal to zero, which indicates considerable asymmetry, while the kurtosis also shows the returns series are leptokurtic. This is an indication of a substantial violation of normality.

Table 1: Summary Statistics of the Returns of Naira Exchange Rates

	Minimum	Maximum	Skewness	Kurtosis
25th Nov, 2014				
USD	-0.019	0.011	-9.026	302.232
Yuan	-0.019	0.009	-2.128	33.703
Pounds	-0.017	0.012	-0.298	5.639
Euro	-0.038	0.038	-0.173	47.442
27th Nov, 2014				
USD	-0.020	0.011	-7.896	272.740
Yuan	-0.019	0.011	-1.364	32.065
Pounds	-0.017	0.012	-0.230	5.706
Euro	-0.037	0.038	-0.166	46.877
19th Feb, 2015				
USD	-0.020	0.074	25.358	764.148
Yuan	-0.019	0.011	-1.299	33.185
Pounds	-0.017	0.075	12.907	307.158
Euro	-0.037	0.074	7.012	156.715
21st Feb, 2015				
USD	-0.020	0.074	25.358	764.148
Yuan	-0.019	0.074	18.763	509.744
Pounds	-0.017	0.075	12.937	308.081
Euro	-0.037	0.074	7.065	158.354

IV.2 Empirical Results

The aim of this section is to estimate VaR and ES risk measures at both 97.5 per cent and 99 per cent levels, in line with Basel III decision (Danielsson, 2013), using a range of risk forecast models (historical simulation, APARCH, Normal, Student t, GARCH and EVT) to returns on the exchange rate described in Section IV.1. All error terms are assumed to be normal, where applicable, in all the risk forecast models. Results from the estimated models discussed in the previous sections are presented in Table 2 for various dates of policy announcements. The risk is forecasted on a day-ahead basis with a portfolio value of N1000 and the estimation window is 1,000 days as studied by Danıelsson (2002) and Danielsson (2015b). As shown in Table 2 panels 2a-2d, model risk is evaluated using the Danielsson et al. (2014) risk ratios methodology. It should be noted that each of the risk measures for the policy announcements are forecasted with data up to a business day before the event.

IV.2.1 Analysis of Model risk for Naira/USD Exchange Rate

Table 2, Panel 2a shows the result of estimated risk measures as presented in columns 3-8. Column 1 shows the risk measure and its associated confidence level, column 2 displays the date the forecast is made for while the last column (column 9) shows the calculated risk ratio. For instance, the second row starts with VaR 97.5 per cent while the second column has 25/11/2014 implying that VaR forecast at 97.5 per cent confidence level for 25th November, 2014 using Historical method (3rd column) is 0.09 and using GP EVT method (5th column) is 0.13. The risk ratio for that day's forecast is 15.87 as shown in the last (9th) column labelled “Risk Ratios”.

Panel 2a shows significant divergences among the various models before and after the 1st and 2nd announcements and model risk fluctuates between value-at-risk (VaR 97.5 per cent and VaR 99 per cent) than expected shortfall (ES 97.5 per cent and ES 99 per cent) measures for the Naira/USD exchange rates. The disagreement is because the various models utilise the returns regimes, in Figure 1, which shows a lot of spikes and the models use different assumptions of the data to estimate the risk measures.

When the risk ratio model risk methodology is applied to the range of risk forecast models and their associated measures, it became apparent that model risk is always existing, as observed by Danielsson et al. (2017), regardless of the risk measure (VaR or ES), confidence level (97.5 per cent or 99 per cent) and which policy announcement (25/11,27/11,19/02 or 21/02). This is seen in the right-most column identified as Risk Ratios.

Before the first policy announcement on 25/11/2014, model risk estimated for ES at 97.5 per cent is higher than that of VaR at 97.5 per cent. The same outcome is observed at 99 per cent confidence level. The risk measures also revealed higher model risk for ES at 97.5 per cent against VaR at 97.5 per cent as well as at 99 per cent confidence level. However, model risk reduced after the first announcement for all risk measures at same confidence level, as observed by Danielsson (2015b). For instance, model risk for VaR 97.5 per cent was 15.87 before the announcement but reduced to 13.99 two days after the announcement.

For the second policy announcement of 19/02/2015 and its two days after, model risk estimated for ES at 97.5 per cent is lower than that of VaR at 97.5 per cent. The same outcome is observed at 99 per cent confidence level.

Table 2, Panel 2a: Risk Forecasts and Model Risks for Naira/USD Exchange Rate

Risk Measure and c.l.	Policy Announcement	Risk Measure estimated using a particular method						Risk Ratios
		Historical	Normal	GP EVT	Student T	GARCH	APARCH	
VaR 97.5 per cent	25/11/2014	0.09	1.33	0.13	0.87	8.68	15.96	15.87
VaR 99 per cent	25/11/2014	4.51	4.58	0.16	5.16	29.93	55.05	54.89
ES 97.5 per cent	25/11/2014	0.23	0.83	0.19	0.71	16.36	30.08	29.89
ES 99 per cent	25/11/2014	0.10	0.05	0.11	7.74	34.29	63.07	63.02
VaR 97.5 per cent	25/11/2014 + 2 days after	0.11	1.37	0.14	0.89	5.17	14.09	13.99
VaR 99 per cent	25/11/2014 + 2 days after	5.27	4.71	0.18	5.31	17.84	48.60	48.43
ES 97.5 per cent	25/11/2014 + 2 days after	0.24	0.85	0.20	0.73	9.75	26.56	26.36
ES 99 per cent	25/11/2014 + 2 days after	0.11	0.05	0.11	7.97	20.44	55.68	55.63
VaR 97.5 per cent	19/02/2015	0.11	1.41	0.14	0.92	0.12	0.21	1.30
VaR 99 per cent	19/02/2015	6.33	4.86	0.18	5.48	0.40	0.73	6.15
ES 97.5 per cent	19/02/2015	0.24	0.88	0.18	0.75	0.22	0.40	0.70
ES 99 per cent	19/02/2015	0.12	0.05	0.10	8.23	0.46	0.84	8.18
VaR 97.5 per cent	19/02/2015 + 2 days after	0.28	3.88	0.26	2.54	0.16	4.63	4.48
VaR 99 per cent	19/02/2015 + 2 days after	6.18	13.40	0.36	15.10	0.54	15.98	15.62
ES 97.5 per cent	19/02/2015 + 2 days after	0.41	2.43	0.26	2.07	0.30	8.73	8.47
ES 99 per cent	19/02/2015 + 2 days after	0.28	0.14	0.12	22.66	0.62	18.31	22.53

For the Naira/USD exchange rate, model risk is significantly much higher on the day of the first policy announcement (25/11/2014) than on the day of the second policy announcement (19/02/2015) for each risk measure at corresponding confidence level (i.e. for VaR 97.5 per cent. ES 97.5 per cent, etc.). For instance, model risk for VaR 97.5 per cent on 25/11/2014 was 15.87 but reduced to 13.99 two days after the announcement.

The reverse is observed for the second policy announcement as model risk significantly increased two days after the announcement for the corresponding risk measure at same confidence level. For instance, ES at 97.5 per cent was 0.70 on the day of second policy announcement but increased more than ten-fold to 8.47 two business days after the policy announcement. As recommended by Basel III, what about model risk between ES 97.5 per cent against VaR 99 per cent? For the Naira/USD exchange rate, model risk is significantly much higher for VaR 99 per cent with 54.89 against ES 97.5 per cent with 29.89 on the day of the first policy announcement. Two business days after the first policy announcement, the same outcome was observed as model risk from VaR 99 per cent was 48.43 against that of ES 97.5 per cent with 26.36.

For the second policy announcement, model risk is significantly much higher for VaR 99 per cent with 6.15 against ES 97.5 per cent with 0.70 on the day of the second policy announcement. Two business days after the second policy announcement, the same outcome was observed as model risk from VaR 99 per cent was 15.62 against that of ES 97.5 per cent with 8.47.

We can therefore conclude that for the Naira/USD exchange rate, ES 97.5 per cent resulted in significantly much lower model risk than VaR risk measure at 99 per cent confidence level. This supports the Basel III decision taken to switch from VaR 99 per cent to ES 97.5 per cent for regulatory capital decisions (Danielsson, 2013). We also observe significant differences or disagreements among the various estimated risk measures (ES and VaR) for the six models as evidenced by varying risk ratios before and after the first and second policy announcements, as reported by Danielsson et al. (2017).

IV.2.2 Analysis of Model risk for Naira/ Yuan Exchange Rate

Panel 2b shows the estimated model risk as risk ratios in column 9 for the Naira/Yuan exchange rates indicating significant differences among the various models before and after the first and second policy announcements. The description of the columns is as given in Panel 2b and will also be used for Panels 2c and 2d.

Table 2, Panel 2b: Risk Forecasts and Model Risks for Naira/Yuan Exchange Rate

Risk Measure and c.l.	Policy Announcement	Risk Measure estimated using a particular method						Risk Ratios
		Historical	Normal	GP EVT	Student T	GARCH	APARCH	
VaR 97.5 per cent	25/11/2014	1.22	2.23	4.83	1.46	1.40	2.37	3.61
VaR 99 per cent	25/11/2014	8.42	7.70	5.16	8.68	4.82	8.16	3.86
ES 97.5 per cent	25/11/2014	1.16	1.40	2.43	1.19	2.64	4.46	3.30
ES 99 per cent	25/11/2014	0.12	0.08	3.06	13.03	5.53	9.35	12.95
VaR 97.5 per cent	25/11/2014 + 2 days after	1.19	2.29	4.86	1.50	4.94	6.47	5.28
VaR 99 per cent	25/11/2014 + 2 days after	8.93	7.91	5.18	8.91	17.04	22.31	17.13
ES 97.5 per cent	25/11/2014 + 2 days after	1.18	1.43	2.40	1.22	9.31	12.19	11.02
ES 99 per cent	25/11/2014 + 2 days after	0.13	0.08	3.04	13.37	19.52	25.56	25.48
VaR 97.5 per cent	19/02/2015	1.11	2.31	4.62	1.51	0.27	2.47	4.35
VaR 99 per cent	19/02/2015	10.22	7.96	4.92	8.97	0.95	8.52	9.27
ES 97.5 per cent	19/02/2015	1.16	1.44	2.11	1.23	0.52	4.66	4.14
ES 99 per cent	19/02/2015	0.15	0.08	2.76	13.47	1.08	9.76	13.38
VaR 97.5 per cent	19/02/2015 + 2 days after	0.94	4.31	4.73	2.82	0.18	34.70	34.52
VaR 99 per cent	19/02/2015 + 2 days after	10.66	14.86	5.10	16.75	0.62	119.69	119.06
ES 97.5 per cent	19/02/2015 + 2 days after	1.33	2.69	2.50	2.30	0.34	65.40	65.06
ES 99 per cent	19/02/2015 + 2 days after	0.31	0.15	3.09	25.13	0.71	137.12	136.97

For the Naira/Yuan exchange rate, model risk is significantly much lower on the day of the first policy announcement (25/11/2014) than two days after the policy announcement for each risk measure at corresponding confidence level (i.e. for VaR 97.5 per cent. ES 97.5 per cent, etc.). For instance, model risk for VaR 99 per cent on 25/11/2014 was 3.30 but was 5.28 two days after the policy announcement.

This pattern is reversed for the second policy announcement as model risk significantly increased two days after the announcement for the corresponding risk measure at same confidence level. For instance, ES at 99 per cent was 13.38 on the day of second policy announcement but increased by about ten-fold to 136.97 two business days after the policy announcement.

What about model risk between ES 97.5 per cent and VaR 99 per cent as recommended by Basel III? Model risk is higher for VaR 99 per cent with 3.86

against ES 97.5 per cent with 3.30 on the day of the first policy announcement. Two business days after the first policy announcement, the same outcome was observed as model risk from VaR 99 per cent was 17.13 against that of ES 97.5 per cent with 11.02.

For the second policy announcement, model risk is significantly much higher for VaR 99 per cent with 9.27 against ES 97.5 per cent with 4.14 on the day of the second policy announcement. Two business days after the second policy announcement, the same outcome was observed as model risk from VaR 99 per cent was 119.06 against that of ES 97.5 per cent with 65.06.

The same conclusion is reached for the Naira/Yuan exchange rate as Naira/USD exchange rate. That is ES 97.5 per cent resulted in significantly much lower model risk than VaR risk measure at 99 per cent confidence level. We also observe significant differences or disagreements among the various estimated risk measures (ES and VaR) for the six models as evidenced by varying risk ratios before and after the first and second policy announcements.

IV.2.3 Analysis of Model risk for Naira/Pound Exchange Rate

Panel 2c shows the estimated model risk as risk ratios in column 9 for the Naira/Pound exchange rates indicating significant differences among the various models before and after the first and second policy announcements**.**

Similar to the Naira/Yuan, for the Naira/Pound exchange rate, model risk is lower on the day of the first policy announcement (25/11/2014) than two days after the policy announcement for each risk measure at corresponding confidence level (i.e. for VaR 97.5 per cent. ES 97.5 per cent, etc.). As in Naira/Yuan, for the Naira/Pound exchange rate, this pattern changes for the second policy announcement as model risk significantly increased two days after the announcement for the corresponding risk measure at same confidence level.

The same conclusion is reached for the Naira/Pound exchange as for Naira/Yuan and Naira/USD exchange rates. That is ES 97.5 per cent resulted in significantly much lower model risk than VaR risk measure at 99 per cent confidence level. We also observe significant differences or disagreements among the various estimated risk measures (ES and VaR) for the six models as evidenced by varying risk ratios before and after the first and second policy announcements.

The decision of BCBS to switch from VaR99 per cent to ES97.5 per cent seems to be supported by all the Naira/Yuan and Naira/Pounds exchange rates.

Table 2, Panel 2c: Risk Forecasts and Model Risks for Naira/Pound Exchange Rate

Risk Measure and c.l.	Policy Announcement	Risk Measure estimated using a particular method						Risk Ratios
		Historical	Normal	GP EVT	Student T	GARCH	APARCH	
VaR 97.5 per cent	25/11/2014	2.65	3.23	7.04	2.65	3.78	4.68	4.39
VaR 99 per cent	25/11/2014	11.73	11.15	8.02	12.56	13.04	16.14	8.12
ES 97.5 per cent	25/11/2014	1.95	2.02	3.60	1.66	7.13	8.82	7.16
ES 99 per cent	25/11/2014	0.14	0.11	4.56	14.87	14.94	18.50	18.38
VaR 97.5 per cent	25/11/2014 + 2 days after	2.63	3.25	7.03	2.63	2.87	5.55	4.41
VaR 99 per cent	25/11/2014 + 2 days after	11.94	11.21	8.02	12.66	9.91	19.13	11.12
ES 97.5 per cent	25/11/2014 + 2 days after	1.96	2.03	3.58	1.68	5.42	10.45	8.78
ES 99 per cent	25/11/2014 + 2 days after	0.15	0.12	4.54	15.15	11.36	21.92	21.80
VaR 97.5 per cent	19/02/2015	2.50	3.28	6.98	2.52	0.52	3.58	6.47
VaR 99 per cent	19/02/2015	12.09	11.31	7.94	12.90	1.78	12.35	11.12
ES 97.5 per cent	19/02/2015	1.95	2.05	3.54	1.71	0.97	6.75	5.77
ES 99 per cent	19/02/2015	0.16	0.12	4.50	16.37	2.04	14.14	16.25
VaR 97.5 per cent	19/02/2015 + 2 days after	2.34	4.91	7.20	3.52	4.63	34.46	32.12
VaR 99 per cent	19/02/2015 + 2 days after	12.31	16.94	8.11	19.35	15.95	118.85	110.74
ES 97.5 per cent	19/02/2015 + 2 days after	2.11	3.07	3.56	2.59	8.72	64.94	62.82
ES 99 per cent	19/02/2015 + 2 days after	0.32	0.17	4.56	26.46	18.28	136.16	135.99

IV.2.4 Analysis of Model risk for Naira/Euro Exchange Rate

Panel 2d shows the estimated model risk as risk ratios in column 9 for the Naira/Euro exchange rates indicating significant differences among the various models before and after the first and second policy announcements.

As opposed to the Naira/Yuan and Naira/Pound, for the Naira/Euro exchange rate, model risk is lower on the day of the first policy announcement (25/11/2014) than two days after the policy announcement for all risk measures at corresponding confidence level (.e. for VaR 97.5 per cent . ES 97.5 per cent, ES 99 per cent) except VaR 99 per cent.

As in Naira/Yuan and Naira/Pound, for the Naira/Euro exchange rate, this pattern changes for the second policy announcement as model risk significantly increased two days after the announcement for the corresponding risk measure at same confidence level.

Table 2, Panel 2d: Risk Forecasts and Model Risks for Naira/Euro Exchange Rate

Risk Measure and c.l.	Policy Announcement	Risk Measure estimated using a particular method						Risk Ratios
		Historical	Normal	GP EVT	Student T	GARCH	APARCH	
VaR 97.5 per cent	25/11/2014	3.14	4.69	9.07	3.24	4.22	6.85	5.93
VaR 99 per cent	25/11/2014	14.40	16.16	10.18	18.40	14.56	23.63	13.45
ES 97.5 per cent	25/11/2014	2.37	2.93	4.68	2.49	7.95	12.91	10.55
ES 99 per cent	25/11/2014	0.23	0.17	5.88	26.09	16.68	27.08	26.91
VaR 97.5 per cent	25/11/2014 + 2 days after	3.13	4.70	9.08	3.22	5.06	6.80	5.95
VaR 99 per cent	25/11/2014 + 2 days after	15.16	16.21	10.19	18.43	17.45	23.46	13.27
ES 97.5 per cent	25/11/2014 + 2 days after	2.38	2.94	4.68	2.50	9.54	12.82	10.44
ES 99 per cent	25/11/2014 + 2 days after	0.24	0.17	5.88	26.33	19.99	26.88	26.71
VaR 97.5 per cent	19/02/2015	3.11	4.72	9.05	3.09	0.83	5.58	8.21
VaR 99 per cent	19/02/2015	15.21	16.30	10.13	18.36	2.88	19.26	16.38
ES 97.5 per cent	19/02/2015	2.34	2.95	4.69	2.52	1.57	10.52	8.95
ES 99 per cent	19/02/2015	0.24	0.17	5.88	27.56	3.30	22.07	27.39
VaR 97.5 per cent	19/02/2015 + 2 days after	2.95	5.98	9.23	3.91	1.38	11.33	9.95
VaR 99 per cent	19/02/2015 + 2 days after	15.65	20.61	10.28	23.23	4.76	39.09	34.33
ES 97.5 per cent	19/02/2015 + 2 days after	2.51	3.73	4.72	3.19	2.60	21.36	18.85
ES 99 per cent	19/02/2015 + 2 days after	0.39	0.21	5.95	34.85	5.46	44.79	44.57

The same conclusion is reached for the Naira/Euro as the other exchange rates. That is ES 97.5 per cent resulted in significantly much lower model risk than VaR risk measure at 99 per cent confidence level. We also observed significant differences or disagreements among the various estimated risk measures (ES and VaR) for the six models as evidenced by varying risk ratios before and after the first and second policy announcements.

IV.2.5 Analysis of Performance of Risk Measures across exchange rate pairs

Table 3 presents the risk ratios for the Naira exchange rate pairs that were presented in Table 2. That is for analysis across the exchange rate pairs.

Figures 2 shows the risk ratios as model risks for the 4 exchange rates for 25th November, 2014, on the day of the announcement, (Figure 2, left) and two business days after (right). As seen from the left plot for on the day of the announcement, the highest model risk is from Naira/USD exchange rate forecasted using ES 99 per cent followed by VaR 99 per cent risk measures. The least model risk is from VaR 97.5 per cent forecasted using Naira/Yuan exchange rate.

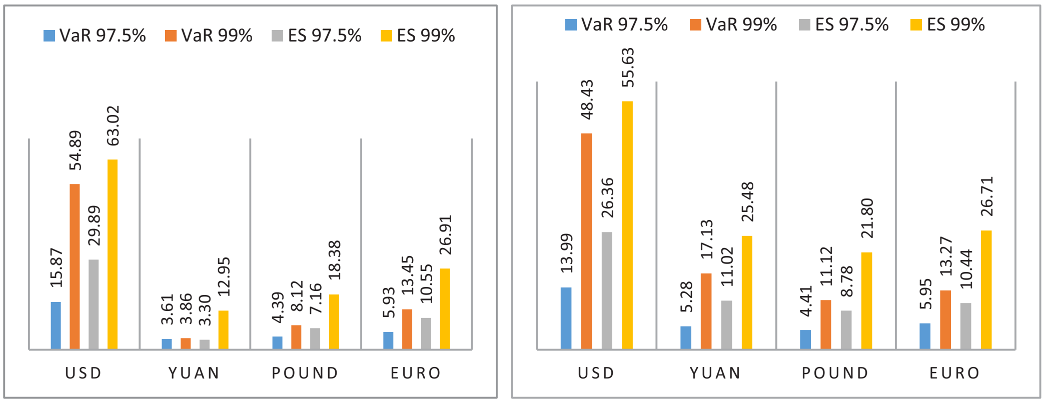
Table 3: Risk Ratios for the Naira against the 4 currencies

		USD	Yuan	Pound	Euro
24/11/2014	VaR 97.5 per cent	15.87	3.61	4.39	5.93
24/11/2014	VaR 99 per cent	54.89	3.86	8.12	13.45
24/11/2014	ES 97.5 per cent	29.89	3.30	7.16	10.55
24/11/2014	ES 99 per cent	63.02	12.95	18.38	26.91
25/11/2014 + 2 days after	VaR 97.5 per cent	13.99	5.28	4.41	5.95
25/11/2014 + 2 days after	VaR 99 per cent	48.43	17.13	11.12	13.27
25/11/2014 + 2 days after	ES 97.5 per cent	26.36	11.02	8.78	10.44
25/11/2014 + 2 days after	ES 99 per cent	55.63	25.48	21.80	26.71
19/02/2015	VaR 97.5 per cent	1.30	4.35	6.47	8.21
19/02/2015	VaR 99 per cent	6.15	9.27	11.12	16.38
19/02/2015	ES 97.5 per cent	0.70	4.14	5.77	8.95
19/02/2015	ES 99 per cent	8.18	13.38	16.25	27.39
19/02/2015 + 2 days after	VaR 97.5 per cent	4.48	34.52	32.12	9.95
19/02/2015 + 2 days after	VaR 99 per cent	15.62	119.06	110.74	34.33
19/02/2015 + 2 days after	ES 97.5 per cent	8.47	65.06	62.82	18.85
19/02/2015 + 2 days after	ES 99 per cent	22.53	136.97	135.99	44.57

For two days after the 24/11/2014 announcement as seen from the right plot of Figure 2, the highest model risk is from Naira/USD exchange rate forecasted using

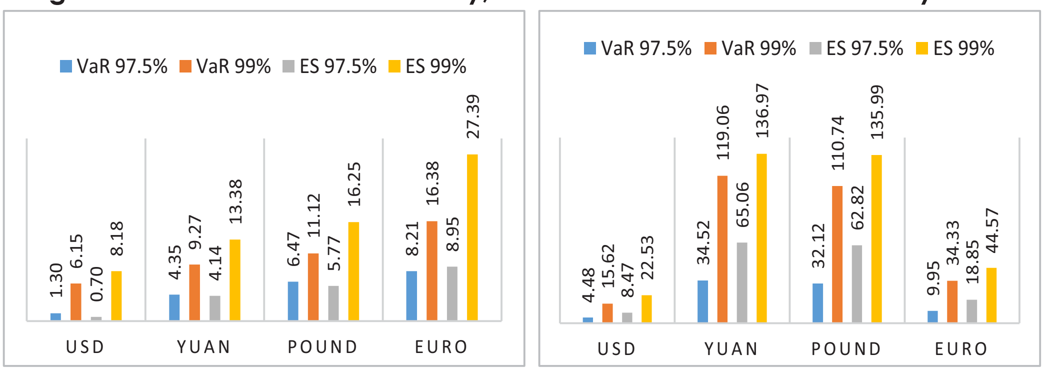
ES 99 per cent followed by VaR99 per cent risk measures. This is similar to what obtained for Naira/USD. The least model risk is from VaR 97.5 per cent forecasted using Naira/Pound exchange rate.

Figure 2: Risk ratios for 25th November 2014 announcement and two days after



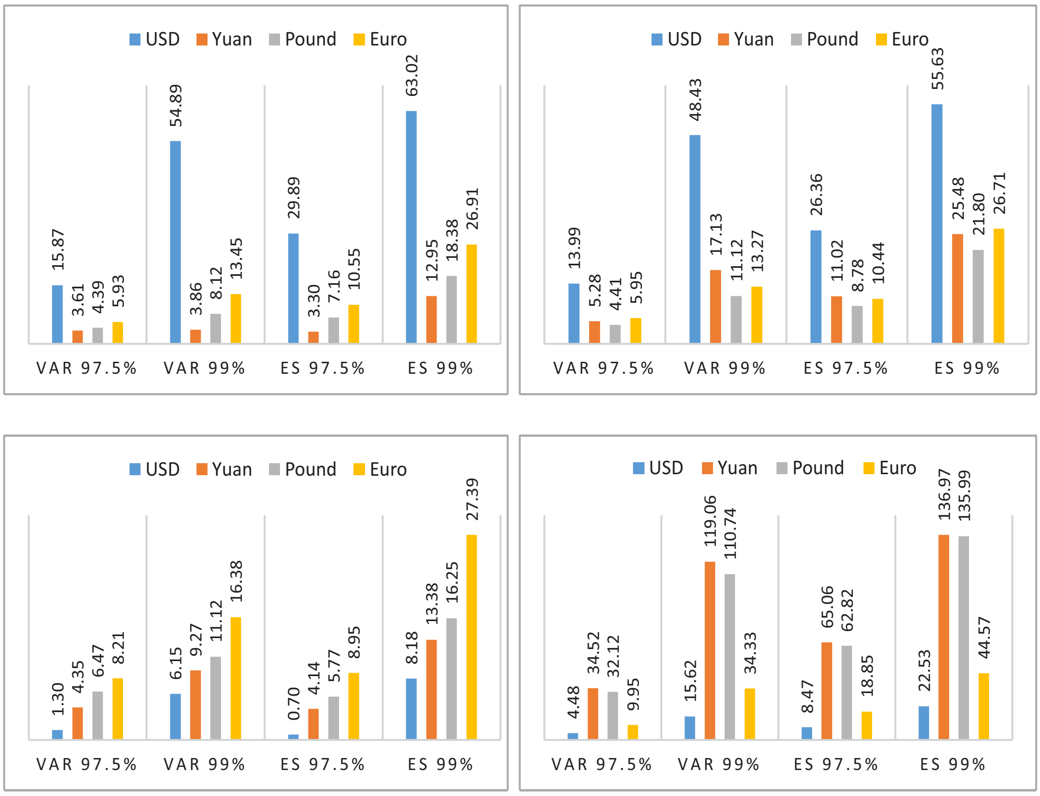
Figures 3 shows the risk ratios as model risks for the 4 exchange rates for 19th February, 2015, on the day of the announcement, (Figure 2, left) and two business days after (right). As seen from the left plot for the day of the announcement, the highest model risk is from Naira/Euro exchange rate forecasted using ES 99 per cent followed by VaR99 per cent risk measures. The least model risk is from ES97.5 per cent forecasted using Naira/USD exchange rate. For two days after the 19/02/2015 announcement as seen from the right plot of Figure 3, the highest model risk is from Naira/Pound exchange rate forecasted using ES 99 per cent followed by Naira/Yuan exchange rate forecasted using ES 99 per cent risk measures. The least model risk is from VaR97.5 per cent forecasted using Naira/USD exchange rate.

Figure 3: Risk ratios for 19th February, 2015 announcement and two days after



Figures 4 shows the risk ratios as model risks for the 4 exchange rates for 25th November, 2014 (top left panel), its two business days after (top right panel), 19th February, 2015 (bottom left panel) and its two business days after (bottom right panel) grouped according to the risk measures. For 25th November, 2014 announcement, Naira/USD exchange rate is undoubtedly the exchange rate with the highest model risk (ES 99 per cent, VaR 99 per cent and ES 97.5 per cent, in decreasing order of magnitude). That is followed by Naira/Euro forecasted with ER 99 per cent while Naira/Yuan has the least model risk with ES 97.5 per cent. For its two days after the announcement, the risk measures with the first two highest model risk were forecasted using Naira/USD while Naira/Yuan has the least model risk with VaR 97.5 per cent.

Figure 4: Risk ratios for announcements of 25th November 2014, 19th February, 2015 and two days after



In the case of 19/02/2015 announcement (Figure 4, bottom-left panel), the Naira/Euro exchange rate produced the highest model risk (ES 99 per cent and VaR 99 per cent in decreasing order of magnitude). That is closely followed by Naira/Pound forecasted with ER 99 per cent while Naira/USD has the least model risk with ES 97.5 per cent. For its two days after the announcement (Figure 4, bottom-right panel), the risk measures with the first two highest model risk were forecasted using Naira/Yuan at ES 99 per cent followed by Naira/Pound at ES99 per cent, while Naira/USD has the least model risk with VaR 97.5 per cent

Figures 5 displays the risk ratios as model risks for the 4 exchange rates for 25th November, 2014, its two business days after, 19th February, 2015 and its two business days after for ES risk measures at both 97.5 per cent and 99 per cent confidence levels.

Figure 5: ES Risk ratios for all announcements and their two business days after

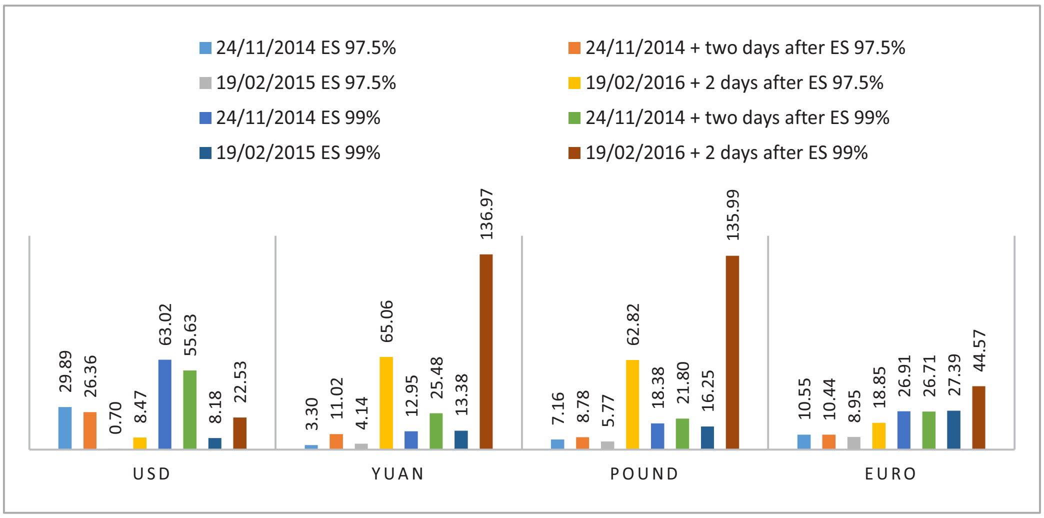
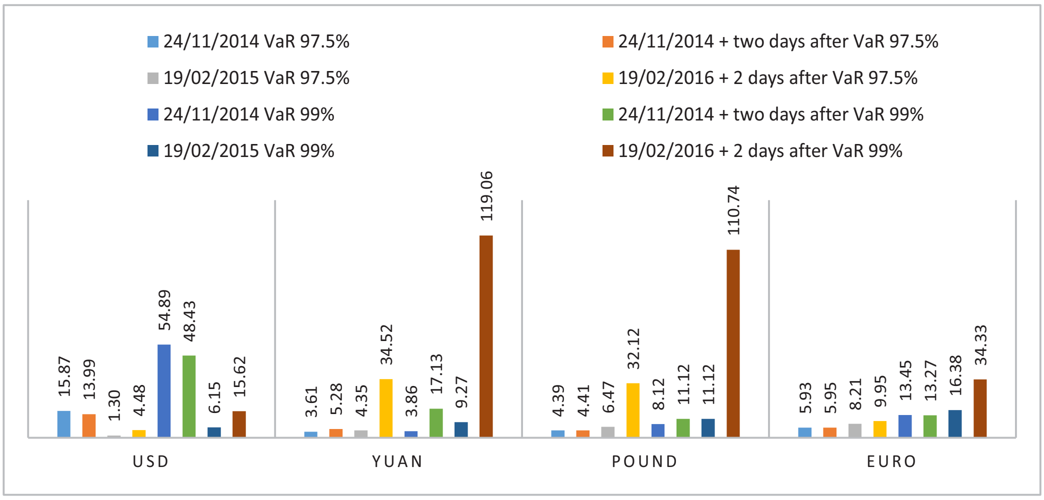


Figure 5 shows that the highest two model risk values was produced by ES at 99 per cent confidence level for Naira/Yuan with the highest model risk, closely followed by Naira/Pound all for two days after the second announcement. The least model risk based on ES was forecasted for Naira/USD at 97.5 per cent for 19/02/2015 with the next least risk measure at 3.30 for Naira/Yuan for 24/11/2014 announcement at 97.5 per cent.

Figures 6 displays the risk ratios as model risks for the 4 exchange rates for 25th November, 2014, its two business days after, 19th February, 2015 and its two business days after for VaR risk measures at both 97.5 per cent and 99 per cent confidence levels.

Figure 6: VaR Risk ratios for all announcements and their two business days after



As shown in Figure 6, the highest two model risk values were produced by VaR at 99 per cent confidence level for Naira/Yuan with the highest model risk, closely followed by Naira/Pound all for two days after the second announcement. Therefore, Naira/Yuan followed by Naira/Pound produced the highest model risk for the four series (announcements of 25/11/2014, 19/02/2015 and their two days after). The least model risk based on VaR was forecasted for Naira/USD at 97.5 per cent for 19/02/2015 with the next least risk measure at 3.61 for Naira/Yuan for 24/11/2014 announcement at 97.5 per cent.

Figures 5 and 6 showed that the model risk from the first two highest risk measures were obtained two days after the announcement of 19/02/2015 and were about twice the third highest model risk forecast. Also, the highest model risk was for the Naira/Yuan exchange rate, closely followed by Naira/Pound. The least model risk based on ES and VaR was forecasted for Naira/USD at 97.5 per cent for 19/02/2015 with the next least risk measure for Naira/Yuan for 24/11/2014 announcement at 97.5 per cent.

V. Conclusion and Policy Recommendation

This study used daily data for the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates covering 18th October, 2010 to 21st November, 2014 as well as 12th January, 2011 to 18th February, 2015 for the CBN's policy decisions of 25th November, 2014 and 19th February, 2015, respectively. The study evaluated model risk of VaR and ES risk measures as a result of the CBN's policy decisions implemented using historical simulation, APARCH, Normal, Student t, GARCH and extreme value theory models for the day of the announcements (25th

November 2014 and 19th February, 2015) and two business days after each one.

The implementation of Basel III recommends the switchover from VaR to ES and a reduction in confidence levels from 99 per cent to 97.5 per cent. The paper estimated VaR and ES at both 97.5 per cent and 99 per cent levels and evaluated their accuracy using the risk ratios methodology. The study supports the Basel III decision to adopt ES 97.5 per cent over VaR 99 per cent as ES 97.5 per cent resulted in significantly much lower model risk than VaR risk measure at 99 per cent confidence level for all naira exchange rates. However, the study found that ES 99 per cent produces higher model risk than VaR 99 per cent and ES 97.5 per cent gives higher model risk than VaR 97.5 per cent.

For the Naira/USD, Naira/Yuan, Naira/Pound and Naira/Euro exchange rates, the study found disagreements between the various risk measures (ES and VaR) based on the various models as observed in previous studies. The finding also supports prior studies that model risk is always present, regardless of the asset or exchange rate series and seems to increase significantly during market distress as encountered during the policy announcements, see Danielsson (2015b), for instance.

The study has shown that there are reasons for genuine concerns about the risk models used in foreign exchange market risk forecast and capital allocation given the high levels of model risk and lack of a predictable pattern amongst exchange rates or based on the dates of policy announcements. Model risk should therefore be a high priority for Nigerian banks and financial institutions. Regulators should examine how regulated entities build, approve and maintain models. Regulators and other financial sector participants also need to pay a lot of attention to model risk analysis and make it part of regulatory design process. Some of the actions to take include extensive analysis of model risk in the general financial system, establishing limits on model usage, monitoring model performance, and general model risk management. Most importantly, the CBN should also use the Basel III recommendation of substitution of 99 per cent VaR with 97.5 per cent ES and the setting of a risk forecast to its worst outcome based on history for calculating market risk capital charges, at least for foreign exchange.

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