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# Value-at-risk modeling of naira exchange rates

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## Abstract

The naira exchange rate has experienced extreme volatility, and the use of derivatives to control interest rates and currency risks has grown quickly. These developments have made risk management research necessary. To this effect, this paper investigated the optimal volatility model that offers the best VaR forecasts and minimizes expected loss in the Naira exchange rate. The data was collected from FX time and consisted of the Euro to Naira exchange and the daily closing rate of the US dollar to Naira exchange rate from 24/10/2016 to 15/06/2018. These data were estimated using different symmetric and asymmetric GARCH models. The finding shows that there is less volatility in the USD to Naira exchange rate compared to the Euro to Naira exchange rate. The study shows that SPLINE- GJR under skewed student t distribution is the optimal model for the Euro to Naira exchange rate while GARCH is the optimal model for the US dollar to Naira exchange rate. This study suggests that model risk assessments be given careful consideration by regulators, banks, and other stakeholders and integrated into the process of operational and regulatory design.

**Keyword:** GARCH; Value-at-Risk; Naira; Exchange rate

**JEL Classification**: C22

## 1. Introduction

The search for appropriate risk-measuring methodologies has been followed by a global increase in financial uncertainty, and economic turmoil (global financial crisis) and the increased volatility of financial markets has induced the design and development of more sophisticated tools for measuring and forecasting risk. With the growing importance of measuring and controlling market risk, several methodologies have been proposed such as sensitivity analysis and scenario analysis. At that time the world suffered from the economic recession that led to severe bank losses and defaults. These disasters concluded that immense money could be lost due to the lack of market risk supervision and management. This led financial institutions and regulators to adopt a new risk framework, the Value-at-Risk (VaR) modelling. After the presentation of the VaR method, it has been the most widely used market risk method since it is easy to implement and interpret, at the end of the analysis we get a single value in real currency amounts, which is why VaR is widely used and preferred. The value-at-risk method is simply a method that uses historical data to calculate the maximum level of loss in real currency amounts at a certain time, given a certain confidence level. [1] describe VaR as the quantile of the projected distribution of losses and gains of an investment over a target horizon. Var answers How much can I lose with q% probability over a certain holding period" The basic idea behind VaR is straightforward since it gives a simple quantitative measure of portfolio's downside risk. VaR has two important and appealing characteristics. First, it provides a common consistent measure of risk for different positions and instrument types and it takes into account the correlation between different risk factors

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Accurate measuring and forecasting of market losses seem to play a crucial role both in developed and emerging financial markets. Unlike the financial markets of developed countries, emerging financial markets are characterized by insufficient liquidity, a small scale of trading and an asymmetrical and low number of trading days with certain securities [2]. In their study of 16 emerging markets in Europe, Latin America and Asia [3] point out that average daily returns are not significantly different from zero for the emerging markets. Their return volatilities are twice the volatilities of developed markets. Furthermore, return series exhibit significant positive or negative skewness coefficients.

Nowadays, there have been already various methods to estimate VaR, including traditional and modern approaches. Mature methods, such as Weighted Historical Simulation [4], Filtered Historical Simulation [5], Conditional VaR [6], VaR under t-distribution and VaR under normal distribution, can already forecast VaR accurately. Meanwhile, there are also some new approaches being developed in recent years. All the above methods are devoted to making VaR more efficient. Plenty of papers [7-9] estimate VaR for stock markets in the US and Western countries, using data such as the S&P500, Dow Jones Industrial Average Index and NASDAQ Composite Index. However, not many researchers have adopted data from the Naira exchange market. [10] concluded higher expected returns with higher downside risk in twenty-seven emerging stock markets, including Nigeria.

It is of policy importance to central banks and FOREX traders in Nigeria to determine the volatility that gives the best accurate VaR forecasts in Naira exchange rates using GARCH variants. This research will investigate the optimal volatility model that offers the best VaR forecasts and minimises expected loss in the Naira exchange rate. Although much literature estimates VaR by various methods applying different market data to our knowledge, our work is the first to apply VaR methodology to the Naira exchange rate, very few talk about emerging financial markets, especially the Naira exchange market. The data was collected from FX time and consists of the Euro to Naira exchange and US dollar to Naira exchange daily closing rate from 24/10/2016 to 15/06/2018. The rest of the paper is structured as follows, Section 2 presents the literature review of stylized facts of asset returns and GARCH volatility models. Section 3 present the methodology Section 4 empirically models the two pairs of exchange rates using several GARCH volatility models. The last Section concludes, presents findings and offers some policy implications of modelling foreign exchange volatility

## 2. Review of Literature

Risk considerations have become a key focus of portfolio management since [11] wrote one of the influential papers on diversification. Subsequent literature has expanded since then, placing a great emphasis on modelling these second moments and driving risk management with statistical evaluations. Of these, the VaR has emerged as an industry benchmark [1].

[2] investigate the performance of extreme value theory (EVT) with the daily stock index returns of four different emerging markets using the Serbian (BELEXline), Croatian (CROBEX), Slovenian (SBI20), and Hungarian (BUX) stock indexes using the data from January 2006 to September 2009 using synthesis and statistical methods. His main findings showed that under stable market conditions, the parametric and historical simulation models gave good forecasts of VaR estimation with 95% confidence level, while under the conditions if market volatility analysed models give good estimations of VaR parameters with a 99% confidence level.

Similarly [12] investigated the change in volatility of the Malaysian stock market, concerning the global financial crisis of 2007/2008, using both symmetric and asymmetric GARCH models. Using the Kuala Lumpur Composite Index (KLCI), two periods are selected. The first period is from June 2000, after the recovery of the East Asian crisis, to the end of 2007 and excludes the global financial crisis 2007/2008 and the second period includes the crisis, i.e., from June 2000 to March 2010. AR (4) was found to be the best in modelling the conditional mean and GARCH (1, 1), EGARCH (1, 1), GJR-GARCH (1, 1) model for conditional variance. As expected from financial time series, for both periods, the KLCI exhibits stylized characteristics such as leptokurtosis, clustering effect and asymmetric and leverage effect. It is also found that there was a significant increase in volatility and leverage effect but just a small drop in persistence due to the financial crisis. [13] investigated the performance of the Risk Metrics method, as well as the GARCH and IGARCH models in VaR forecasting of a stock exchange index in the Serbian financial market. They concluded that GARCH models combined with extreme value theory (the peaks-over-threshold method) decrease the mean value of VaR, and that these models are better than the Risk Metrics method and the IGARCH model. Mladenovic et al. (2012) concluded that the methodology of extreme value theory is slightly better than the GARCH model regarding the calculation of VaR, based on their analysis of stock exchange indices in Central and Eastern European countries (Bulgaria, Czech Republic, Hungary, Croatia, Romania and Serbia.

[14] implemented GARCH models that involve time-varying volatility and heavy tails to the empirical distribution of returns, in selected Central and Eastern European emerging capital markets (Croatia, Czech, Hungary, Romania and Serbia). They showed that GARCH models with a t-distribution of residuals in most analysed cases give a better VaR estimation than GARCH models with normal errors in the case of a 99% confidence level, while the opposite is true in the case of a 95% confidence level. [15] tested the relative performance of selected GARCH-TYPE and showed the most adequate GARCH family models. He used the daily returns of the Macedonian stock exchange index-MBI 10 and tested the performance of the symmetric GARCH (1,1) and the GARCH-M model as well as of the asymmetric EGARCH (1,1) model, the GARCH-GJR model and the APARCH (1,1) model with different residual distributions. His results showed that the most adequate GARCH family models were the asymmetric EGARCH model with Student's t-distribution, the EGARCH model with normal distribution and the GARCH-GJR model and he concluded that the econometric estimation of VaR is related to the chosen GARCH model.

[16] presented a comparative evaluation of the predictive performance of conventional univariate VaR models including the unconditional normal distribution model, EWMA/Risk Metrics, Historical Simulation, Filtered Historical Simulation, GARCH-normal and GARCH Students t models in terms of their forecasting accuracy using daily closing prices of the USD/KES exchange rates over the period starting January 03, 2003 to December 31, 2016. The empirical results demonstrate that the GJR-GARCH-t approach and Filtered Historical Simulation method with GARCH volatility specification perform competitively accurately in estimating VaR forecasts for both standard and more extreme quantiles thereby generally outperforming all the other models under consideration. [17] examined the volatility characteristics on Jordan's capital market that include: clustering volatility, leptokurtosis, and leverage effect. He used selected symmetric and asymmetric models from GARCH family such as ARCH, GARCH, and EGARCH to investigate the behaviour of stock return volatility for the Amman Stock Exchange (ASE) covering the period from Jan. 1 2005 through Dec.31 2014. The main findings suggested that the symmetric ARCH /GARCH models can capture characteristics of the Amman Stock Exchange, and provide more evidence for both volatility clustering and leptokurtic, whereas EGARCH output reveals no support for the existence of leverage effect in the stock returns at the Amman Stock Exchange. [18] estimated the dynamic pattern of Nigeria All share index (ASI) using quasi maximum likelihood (QML) approach and they detected that IGARCH-t was the best model for predicting volatility in the ASL but in estimating the GAS variants the Beta t EGARCH model proves to predict the volatility in the stock returns better than the IGARCH-t. [19] in the article considered the adequacy of the GARCH model used in measuring risk in the Montenegrin emerging market before and during the global financial crisis. The daily return of the Montenegrin stock market index (MONEY) was analysed for the period January 2004 - February 2014. Similarly, Vladimir (2017) tested the performances of the parametric and non-parametric VaR models in the markets of the countries of the Southeast European region. The application of MANOVA analysis, discriminant analysis, and Roy's test were used in the case of selected regional countries. The research results indicate the significance of the analyzed VaR model's application in the analyzed markets and expand the potential for further research in the subject field. The results obtained in the research (rolling windows 100 and 300 days) implicate that statistically significant differences exists in the application of both parametric and non-parametric VaR models.

## 3. Methodology

VaR is a measure that gives the maximum loss that can be realized from certain investments over a given time horizon (usually 1 day or 10 days), with a certain probability [1]. Mathematically, VaR for the period of the k day in day t can be represented as follows

$$\Pr ob(p_t - p_{t-k} \leq VaR(t,k,\alpha) = \alpha \qquad (1)$$

where $p_t$ is the price of a particular type of financial asset at t and $p_{t-k}$ is the price of the asset at time t - price of the asset at time k, and $\alpha$ represent a given level of probability. VaR can be expressed in terms of a percentile of the return distributions. Specifically, if $q_\alpha$ is the $\alpha - th$ percentile of the continuously compound return, VaR is calculated as follows

$$VaR(t,k,\alpha) = (\exp(q) - 1)\, p_{t-k} \qquad (2)$$

The previous equation implies that a good estimate of VaR can only be produced with an accurate forecast of the percentiles, qα, obtained on the corresponding volatility modeling. Therefore, below we discuss the value of VaR for a series of returns. Define a one-day return on day t as: $r_t = log(p_t) - log(P_{t-1}) \qquad (3)$

For the time series of return $r_t$, VaR can be expressed as: $Prob[r_t < V aR|I_{t-1}] = \alpha \qquad [4]$

From this equation it follows that finding the VaR values is the same as finding a 100$\alpha$% conditional quantile. Formally, it is possible to develop models for the stock returns rt as follows

$$r_t = \mu_t + \varepsilon_t\,,\ \ \varepsilon_t = \alpha_t \eta_{t,}\ \ \mu_t = \mu(I_{t-1} \mid \theta),\ \ \sigma^2 = \sigma^2(I_{t-1} \mid \theta) \qquad (5)$$

where $I_{t-1}$ is a set of information available at time $t - 1$, and where $\mu$ and $\sigma$ are functions of a certain dimensional vector of parameter values $\theta$. In this model $\epsilon_t$ is innovation, $\alpha_t$ is the unobserved volatility, and $\eta_t$ is martingale difference sequence satisfying

$E(\eta/I_{t-1}, \theta) = 0$, $V[\eta/I_{t-1}, \theta] = 1$ (6)

As a consequence, we have $E(r_1/I_{t-1}, \theta) = \eta$, $V(r/I_{t-1}, \theta) = \sigma^2$, $\epsilon_t/I_{t-1}\ D(0, \sigma^2)$ (7)

There are traditional approaches to VaR, such as the non-parametric approaches, which aim to estimate VaR without the specific assumptions on the loss distribution, and are mainly based on historical simulation. The Historical simulation does not make any assumption for the distribution of asset returns and does not need a variance or covariance. The other approach is the Variance-covariance approach which is the most popular and most widely used value at risk calculation. It is widely used by risk metrics. It can be used under different distributions.

According to the VaR definition, we can obtain the VaR under normal distribution

$$VaR_\alpha(L) = \mu + \sigma Z\alpha \qquad (8)$$

where $\mu$ denotes the sample average loss, $\sigma$ is the sample standard variance and $Z_\alpha$ denotes the $\alpha$-quantile from standard normal distribution.

According to the VAR definition, we can obtain the VAR under student t distribution

$$VaR_\alpha = \mu + \sqrt{\frac{\nu - 2}{\nu}}\sigma_{t,\alpha,\nu} \qquad (9)$$

According to the VAR definition, we can obtain the VAR under Generalised Error Distribution (GED)

$$VaR = \mu + g_\alpha \sigma_t \qquad (10)$$

There are also GARCH Type VAR whose motivation of the method is driven by the volatility clustering, which is very common in financial market data.. There are different versions.

ARCH is given as $$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{a}\left(\alpha_i \Sigma^2{}_{t-1} - 1\right) \qquad (11)$$

The model GARCH (1,1) as established by [4] can be written as $$\sigma_t^2 = \alpha_0 + \alpha_1 \Sigma_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (12)$$

The GARCH (p,q) model permits more persistent volatility which is typical for most stock data[12] can be given as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}(\alpha_1 \Sigma_{t-1}^2) + \sum_{j=1}^{a}(\beta_j \sigma_{t-j}^2) \qquad (13)$$

for $\alpha_0 > 0$, $\alpha_1 > 0$, $i = 1..q$ and $b_j > 0$, j=1...p, the conditional variance is well defined. where p is the order of GARCH and q is the order of ARCH process, $R_t$ is returns of the financial time series (stock exchange index) at time t in natural log (logs), $\mu$ are the mean value of the returns; $\epsilon^2$ is the error term at time t which is assumed to be normally distributed with zero mean and conditional variance $\sigma^2$, and $\mu$, $\alpha_0$, $\alpha_i$, $\beta_j$ are parameters.

Engle and Bollerslev [20] establish IGARCH (1,1) and can be given as $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}(\alpha_1 \Sigma_{t-1}^2) + \sum_{j=1}^{a}(\beta_j \sigma_{t-j}^2)$ (14)

the RiskMetrics model is equal to a normal integrated GARCH IGARCH(1,1) model where the autoregressive parameter is set at a pre-specified value $\lambda$ and the coefficient of $\epsilon^2$ is equal to1 − $\lambda$. In RiskMetrics specification for daily data $\lambda$ is fixed.

To capture the asymmetry in return volatility ("leverage effect"), a new class of models was developed, termed the asymmetric ARCH models. Among the most widely spread asymmetric ARCH, models are the Exponential GARCH (EGARCH), GJR, and the Asymmetric Power ARCH (APARCH) model.

EGARCH model can be expressed as $\log \sigma_t^2 = \omega + \sum_{i=1}^{n} \beta_1 \log \sigma_{t-1}^2 + \sum_{i=1}^{p} \alpha_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ (15)

GARCH-GJR can be expressed as $\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_1 \varepsilon_{t-1}^2 + \sum_{j=1}^{n} \beta j \sigma_{t-j}^2 + \gamma_1 I_{t-1} \varepsilon_{t-1}^2$ (16)

The APARCH(1,1) model is given as $\sigma_t^2 = \omega + \sum_{i=1}^{a} \alpha_1 \left( |\varepsilon_{t-1}| - \gamma_1 \varepsilon_{t-1} \right)^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_t^{\delta} - j$ (17)

where $w$, $\alpha_1$, $\gamma_1$, $\beta_1$ and $\delta$ are parameters to be estimated.

Fractionally integrated ARCH models

FIGARCH(p,d,q) $\sigma_t^2 = \sigma^2 \left(1 - B\right) + \left(1 - B(L) - \phi(L)(1-L)^d (\varepsilon_t^2 - \sigma^2\right) + B(L)\sigma_t^2$ (18)

HYGARCH(p,d,q) can be expressed as

$$\sigma_t^2 = \alpha_0 + \left(1 - B(L) - \phi(L)(1 + \alpha(1-L)^d - 1\right)\varepsilon_t^2 + B(L)\sigma_t^2 \quad (19)$$

Generalized Autoregressive Score

GAS models are built on a framework for a time-varying parameter which is based on the score function of the predictive model density at time t. GAS(1,1)can be given as

$$\sigma_t^2 = \omega + \alpha_1 z_{t-1}^2 \sigma_t^2 + \phi_1 \sigma_{t-1}^2 \quad , \ \varepsilon_t = \sigma_t z_t \sim N(0,1) \quad (20)$$

To pick the optimal model we use Akaike Information Criteria (AIC), BIC and loglikelihood.

## 4. Data and Empirical Results

Essentially, this study covers two variables namely the Euro-Naira exchange rate and US dollars to Naira exchange rate daily closing rate from 24/10/2016 to 15/06/2018. In this paper, continuous returns are obtained by taking logarithms in price changes. Continuously compounded return at time t is defined as $\varepsilon_t = \frac{\log p_t}{\log p_{t-1}}$ .The section provides some preliminary analyses involving the description of relevant statistical properties of the variable under consideration. These analyses are carried out in different phases the first phase involves descriptive statistics for the two variables and their returns, the second involves the performing ARCH LM test to verify the existence of ARCH effects in the series and the last compares different GARCH models using AIC, BIC, and loglikelihood.

**Table 1** Descriptive Statistics

| Statistic | USD-Naira | USDN returns | Euro-Naira | EN returns |
|---|---|---|---|---|
| Mean | 338.56 | 0.00 | 389.49 | 0.00 |
| Median | 359.00 | 0.00 | 419.41 | 0.00 |
| Maximum | 366.00 | 0.07 | 450.24 | 0.06 |
| Minimum | 302.96 | -0.02 | 316.62 | -0.02 |
| standard deviation | 23.22 | 0.00 | 46.33 | 0.01 |
| Skewness | -0.17 | 5.49 | -0.17 | 4.17 |
| Kurtosis | 1.08 | 77.91 | 1.21 | 52.58 |
| Jarqebera | 66.86 | 101028.00 | 58.34 | 44556.72 |
| p value | 0.00 | 0.00 | 0.00 | 0.00 |

From Table 1 above there is much variation in the trends in the US dollar to Naira as shown by

difference between the minimum 302.96 and the maximum 366 as well as when compared with a mean value of 338.56 same for the case of the Euro-Naira there is much variation in the trends in the Euro to Naira as shown by the difference between the minimum 419.41 and the maximum 450.24 as well as when compared with mean value of 338.56, the p-value is smaller than 0.05 at the significant level 5%. Overall the Jarque Bera (JB) statistics that use the information from skewness and kurtosis to test for both USD-Naira and Euro-Naira is significant, the alternative inferential statistics that follow non-normal are appropriate in the case, but the USD-Naira rate has smaller mean and standard deviation in the level and return series hence it has lower volatility compared to Euro-Naira exchange rate.

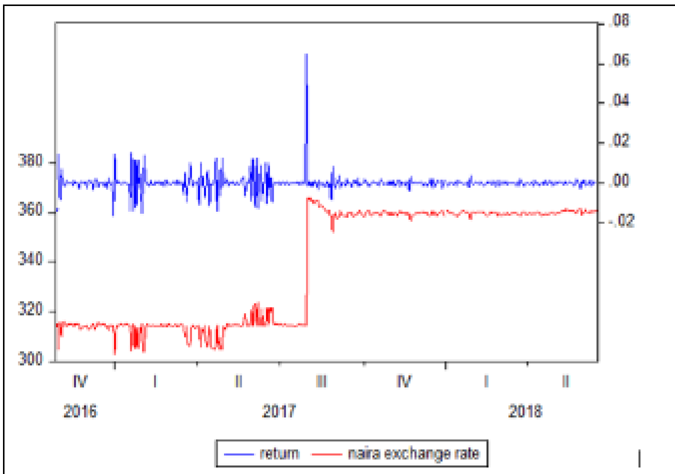


**Figure 1** USD-Naira exchange rate

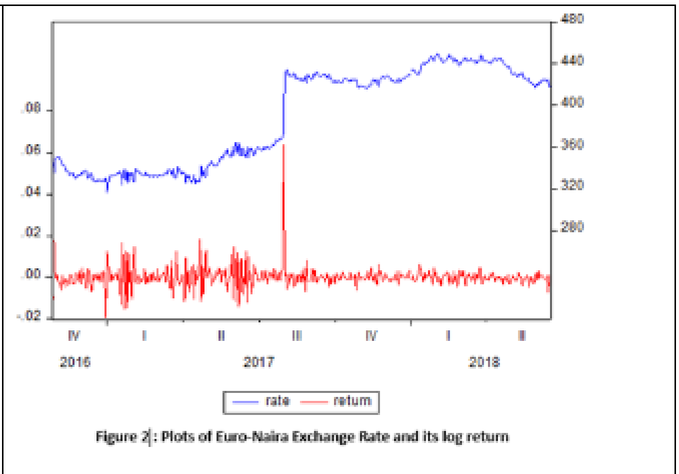


**Figure 2** Euro-Naira exchange rate

Table 2 shows the Engle test statistics for testing the probable existence of ARCH effects in the USD-Naira and Euro-Naira as well as their return, the test confirms the evidence of ARCH effect in both and so we conclude that the test statistics are stationary significant and thus reject the "No ARCH effects" hypothesis. Hence the null hypothesis of no heteroscedasticity is rejected in both series.

**Table 2** Testing for ARCH Effect ARCH Test

| Statistic | US Dollar- Naira | US Dollar- Naira returns | Euro- Naira | Euro- Naira Returns |
|---|---|---|---|---|
| Q(5) | 2010.4 | 8.9498 | 2078 | 24.53 |
| Q2(5) | 656.17 | 0.0299*** | 1744.8 | 0.1241 |
| ARCH(1) | 224.55 | 0.0057*** | 3043.57 | 0.0717 |
| ARCH(5) | 81.5 | 0.0058*** | 749.54 | 0.0224*** |

*** indicate significance of $Q^2$(Ljung-Box) and ARCH effect statistics at 5%

**Table 3** Volatility models with Distributions assumption using Euro to Naira exchange return

| Model | Criteria | Normal | Student-t | GED | Skewed Student t |
|---|---|---|---|---|---|
| GARCH(1,1) | Loglikelihood | -248.45 | -164.95 | -159.86 | -148.10 |
| | AIC | 1.19 | 0.80 | 0.78 | 0.73 |
| | BIC | 1.23 | 0.84 | 0.83 | 0.84 |
| APARCH(1,1) | Loglikehood | -237.33 | -152.50 | -157.86 | -142.01 |
| | AIC | 1.15 | 0.75 | 0.78 | 0.71 |
| | BIC | 1.20 | 0.81 | 0.85 | 0.79 |
| EGARCH(1,1) | Loglikehood | -246.87 | -148.44 | -159.31 | -145.79 |
| | AIC | 1.20 | 0.73 | 0.79 | 0.73 |
| | BIC | 1.25 | 0.79 | 0.85 | 0.80 |
| GJR | Loglikehood | -239.80 | -148.29 | -159.74 | -148.22 |
| | AIC | 1.16 | 0.72 | 0.78 | 0.73 |
| | BIC | 1.21 | 0.77 | 0.84 | 0.79 |
| Riskmetrics | Loglikehood | -322.41 | -172.50 | -176.84 | -172.48 |
| | AIC | 1.53 | 0.83 | 0.85 | 0.83 |
| | BIC | 1.21 | 0.84 | 0.86 | 0.86 |
| IGARCH | Loglikehood | -295.62 | -169.00 | -157.17 | -168.90 |
| | AIC | 1.41 | 0.81 | 0.76 | 0.82 |
| | BIC | 1.45 | 0.84 | 0.79 | 0.86 |
| HYGARCH | Loglikehood | -243.36 | -149.16 | -161.80 | -149.07 |
| | AIC | 1.18 | 0.73 | 0.79 | 0.74 |
| | BIC | 1.24 | 0.79 | 0.85 | 0.80 |
| GAS | Loglikehood | -265.42 | -151.10 | -160.49 | -151.09 |
| | AIC | 1.27 | 0.73 | 0.78 | 0.74 |
| | BIC | 1.31 | 0.77 | 0.82 | 0.79 |
| EGAS | Loglikehood | -324.81 | -150.42 | -162.55 | -150.41 |
| | AIC | 1.55 | 0.73 | 0.79 | 0.73 |
| | BIC | 1.59 | 0.77 | 0.83 | 0.78 |

| | | | | | |
|---|---|---|---|---|---|
| FIEGARCH | Loglikehood | -214.58 | -146.95 | -161.01 | -144.24 |
| | AIC | 1.04 | 0.73 | 0.79 | 0.72 |
| | BIC | 1.12 | 0.79 | 0.86 | 0.80 |
| FIAPARCH | Loglikehood | -231.46 | -142.01 | -153.55 | -140.78 |
| | AIC | 1.13 | 0.71 | 0.76 | 0.70 |
| | BIC | 1.19 | 0.79 | 0.84 | 0.78 |
| FIAPARCHC | Loglikehood | -228.30 | -140.20 | -156.38 | -143.91 |
| | AIC | 1.11 | 0.70 | 0.78 | 0.72 |
| | BIC | 1.18 | 0.78 | 0.85 | 0.79 |
| AEGAS | Loglikehood | -318.25 | -146.29 | -161.01 | -150.19 |
| | AIC | 1.53 | 0.72 | 0.79 | 0.74 |
| | BIC | 1.58 | 0.78 | 0.85 | 0.80 |
| S-GARCH | Loglikehood | -217.70 | -138.39 | -150.24 | -138.42 |
| | AIC | 1.08 | 0.71 | 0.76 | 0.71 |
| | BIC | 1.17 | 0.81 | 0.87 | 0.81 |
| S-GJR | Loglikehood | -212.86 | -133.93 | -148.09 | -132.43 |
| | AIC | 1.05 | 0.69 | 0.75 | 0.68 |
| | BIC | 1.15 | 0.79 | 0.86 | 0.80 |

Table 3 presents the volatility models with different distribution assumptions using Euro to Naira exchange return, it compares the models and chooses the best models of those fifteen analyzed that minimize volatility, since every model has four different distributions of residuals. we used AIC criteria (modified with Bayesian information criterion [BIC] criteria) to choose one model and In the case of the Normal distribution assumption, the best volatility model, based on minimum information criteria (AIC and BIC) is the FIEGARCH model. For the Student t-distribution, the best model is SPLINE-GJR, For GED distribution, the best model is IGARCH, and SPLINE-GJR for skewed-student t. SPLINE- GJR under skewed student t distribution is the overall best model for the Euro-Naira exchange rate.

**Table 4** Volatility models with Distributions assumption using USD to Naira exchange return

| Model | Criteria | Normal | Student-t | GED | Skewed Student t |
|---|---|---|---|---|---|
| GARCH(1,1) | Loglikehood | -274.19 | 114.36 | 136.36 | 114.88 |
| | AIC | 1.32 | -0.52 | -0.63 | -0.51 |
| | BIC | 1.35 | -0.47 | -0.57 | -0.46 |
| APARCH | Loglikehood | -237.71 | 117.39 | 131.58 | 120.63 |
| | AIC | 1.32 | -0.53 | -0.59 | -0.53 |
| | BIC | 1.38 | -0.45 | -0.52 | -0.46 |
| EGARCH | Loglikehood | -268.79 | 104.81 | 132.03 | 109.96 |
| | AIC | 1.30 | -0.46 | -0.59 | -0.48 |
| | BIC | 1.36 | -0.40 | -0.52 | -0.41 |
| GJR | Loglikehood | -270.19 | -147.70 | 136.36 | 120.58 |
| | AIC | 1.30 | -0.51 | -0.62 | -0.54 |
| | BIC | 1.35 | -0.46 | -0.56 | -0.47 |

| | | | | | |
|---|---|---|---|---|---|
| RiskMetrics | Loglikehood | -256.96 | 26.93 | 100.81 | 26.93 |
| | AIC | 1.22 | -0.12 | -0.47 | -0.11 |
| | BIC | 1.23 | -0.10 | -0.45 | -0.08 |
| IGARCH | Loglikehood | -210.19 | 111.16 | 131.23 | 111.67 |
| | AIC | 1.01 | -0.51 | -0.60 | -0.50 |
| | BIC | 1.04 | -0.47 | -0.56 | -0.46 |
| HYGARCH | Loglikehood | -276.00 | 114.75 | 134.50 | 95.86 |
| | AIC | 1.31 | -0.51 | -0.60 | -0.42 |
| | BIC | 1.37 | -0.44 | -0.54 | -0.38 |
| GAS | Loglikehood | -312.92 | 74.75 | 120.34 | 75.06 |
| | AIC | 1.49 | -0.33 | -0.59 | -0.33 |
| | BIC | 1.35 | -0.46 | -0.56 | -0.47 |
| EGAS | Loglikehood | -293.01 | 114.75 | 134.50 | 95.86 |
| | AIC | 1.40 | -0.44 | -0.59 | -0.44 |
| | BIC | 1.44 | -0.40 | -0.54 | -0.39 |
| FIEGARCH | Loglikehood | -36.98 | 104.91 | 126.23 | 109.96 |
| | AIC | 1.21 | -0.46 | -0.56 | -0.48 |
| | BIC | 0.27 | -0.38 | -0.48 | -0.39 |
| FIAPARCH | Loglikehood | -258.02 | 115.27 | 131.59 | 118.04 |
| | AIC | 1.25 | -0.51 | -0.58 | -0.52 |
| | BIC | 1.32 | -0.43 | -0.51 | -0.43 |
| FIAPARCHC | Loglikehood | -216.63 | 108.02 | 134.75 | 106.30 |
| | AIC | 1.06 | -0.47 | -0.60 | -0.46 |
| | BIC | 1.12 | -0.40 | -0.52 | -0.37 |
| AEGAS | Loglikehood | -28.12 | 99.64 | 129.35 | 105.00 |
| | AIC | 0.16 | -0.44 | -0.58 | -0.46 |
| | BIC | 0.20 | -0.39 | -0.53 | -0.40 |
| S-GARCH | Loglikehood | -217.70 | -138.39 | -150.24 | -138.42 |
| | ALC | 1.08 | 0.71 | 0.76 | 0.71 |
| | BIC | 1.17 | 0.81 | 0.87 | 0.81 |
| S-GJR | Loglikehood | -212.86 | -133.93 | -148.09 | -132.43 |
| | AIC | 1.05 | 0.69 | 0.75 | 0.68 |
| | BIC | 1.15 | 0.79 | 0.86 | 0.80 |

Table 4 presents the volatility models with different distribution assumptions using USD to Naira exchange return, it compares the models and chooses the best models of those fifteen analyses that minimize volatility since every model has four different distributions of residuals. we used AIC criteria (modified with Bayesian information). criterion [SBIC] criteria) to choose one model In the case of Normal distribution assumption, the best volatility model, based on minimum information criteria (AIC and SBIC) is the AEGAS model. For the Student t- distribution, the best model is

APARCH, For GED distribution, the best model is GARCH and GJR-GARCH for skewed-student t. As summarised in Table 4, GARCH(1,1) under GED is the overall best model for the USD-Naira exchange rate followed by the GJR-GARCH model.

## 5. Conclusion

This paper mainly studies the application of the risk measurement model to the Nigerian exchange market. This paper aims to investigate the optimal volatility model that gives the best VaR forecasts and minimize expected loss in the Naira exchange rate. Different VaR GARCH model estimates the risk of the exchange market under Normal distribution, Student t-distribution, generalized error distribution, and skewed student t-distribution considering asymmetry, leverage, heteroskedasticity, and volatility clustering. Through the research, the following conclusions can be reached: Descriptive statistics show that the US dollar to Naira has a smaller mean and standard deviation in the level and returns series, hence it has lower volatility compared to the Euro-Naira rate. The calculation of VaR is based on the GARCH-type model applied to the Naira exchange market. For the Euro-Naira exchange rate, the SPLINE- GJR under skewed student t distribution is the optimal volatility model that gives the best VaR forecast. In contrast, for the USD-Naira exchange rate, GARCH under the GED model appears to be the optimal volatility model that gives the best VaR forecast. This study suggests that model risk assessments be given careful consideration by regulators, banks, and other stakeholders and integrated into the process of operational and regulatory design.

## Compliance with ethical standards

*Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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