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Article

Nigeria Exchange Rate Volatility: A Comparative Study of Recurrent Neural Network LSTM and Exponential Generalized Autoregressive Conditional Heteroskedasticity Models

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Abstract: Business merchants and investors in Nigeria are interested in the foreign exchange volatility forecasting accuracy performance because they need information on how volatile the exchange rate will be in the future. In the paper, we compared Exponential Generalized Autoregressive Conditional Heteroskedasticity with order p=1 and q= 1, (EGARCH (1,1)) and Recurrent Neural Network (RNN) based on long short term memory (LSTM) model with the combinations of p = 10 and q = 1 layers to model the volatility of Nigerian exchange rates. Our goal is to determine the preferred model for predicting Nigeria's Naira exchange rate volatility with Euro, Pounds and US Dollars. The dataset of monthly exchange rates of the Nigerian Naira to US dollar, Euro and Pound Sterling for the period December 2001 – August 2023 was extracted from the Central Bank of Nigeria Statistical Bulletin. The model efficiency and performance was measured with the Mean Squared Error (MSE) criteria. The results indicated that the Nigeria exchange rate volatility is asymmetric, and leverage effects are evident in the results of the EGARCH (1, 1) model. It was observed also that there is a steady increase in the Nigeria Naira exchange rate with the euro, pounds sterling and US dollar from 2016 to its highest peak in 2023. Result of the comparative analysis indicated that, EGARCH (1,1) performed better than the LSTM model because it provided a smaller MSE values of 224.7, 231.3 and 138.5 for euros, pounds sterling and US Dollars respectively.

Keywords: Exchange Rate Volatility; EGARCH (1,1); LSTM; MLP; RNN

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1. Introduction

The value of the Nigerian Naira has fluctuated over time in reaction to the state of the market. This was an attempt to achieve an exchange rate structure that would improve economic growth, diversity, and the strengthening of the economy's productive structures. These variations don't seem to be having the anticipated impact, though. As an example, Nigeria is actually characterized as a mono-economy, with the majority of its income coming from the sale of crude oil. Formally productive industries, like manufacturing and agriculture, are neglected and their past and future earnings are disregarded. Macroeconomic policy aims to achieve a number of goals in every economy, including rapid economic growth and minimal or nonexistent currency fluctuation, [1]. Because of its degree of development, exchange rate management in Nigeria is typified by official intervention in the foreign exchange market. The exchange rate management system may be considered a "dirty" float even though it is a floating system. One of the main de facto features of currency rate regimes in emerging nations is the dread of "clean" float, as has been recognized recently, [2]. Since the exchange rate affects Nigeria's trade relations with other nations, both as an import-dependent developing country and as a mono-product exporter of oil, in addition to the nation's competitiveness and overall economic growth, it has historically played a significant role in the country's monetary policy. In order to achieve the macroeconomic goal of price stability, the monetary authorities (Central Bank of Nigeria) have thus on multiple occasions in the recent past participated in distinct exchange rate adjustment strategies (fixed and flexible). However, more exchange rate flexibility is required, in line with major industrial economies, in order to contain real shocks related to the shift to a market economy and the depletion of oil production, which is thought to be the primary source of external and government revenues, and to enable the real exchange rate to converge with its equilibrium level with ease, [3].

It is difficult for traditional econometric models to capture the complex patterns of exchange rate changes, especially in a time when financial markets are changing quickly. Deep learning techniques such as recurrent neural networks (RNN) based on Long Short-term Memory (LSTM) methodology, which can handle financial data forecasting, have opened up new prospects to improve the accuracy of currency exchange rate predictions, [4]. One kind of machine learning model that handles consecutive data inputs and outputs is the recurrent neural network (RNN). By providing feed forward neural networks with feedback, RNN is able to capture the temporal relationship between input/output sequences. Recurrent layers are added to the neural network (NN) model to create an RNN. A generic RNN model consists of three sets of layers: input, recurrent, and output. The input layers convey the features of the input once the input data have first been converted into a vector. Next, the feedback-providing recurrent layers are implemented. The model then ends with fully connected (FC) layers at the end, also known as RNN model output layers, in the same manner as other NN models. The two main types of RNN models are LSTM-based RNN models and GRU-based RNN models [5]. The recurrent layers that are used in each model set them apart from one another.

Recurrent neural networks (RNNs) include Long-Short Term Memory (LSTM). It employs gate approaches and recurrent mechanisms to process information in sequences. When modeling time series, including audio and video, LSTM is superior to other feedforward and recurrent neural networks in a number of ways, [6].

To fully utilize the long short term memory (LSTM) in time series modeling, it is supplemented with other identification techniques. The simulation model, which is utilized for multistep prediction, is incompatible with it. They must make advantage of the previous test results, [7]. The NN's output that feeds back to the input enables the modeling of data chains or sequences. The RNN training approach has a Vanishing Gradient problem since it requires backpropagation over time. Several gated units are used by LSTM to prevent this. Sequence prediction, natural language processing, audio recognition, and time series modeling are just a few of the fields in which LSTM has been extensively used [8].

The financial series' trend is implied to be variable and unstable by volatility, which is typically not constant. Because of this, autoregressive conditional heteroskedasticity econometric models, or ARCH-type models, must be used instead of the traditional models with homoscedastic variance. The ARCH model has the benefit of taking conditional volatility into account, but it also has the drawback of typically requiring a very high number of parameters to be estimated, which leads to worse fits for this kind of financial data. Given that the conditional variance depends on both the squares of the observations and the conditional variances of earlier periods, the GARCH model has an advantage over the ARCH model. It does not, however, provide the variation's sign (positive or negative). The EGARCH model solves this problem by making it possible to determine whether price changes are positive or negative. Similarly, statistical models like the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model can assist explain time-varying volatility patterns [9-11]. Although these sophisticated modeling techniques have great potential, there are still obstacles in successfully implementing them in the Nigerian setting. Among other things, non-stationarity, feature selection, and data quality are concerns in exchange rate forecasting.

Furthermore, it's critical to determine how well statistical and deep learning models capture the nuances of Nigeria's exchange rate volatility.

We need to develop robust prediction models that can properly and timely notify us when Nigeria's major exchange rate fluctuations will occur. These models must handle the specific difficulties and dynamics of Nigeria's currency rate market, taking into account factors such as oil prices, government policies, global economic conditions, and domestic economic indicators [12]. This study aims to compare the efficacy of deep learning and statistical models to traditional forecasting techniques, with the ultimate goal of determining the most reliable strategy for mitigating the negative effects of exchange rate volatility on Nigeria's economic expansion and stability.

The main objective of this study was to compare the forecasting accuracy of the LSTM model and EGARCHs model based on the volatility returns of Nigeria's Naira to US dollar, Euro and Pound Sterling for the period December 2001 – August 2023. This study should be of significant interest to the Nigeria Government and economic planning agencies in countries that utilizes foreign countries like Euros, Pounds sterling and US Dollar for their foreign transaction and other business engagements. The remaining structure of our study are; Section 2 presents the review of related literature regarding the utilization of RNN, LSTM and EGARCH models on exchange rate volatility. Section 3 presents the source of data employed in the study and description of the two models. Section 4 produced the result generated from the analysis. Section 5 presents the discussion of findings while the last section presented the conclusions.

2. Literature Review

Researchers have recently concentrated on modeling and forecasting volatility in foreign currency rates due to their relevance in international trade, education and health tourism, business, and other financial transactions. There are several studies that focus on foreign exchange, either in terms of current or prospective rates. In a study, [13] evaluates the currency rate volatility using a GARCH-type model of the daily exchange rate return series from January 2012 to August 2016 for Naira/Chinese Yuan, Naira/India Rupees, Naira/Spain Euro, Naira/UK Pounds, and Naira/US Dollar. The studies compare estimates from the GARCH (1, 1), EGARCH (1, 1), TGARCH (1,1), and GJR-GARCH (1,1) models. GJR-GARCH (1,1) was shown to be the best-fitting model for all nations, followed by GARCH (1,1), TGARCH (1,1), and EGARCH (1,1) in that order. The study by [14] compares the GARCH model against the Back Propagation Artificial Neural Network (BPANN) in forecasting four internationals, including two Asian stock market indexes. The fitted GARCH models outperformed the fitted standard BP-ANN models in forecasting the four worldwide market indices, with the exception of one market. [15] investigated the forecast accuracy of data-driven models for monthly stream flow in the Urmia lake basin, employing the Autoregressive conditionally heteroskedastic time-series model. The results showed that ARCH-CHAID models outperformed all other models in the two stations under consideration. A study by [16] investigated India VIX (NIFTY 50 volatility index) to characterize the behavior of the Indian stock market in terms of volatility, and then evaluated the forecasting performance of GARCH- and RNN-based LSTM models using India VIX as sample data. The results showed that the volatility of the NIFTY 50 index is asymmetric, and leverage effects may be seen in the EGARCH (1, 1) model. Asymmetric GARCH models, such as EGARCH (1, 1) and TARCH (1, 1), produced somewhat higher predicting accuracy than symmetric GARCH models, such as GARCH (1, 1). Overall, the results demonstrated that GARCH models outperformed RNN-based LSTM models in forecasting NIFTY 50 index volatility. [17] investigated the efficacy of artificial neural networks (ANN) and GARCH models in predicting the volatility of Indian stock market indexes. The most recent 20% of the observations were subjected to out-of-sample testing using the GARCH (1,1) and recurrent neural networks. The results clearly revealed that the GARCH model outperformed the ANN. The ANN may be a superior indicator in periods of low volatility, but its effectiveness deteriorates in moments of high volatility. [18] offered an alternate way to predicting daily exchange rates using an artificial neural network (ANN). The analysis is based on a set of daily data from Tunisia. To assess this strategy, ANN was compared to a generalized autoregressive conditional heteroskedasticity (GARCH) model in terms of performance. The results show that the suggested nonlinear autoregressive (NAR) model is an accurate and fast prediction approach. [19] Forecast bitcoin volatility using hybrid GARCH models and machine learning. Both the in-sample and out-of-sample results of their study demonstrate that these hybrid models can accurately predict how much Bitcoin's price will change. [20] evaluated out-of-sample forecasting accuracy and risk management efficiency. The results show that RNN outperforms GARCH and EWMA on average predicting performance. However, it is less effective in capturing the Bitcoin market's extreme occurrences. Furthermore, the RNN performs poorly in Value at Risk forecasting, implying that it may not work as well as econometric models in explaining severe volatility. [21] investigated stock volatility prediction using time series and deep learning methods, introducing several volatility models based on the Exponential general autoregressive conditional heteroscedasticity (EGARCH), Glosten-Jagannathan-GARCH (GJR-GARCH), and generalized autoregressive conditional heteroscedasticity (GARCH) frameworks. Three types of GARCH models and the LSTM model were tested for their ability to predict stock volatility in three distinct industries. The findings revealed that the LSTM model performed better in predicting volatility in the pharmaceutical sector than in the banking and IT sectors.

The LSTM model, which is based on deep learning, outperformed the GARCH models, as indicated by extremely low RMSE values in all three sectors. In a study that used Neural Networks to describe economic time series with non-constant volatility, [22] used ARCH and GARCH models in a comparative analysis of out-of-sample predictions and discovered that neural network models performed nearly as well as standard statistical models. This implies that they are fair and acceptable in economic models. In another study on the neural stochastic volatility model, [23] proposed a new method for calculating volatility using deep recurrent neural networks. When tested on real-world financial datasets, NSVM outperformed various regularly used models such as GARCH, EGARCH, GJRGARCH, and TARCH, [24]. An artificial neural network was utilized to investigate how to predict the Nigerian stock market. The study examined what happened when artificial neural networks were used to predict the value of specific Nigerian Stock Exchange (NSE) bank market indexes. A multilayer feed forward neural network transmits the intended reaction to input signals to each output unit. The study demonstrated that artificial neural networks can forecast future stock prices. [25] conducted a comparative analysis of ARCH-type models and artificial neural networks. The results revealed little evidence that ANN prediction outperformed traditional models. [26] concluded that the Multilayer Perceptron Neural Network outperformed the GARCH model in forecasting monthly returns. [27] compared the performance of LSTM and GARCH models in predicting the fluctuations of China's equity market.

A summary of the reviewed study above indicates that no study have been conducted on modeling Nigeria's exchange rate volatility using recurrent neural network based on long short-term memory (LSTM) and Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model. This is the first study that straightforwardly compared RNN-LSTM approach with EGARCH model for Nigeria's naira exchange rate volatility with Euro, Pounds and US Dollars.

3. Materials and Methods

3.1. Data

The exchange rate data for Naira to Dollar, Naira to Euro, and Naira to Pounds was obtained from the Central Bank of Nigeria's Bulletin (May, 2024 Edition) [28]. The data covers the period from December 2001 to August 2023, with monthly frequency. The LM-ARCH test will be used to determine whether ARCH is present on the data. Similarly, the EGARCH model will be used to model the volatility of the Exchange rate with ARCH effect while Recurrent Neural Network (RNN) models will utilize the train and test result to model big changes in the Nigerian exchange rate.

3.2. Recurrent Neural Networks (RNNs)

A Recurrent Neural Network (RNN) is a form of neural network that processes sequential data, such as time series data. The term "recurrent" refers to the network's usage of feedback connections to capture temporal links between inputs. RNNs are made up of three primary components: (i) the input gate, which processes the input data and selects what information to store. (ii) hidden state, which saves information from past time steps, allowing the network to recall context; and (iii) output gate, which creates the final output depending on the hidden state. (See Figure 1). RNN are particular neural networks which take into account the temporal structure of the data and are described by a set of parameters $\bar{\theta} = (\bar{\theta}_0, \bar{\theta}_1, \bar{\theta}_2)$, [29]. The distribution of the observations is obtained by managing hidden units $\bar{h}_t \in R$ that are sequentially and deterministically computed through a given activation function $f(.)$ and additional parameters;

$$\bar{\theta}_1 = (W_{hh}, W_{xh}, k): \bar{h}_t = f_{\bar{\theta}_1}(\bar{h}_{t-1}, x_t) = f(W_{hh}\bar{h}_{t-1} + W_{xh}x_t + k) \quad (1)$$

Next, the distribution of the observations is directly deduced from the hidden units,

$$P_{\bar{\theta}}(x_0{:}T) = P_{\bar{\theta}}(x_0)\prod_{t=1}^{T} P_{\bar{\theta}}(x_t/x_{0:t-1}) = P_{\bar{\theta}_0}(x_0)\prod_{t=1}^{T} P_{\bar{\theta}_2}(x_t/\bar{h}_{t-1}) \quad (2)$$

where $\boldsymbol{P_{\bar{\theta}_0}(x_0)}$ and $\boldsymbol{P_{\bar{\theta}_2}(x_t/\bar{h}_{t-1})}$ are given parametrized distributions. Since by construction the likelihood $\boldsymbol{P_{\bar{\theta}}(x_0{:}T)}$ is computable, the parameters $\boldsymbol{\bar{\theta}}$which define (2) can be estimated by applying a gradient ascent method. In particular, the popular backpropagation algorithm [30] provides a solution to compute this gradient.

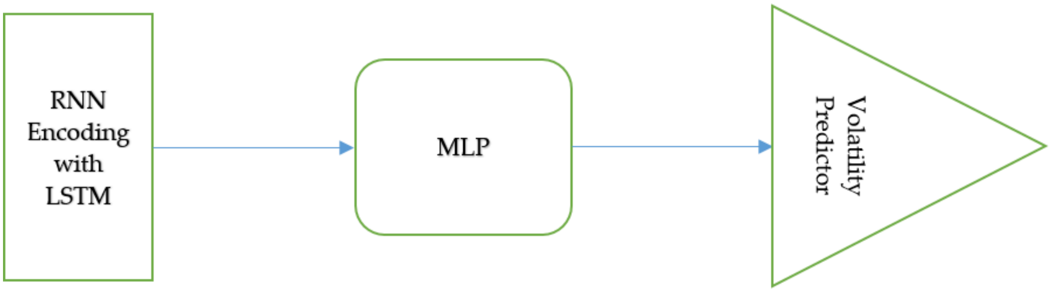

Figure 1. Architect of Recurrent Neural Network (RNN) model

In this study, LSTMs with better design and gates to control information flow will be used to function as memory units. A typical RNN contains a single hidden state that is updated over time, making it difficult for the network to learn long-term dependencies. The LSTM model addresses this issue by incorporating a memory cell, which is a container capable of storing information for an extended length of time. LSTM architectures can learn long-term dependencies in sequential data, making them ideal for tasks like language translation, speech recognition, and time series forecasting, [31]. In LSTM designs (see Figure 2), the memory cell is controlled by three gates: the input gate, the forget gate, and the output gate. These gates determine what information is added to, removed from, and output from the memory cell. (i) The input gate determines what information is added to the memory cell. (ii) The forget gate determines which information is erased from the memory cell. (iii)The output gate determines what information is output by the memory cell. The LSTM maintains a concealed state that functions as the network's short-term memory. The input layer is represented at the bottom, the output layer is represented at the top and the unfolded recurrent layers are represented horizontally. A unit layer is called a cell that takes external inputs, inputs from the previous time cells in a recurrent framework, produces outputs, and passes information and outputs to the cells ahead in time. The cell state is defined as the information that flows over time in this network (as recurrent connections) with the information content having a value of $c(t)$ at time t. The cell state would be affected by inputs and outputs of the different cells, as we go over the network (or more concretely in time over the temporal sequences). Similarly, the network passes the output y(t) from the previous time to the next time as a recurrent connection, [32].

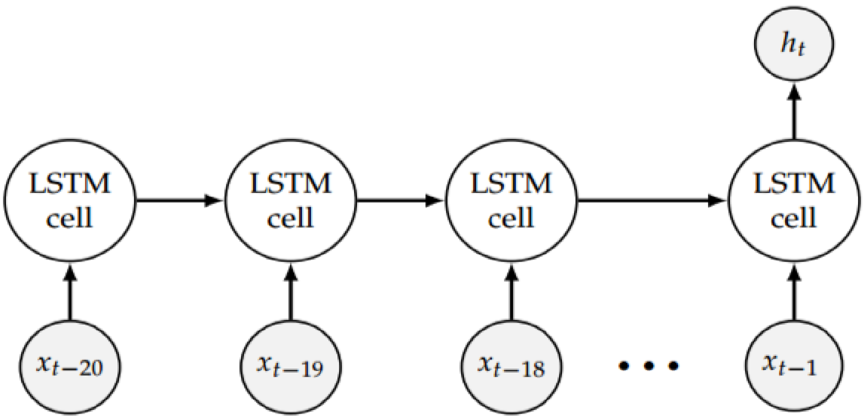

Figure 2. Architecture with Long Short-Term Memory (LSTM) cells

3.3. Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH)

Nelson (1991) [33] developed the EGARCH model, which allows for asymmetric impacts between positive and negative asset returns. It captures financial time series, similar to how volatility is captured. If the volatility was high at time t-1, it is more likely to be high at time t. While GARCH models begin with the assumption that positive and negative error components have an uneven influence on volatility, earlier research has shown that this effect is indeed asymmetric in financial time series due to market imperfections such as transaction costs and volatility, [34]. The model does not require any parameter restrictions because the equation is based on log variance rather than variance itself. The positivity of the variance is automatically satisfied, which is the primary advantage of using the EGARCH model. In general, likelihood maximization without constraints leads to faster and more reliable optimizations. As a result, EGARCH models are probably better suited for analyzing financial time series. Three key flaws in the GARCH model were proposed to be addressed by the EGARCH, which considers the asymmetric features of volatility and returns.

They are: constraints on parameters that assure positive conditional variance, insensitivity to volatility's asymmetric reaction to shock, and difficulties quantifying persistence in a strong stationary series, [35].

Considering a return time series;

$$\sigma_t = \mu + \varepsilon_t \tag{3}$$

Where μ is the expected is return and $\varepsilon_t$is a zero-mean white noise. Despite of being serially uncorrelated, the series ε_t does not need to be serially independent. It can be presented as a conditional heteroskedasticity.

The conditional heteroskedasticity is represented by a specific parametric form in the EGARCH model. The EGARCH model's log of conditional variance shows that the leverage effect is exponential rather than quadratic. One significant advantage of the EGARCH model over the symmetric GARCH model is that it does not limit the sign of the model parameters because volatility is stated in terms of its logarithmic transformation. As a result, there are no constraints on the parameters to ensure that the variability is positive, [36].

The following is a general description of the EGARCH (p, q) model's conditional variance.

$$\log(\sigma_t^2) = \beta_0 + \sum_{i=1}^{q} \beta_i \left|\frac{\mu_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{q} \gamma_i \frac{\mu_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \alpha_j \log(\sigma_{t-j}^2) \quad (4)$$

In this model, good news implies that μ_{t-i} is positive with total effects $(1+\gamma_i)|\mu_{t-i}|$ and bad news implies μ_{t-i} is negative with the total effect$(1-\gamma_i)|\mu_{t-i}|$. Whenγ_i< 0, the expectation is that bad news would have a higher impact on volatility (leverage effect is present) and the news impact is asymmetric if $\gamma_i \neq 0$. The EGARCH model achieves covariance stationarity when $\sum_{j=1}^{p} \alpha_j$< 1. The EGARCH (1, 1) is specified as:

$$\log(\sigma_t^2) = \beta_0 + \beta_1 \left|\frac{\mu_{t-1}}{\sigma_{t-1}}\right| + \gamma_1 \frac{\mu_{t-1}}{\sigma_{t-1}} + \alpha_1 \log(\sigma_{t-1}^2) \quad (5)$$

The total effect of good news for EGARCH (1, 1) is $(1+\gamma_1)|\mu_{t-1}|$ and the total effect of bad news for EGARCH is $(1-\gamma_1)|\mu_{t-1}|$. If the null hypothesis that γ_1= 0 is rejected then, a leverage effect is present, that is, bad news has a stronger effect than good news on the volatility of the stock index return, and the forecasts can be tested by the hypothesis γ_1< O.

3.4. Model Evaluation

The Mean Squared Error (MSE), an empirical risk function, will be used in the study to calculate the difference between the estimated true risk, which is the average loss of the actual population distribution, and the average loss of the observed value. The MSE will produce the preferred model from the two competing models., it is written as;

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2 \quad (6)$$

4. Empirical Result

In this section, Nigeria' Naira exchange rate with Euro, Pounds and Dollar was examined. The descriptive statistics, graph of the three currencies against Nigeria Naira at period and first differencing preceded the analysis. The test for stationary was then provided, which was followed by the ARCH, GARCH and RNN results and finally the comparison based on MSE result was presented. Table 1 presents the descriptive statistics of the Euro, Pounds Sterling and US Dollar. The data comprises of 261 observations each. The mean Euro, Pounds Sterling and US Dollar is 258.8119, 316.8514 and 218.0724, which implies that pounds sterling has the highest exchange rate with naira. The Minimum values of the variables are 98.12310, 160.6695 and 112.9500 respectively while the maximum values are 840.3305, 979.3841 and 770.3800 respectively. The sample variances, which show a measure of how much the currency values deviate from the mean, are 15759.31, 17502.15 and 14311.17 respectively. The standard deviations of the currencies are 125.5, 132.3 and 119.6 respectively. This indicates that pounds sterling has the greatest variability. The kurtosis values are 6.4, 8.4 and 6.3, while the skewness values are; 1.6, 1.9 and 1.6. Figure 3 depicts the graph of exchange rate from naira to euro, pounds sterling and us dollar data. The graph reveals that there is a steady increase in the Nigeria Naira exchange rate with the euro, pounds sterling and US dollar from 2016 to its highest peak in 2023.

Table 1. Descriptive Statistics for the Variables

	Euro	Pounds Sterling	US Dollar
Mean	1258.8119	1316.8514	1218.0724
Maximum	1840.3305	1979.3841	1770.3800
Minimum	98.12310	160.6695	112.9500
Variance	15759.31	17502.15	14311.17
Std. Dev.	125.5361	132.2957	119.6293
Skewness	1.571082	1.912098	1.608633
Kurtosis	6.432338	8.363764	6.293536
Observations	261	261	261

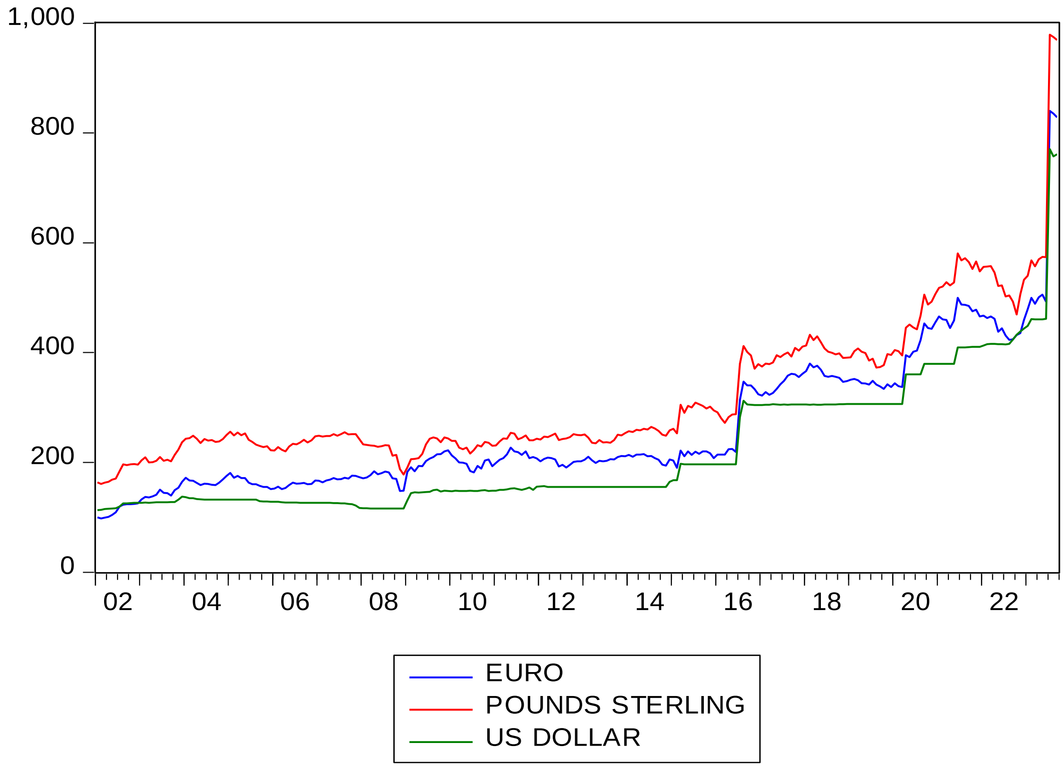

Figure 3. Graph of Exchange Rate from Naira to Euro, Pounds sterling and US dollar.

The study conducted the unit root test to ensure that none of the variables exceeded I(1) and also to establish the appropriateness of applying the methodology. As far as the variables are either purely I (0), I (1), or mixed the methodology can be applied, but any presence of I(2) variables would render the methodology invalid in any case. As such, the results of these tests are presented in Table 2 and Figure 4. Both the ADF and PP results reveal that Euro, Pound sterling and US dollars are stationary at first difference, that is, I (1). Therefore, considering the mix order of integration of the variables, the ARDL approach is the most efficient methodology rather than the standard or convectional co-integration approaches.

In Table 3, the constant in the mean equation passed the t-test, indicating that its value is significant and thus cannot be considered zero. Similarly, all of the lag orders' coefficients passed the t-test (p-value significant at 1%), indicating that their value is substantial and cannot be substituted by zero. In the performance criteria test, all of the coefficients have passed the t-test and coefficient. The AIC value; 10.7, 10.1 and 9.5 and BIC values 10.7, 10.1 and 9.5 respectively confirms the efficiency and asymmetric behavior of the selected EGARCH (1,1) model. As a result, it can be inferred that Nigeria Naira exchange rate with euro, pounds sterling and US dollars volatility is asymmetric throughout the sample period. Furthermore, the R-squared values of 0.81, 0.82 and 0.89 respectively demonstrate that the fitting impact is highly acceptable when seen as a complete model. Positive value beta (GARCH term) indicates that euro, pounds sterling and dollars' volatility returns have a positive risk premium.

Table 2. Unit root test using Augmented Dickey Fuller (ADF) and Philips Perron (PP)

	Level				First Difference				
	ADF		PP		ADF		PP		I(d)
Variables	Constant	Constant & Trend	Constant	Constant & Trend	Constant	Constant & Trend	Constant	Constant & Trend	
Euro	-1.78	-1.88	-0.093	-1.21	-4.65	6.18	5.09**	4.87**	I (1)
	(0.675)	(0.321)	(0.854)	(0.632)	(0.000)**	(0.00)**	(0.000)	(0.000)	
Pounds	-3.99	-1.06	-3.99	-1.73	-4.97	5.42**	5.13**	5.27**	I (1)
Sterling	(0.043)*	(0.521)	(0.043)*	(0.854)	(0.000)**	(0.000)	(0.000)	(0.000)	
US	-1.72	-2.11	-1.38	-2.09	-5.34**	5.91**	6.13**	4.66**	I (1)
Dollar	(0.432)	(0.721)	(0.458)	(0.396)	(0.000)	(0.000)	(0.000)	(0.00)	

*Source: Eviews 12; Note:** & * stand for 1% & 5% levels of significance and values in parenthesis are the P-values, while I (d) stands for the interpretation of the results*

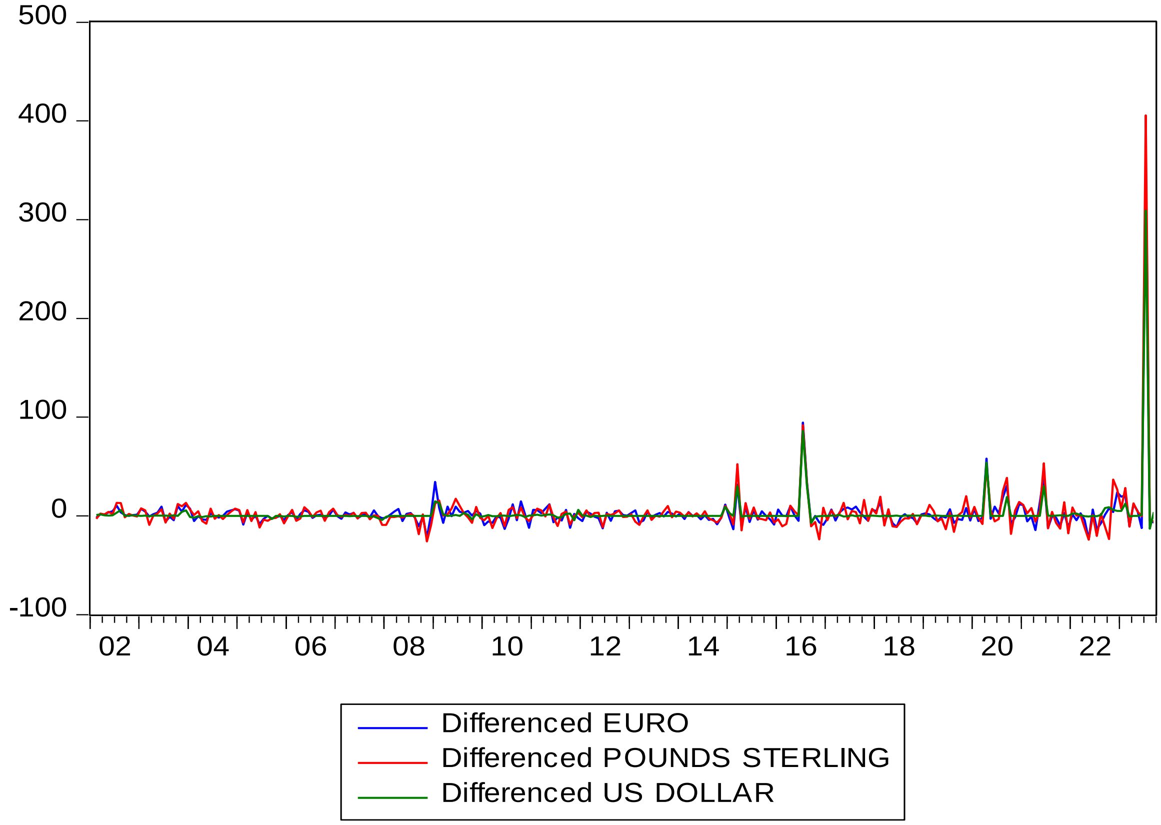

Figure 4. Graph of Differenced Euro, Pounds Sterling and Us Dollar Data

Table 3. EGARCH (1,1) models Fitted for Euro, Pound Sterling and US Dollars.

Particulars	Euro	Pound Sterling	US Dollars
Variable	Coef. (p-value)	Coef. (p-value)	Coef. (p-value)
Constant	4.634 (0.000)	11.341 (0.000)	7.523 (0.000)
1st Lag Order	-0.765 (0.000)	-2.112 (0.000)	3.244 (0.000)
2nd Lag Order	-0.513 (0.000)	-1.763 (0.000)	-2.332 (0.000)
3rd Lag Order	-0.582 (0.000)	-0.352 (0.000)	3.774 (0.000)
4th Lag Order	-0.342 (0.000)	-0.996 (0.000)	3.798 (0.000)
		Performance Criteria	
R-squared	0.812191	0.820555	0.887292
Loglikelihood	-1387.898	-1313.194	-1230.568
Durbin-Watson	2.024220	2.033607	2.018676
AIC	10.66588	10.09344	9.460294
SIC	10.72051	10.14807	9.514922

Note: *AIC is the Akaike info criterion and SC is the Schwarz criterion*

This study compares EGARCH (1,1) with machine learning techniques such as RNN based on LSTM. It is necessary to develop a good LSTM model, which significantly depends on the number of layers to be used. Since the LSTM model is compared with EGARCH (1,1) models, to have a fair comparison, the lag order of the euro, pounds sterling and US dollars exchange rate series for the LSTM model is kept the same as that of the EGARCH models. By comparing the AIC values of training and testing data, the number of layers each of the LSTM was manually determined. We calculated the AIC values for several layer and combinations and selected the one that performed the best. ReLU activation function is used between the layers, and an optimizer was employed used to minimize both the training and testing error. Table 4 presents the performance of the LSTM model using different combinations of layers, and the best combination for euro, pounds sterling and US dollars exchange rate series is found to be LSTM layers with p = 10, q = 1 in each layer, respectively.

Table 4. RNN-LSTM AIC Result for Train and Validation Result for Euro, Pound Sterling and US Dollars

Structure of the LSTM Model	Euro		Pound Sterling		US Dollars	
	AIC of Training	AIC of Testing	AIC of Training	AIC of Testing	AIC of Training	AIC of Testing
p = 1, q = 1	5.44	5.65	5.56	5.64	4.32	4.64
p = 5, q = 1	3.56	3.71	3.88	3.92	2.76	2.97
p = 10, q = 1	3.12	3.22	3.40	3.82	2.22	2.67
p = 20 q = 1	3.32	3.39	3.33	3.91	2.51	2.74
p = 40, q = 1	3.05	3.49	3.46	3.83	2.35	2.53
p = 80, q = 1	7.21	8.12	9.32	9.93	2.69	2.94
p = 4, q = 4	6.63	6.92	7.75	7.92	5.31	5.59
p = 8, q = 8	6.92	7.11	7.87	8.02	5.42	5.88
p = 4, q = 40	6.64	6.93	7.54	7.74	6.42	7.03
p = 8, q = 80	5.31	5.66	6.11	6.63	5.87	6.34

This study compares the performance of the EGARCH (1,1) and LSTM models by forecasting the euro, pounds sterling and US dollars exchange rate series with Nigeria' Naira volatility from each model for the next 30 days by utilizing MSE performance criterion. The reason for using MSE performance metric is to measure the amount of error in the models by assessing how far the predicted values are from actual values. Table 5 presents the out-of-sample version of the EGARCH (1,1) and LSTM models based on the MSE metric in predicting the euro, pounds sterling and US dollars exchange rate series with Nigeria' Naira volatility from each model for the next 30 days. It is discovered that EGARCH(1,1) provided the smaller MSE values of 224.7, 231.3 and 138.5 for euros, pounds sterling and US Dollars respectively. This result confirms that EGARCH(1,1) performed better than the LSTM model.

Table 5. Comparison of EGARCH (1, 1) and LSTM Model for 30 Days Out-of-Samples Forecast

Currency	MSE	
	EGARCH (1,1)	LSTM
Euro	224.7	228.9
Pound Sterling	231.3	554.1
US Dollars	138.5	921.4

5. Discussions

The main purpose of this study was to compare the forecasting accuracy of the RNN-LSTM and EGARCHs models based on Nigeria Naira exchange rate volatility. The study utilized twenty-two years dataset of Nigeria's Naira exchange rate data with euro, pounds sterling and US Dollars. Literature showed that no study have been conducted on modeling Nigeria's exchange rate volatility using recurrent neural network based on long short-term memory (LSTM) and Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model.

The summary statistics indicated that pounds sterling has the highest exchange rate with Nigeria' Naira and there is a steady increase in the Nigeria Naira exchange rate with the euro, pounds sterling and US dollar from 2016 to its highest peak in 2023. Our results also revealed that Euro, Pound sterling and US dollars exchange rates were stationary at first difference. The efficiency and asymmetric behavior or volatility clustering of Nigeria Naira exchange rate was confirmed with the selected EGARCH (1,1) model. This result is consistent with the previous study that EGARCH type models were employed to confirm the asymmetric features of wind poer time series. The model also confirmed improved forecasting precision, [37]. Another study by [38] examined the monthly exchange-rate volatility and the asymmetric properties with GARCH models using. They compared variants of GARCH model with and without volatility breaks and recommended the inclusion of important events in the estimation of GARCH models.

Finding from our research also indicated that EGARCH (1,1) models had a better forecasting efficiency than the RNN-based LSTM, based on Nigeria's Naira exchange rate volatility with euro, pounds sterling and US Dollars. Our result is in agreement with findings of the study by [20] that demonstrate that the RNN model was found to have less efficiency in capturing the bitcoin market's extreme events. Moreover, the RNN shows poor performance in Value at Risk forecasting, indicating that it could not work well as the econometric models in explaining extreme volatility. Another study indicated that GARCH models outperformed the LSTM model in predicting the NIFTY 50 index's volatility, [16].

6. Conclusion

Nigeria's overdependence on foreign money has resulted in exchange rate instability. This is harming Nigeria's trade flow badly. As a result, Nigeria's central bank should interfere by discouraging the release of foreign exchange into the financial sector. This study used one of the GARCH family models to investigate the volatility of the Nigerian naira exchange rate in relation to the euro, pound sterling, and US dollar. This work attempts to discover the anomalies in the volatility of the Nigerian exchange rate by using an empirical analysis of econometric models such as the asymmetric EGARCH (1,1). This study also seeks to determine whether a recurrent neural network employing a long short term memory deep learning technique can capture the volatility of the Nigerian naira exchange rate against the Euro, Pound sterling, and US dollar. The current situation of Nigeria's exchange rate with these international currencies was studied through a comparative analysis of Nigeria's naira with the euro, pound sterling, and US dollar. The study also evaluated the effectiveness of the RNN-based LSTM algorithm to capture the volatility of the Nigerian exchange rate to that of the EGARCH model on out-of-sample data. The results showed that the EGARCH (1,1) model beat the RNN-based LSTM technique. Finally, to strengthen the system, a research study might be done to establish which nations have the ability to affect the Indian stock market. Such a research study would aid in identifying whether or not the spillover effect may be detected in the downside risk due to influential nations, which will aid investors in making better investment selections.

Limitation of the Study

Although an EGARCH-type model was used in this study to explore the returns and volatilities of Nigerian exchange rate volatility, there are some limitations. First, only three currency exchange rates (Euro, Pound Sterling, and US Dollars) were examined in this study. Second, this analysis only used EGARCH-type models and one deep learning model, the RNN-LSTM. Third, this study used limited data, specifically monthly data from December 2001 to August 2023.

Contribution of Authors

This study was created and is the work of all authors. The final version of this manuscript has been approved by all authors, who all participated in the process of revising it.

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