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Time Series Analysis of Exchange Rate Nigerian Naira to Us Dollar (1981-2016)

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Abstract:- This paper includes an empirical examination of modelling and forecasting time series data of the official Nigerian Naira to US Dollar exchange rate. Monthly data from January 1981 to December 2016 were forecasted using the Box-Jenkins ARIMA approach. The study's goals are to quantify the trend, fit a suitable model, and forecast future exchange rates. The Exploratory Data Analysis such as the time plot, Histogram and box plot were plotted. The trend was also estimated using least square and moving average methods. The seasonal variation and seasonal index were estimated using least square method. The data is then differenced once, plotted and the plot indicated that the process is stationary after the first difference. The ACF and PACF were also examined and ADF confirmed the stationary of the process, model identification then follows. Least square method was employed in other to study the pattern of the trend, the regression model $\widehat{T}_t$ = -39.83686386 + 0.535691t shows that as time is progressing there will be an increase in the trend line of about 0.535691. Series of ARIMA were examined and the results shows that ARIMA (1,1,0) has the least AIC of 2642.74. Hence, it is the appropriate model. The diagnostic test was also carried out and the histogram, normal plot of the residual showed that the model fit the data. Hence, the Nigeria exchange rate versus the US Dollar was forecasted for four years (48 months) from January 2017 to December 2020. These forecasts will assist policymakers in both Nigeria and the United States of America in determining the future exchange rate and predicted fluctuation intervals (Nigerian Naira to the US Dollar).

Keywords:- *Time Series, ARIMA, Forecasting, Box-Jenkins, AIC, ACF, PACF, ADF, Time plot, Histogram, box plot, Stationary, Naira, US Dollar.*

I. INTRODUCTION

The exchange rate is the current market price at which one national currency may be exchanged for another. It's usually represented as the number of domestic currency units that will buy one foreign currency unit, or the number of foreign currency units that will buy one domestic currency unit. The naira per US dollar, or US dollars per naira, is an example. One naira may be traded for US$ 0.0042 then one US dollar can be swapped for #240. The rate at which one country's money is exchanged for another country's currency is known as the exchange rate (Dornbusch, 2004). It may also be described as the exchange rate of one country's currency against the currencies of other countries. Mankiw (1997) defines it as the price at which two nations trade goods and services.

How to establish the exchange rate is problem that has grabbed the centre stage of monetary and international economics. Nigeria's monetary policy authority is struggling to maintain a stable and realistic exchange rate that is in line with other macroeconomic factors. This is because fluctuating exchange rates may have a significant negative impact on pricing, investments, and international trade choices. A realistic exchange rate is one that represents the strength of foreign exchange inflows and outflows, the stock of reserves, and ensures balance-of-payments equilibrium that is compatible with trade partners' cost and price levels (Ojo, 1998). Since imports and exports account for such a big portion of the economy, the exchange rate is influenced by the cost and price levels of trade partners (Ojo, 1998)

The exchange rate plays an important role in the economy because imports and exports make up the bulk of the economy. In fact, exchange rate changes affect the price of imported goods, services and exports. When the value of money, for example naira decreases, imports become more expensive, and we often reduce the amount of goods we buy. At the same time, other countries will pay less for some of our exports and that will often increase exports as well as foreign exchange earnings and competitiveness of the exporting industries in international markets.

Official Currency Exchange Rate: The official exchange rate is determined by the central bank. For example, CBN determines the exchange rate for Naira in other currencies around the world. The level of market exchange is basically determined by the market power of demand and supply. When the demand for foreign exchange exceeds supply, the value of Naira will increase, and if the supply exchange rate exceeds demand, the value of Naira will decrease in the case of Nigeria. The end-of-term exchange rate simply refers to the final exchange rate available for a particular period. The end-of-term exchange rate is the exchange rate that governs the last working day of a particular period. For example, we may have weekly, monthly, quarterly and year-end exchange rates depending on the frequency. In the case of the annual frequency, the last exchange rate at the end of December will be considered the end-of-term exchange rate. End-of-term exchange rates generally apply to stock exchanges, such as foreign exchanges and financial assets (Central Bank, 2013)

In recognition of the exchange rate and the declining exchange rate, the naira exchange rate simply refers to the amount of local currency (in this case, Naira) needed to buy foreign currency. When the amount of naira required to buy a foreign currency unit falls, naira is said to appreciate or strengthen or increase in value and when the value of naira increases, naira is said to decrease or weaken or decrease in

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value. Depreciation is caused by a decrease in the demand for domestic currency or an increase in domestic supply, while a decrease is due to an increase in the demand for a local currency or a decrease in a domestic supply.

II. REVIEW OF LITERATURE

A lot of research has been done on analysing the pattern and distribution of data on the exchange rate of Nigeria's Naira for each US dollar in Nigeria. Different time series methods with different purposes are used to analyse data in different papers. Over time, researchers predict exchange rates between developed and developing countries using different methods. Therefore, the handling method may differ from the basic or technical method.

Onasanya O.K. and Adeniji, O. E. (2013), in their work entitled Predicting the exchange rate between Naira and Dollar used the time domain method to create a Naira model for each Dollar, using non-seasonal ARIMA model from January 1994 to December 2011. The result revealed that the ARIMA model (1, 2, 1) fits better with the data.

Ette Harrison (1998), used a technical approach to predict Nigeria naira to the American dollar using the ARIMA seasonal model from 2004 to 2011. He points out that the series (exchange rate) had a negative trend between 2004 and 2007 and stabilized in 2008.

MK Newaz (2008) made a comparison of the performance of a series of time series predicting exchange rates between 1985 and 2006. He compared the ARIMA model, NAIVE 1, NAIVE 2 and exponential smoothing methods to see which ones fit the trading predictions rate. He points out that the ARIMA model provides a better prediction of the exchange rate than any other method; Selection was based on MAE (absolute error means error), MAPE (absolute percentage error), MSE (square measure error), and RMSE (square root mean).

Further work, Olanrewaju I. Shittu and Olaoluwa S.Y (2008) attempted to measure the performance of the ARMA and ARFIMA model predictors in the use of US / UK foreign exchange. They point out that the ARFIMA model was found to be better than the ARMA model. Their persistent result demonstrates that the ARFIMA model is very realistic and closely reflects the current economic reality in the two countries demonstrated by their forecasting tool. They found that their result was consistent with the work of Kwiatkowski et.al. (1992).

Shittu O. I (2008) used intervention analysis to show the level of Nigerian exchanges prior to the period of financial and political instability from the period (1970 -2004). Explaining that modelling for such a series was misleading and predictions from such a model would not be realistic, he went on to discover that the intervention is a pulse activity that has a gradual and linear influence but is important for naira-dollar exchange rates.

S.T Appiah and I.A Adetunde (2011) conducted a study by predicting the exchange rate between Ghana cedi's and the US dollar using a time series analysis from January 1994 to December 2010. watched series and ARIMA (1, 1, 1) was found to be the best model for such a series and a two-year forecast was made from January 2011 to December 2012 also shows that the depreciation of Ghana cedi's against the US dollar is imminent.

A. Aim and Objectives

The purpose of this study is to match the model of the time series that best describes the formation of the exchange rate period (USD to Naira). The objectives are:

- Study the trend of exchange rate using the time plot
- Estimate the trend using least square method
- Estimate the seasonal variation
- Fit the appropriate probability model
- Predict the future exchange rate in Nigeria

B. Scope and Learning Limit

This study covers the period 1981-2016; sample size 36 years. The choice of this period is largely based on the availability of data, and also because the Nigerian economy has implemented different types of exchange rate rules over a given period of time

III. METHODOLOGY

A. Time Series Process

Many statistical methods are related to independent data, or at least unrelated. There are many real situations where data may be associated. This is especially true when repeated checks in a particular system are performed in chronological order. Sequential data collection is called a time series In this study, the prediction and analysis of the time series set by Y_i, $i \geq 1$, was taken in chronological order. In most mathematical models we know, the present recognition is considered independent and any order is equally satisfactory in terms of analysis. In a timely manner, the sequence of observations is important; this separates them from non-time series data. In most systems successive sightings will be equally divided, e.g. daily, weekly, monthly etc.

B. Types of Time Series Models

Time series models can be approached in two ways:

- Deterministic Time Series: If the future values of a time series are precisely defined by some mathematical function, it is said to be deterministic.

$$X_t = cos(2\pi t) \tag{1}$$

- Probabilistic Time Series: If the values of a time series can only be determined in terms of probability distributions, it is said to be probabilistic.

$$X_t = Asin(\omega t + \theta) \tag{2}$$

C. Time Series Model

We can express a series in two useful models as various functions of the component in light of the aforementioned components of a time series $\{X_t\}$. The following are the typical forms:

- $X_t = T_t + S_t + C_t + I_t$. This is called the Additive Model
- $X_t = T_t \cdot S_t \cdot C_t \cdots I_t$. This is called Multiplicative Model

D. Estimation of Trend

One of the objectives of time series analysis is to identify the direction and magnitude of any trend present in the data. To achieve this objective, many methods are available in practice for the estimation of trend in a series; but in this research two methods will be employed to estimate the trend and these are
i Moving Average Method
ii. Least Square Method

E. Moving Average Method

The moving average approach involves replacing a specific measurement with the arithmetic mean of a sequence of measurements in which it is the centre. The moving average is centred as an observed measurement when an odd number is specified. When an even number of measures is chosen, however, the moving average is centred between two observed observations and must be re-cantered before the average and measurement may be compared.

Suppose we are given $X_1, X_2, ..., X_N$ on $\{X_t\}$, the n-point moving are:

(3) $$Y_1 = \frac{X_1 + X_2 + \cdots + X_N}{n}$$

(4) $$Y_2 = \frac{X_2 + X_3 + \cdots + X_N}{n}$$

(5) $$\vdots$$

(6) $$Y_{N-n} = \frac{X_{N-n} + X_{N-n} + \cdots + X_N}{n}$$

(7)

The advantage is that it gives the true nature of the trend, that is, a simple description of the underlying trend particularly when the trend is small. Although, this method losses the extreme values, it should be noted that one can generalize the moving average trend for the series to any point in time.

F. Method of Least Squares

The least squares technique to regression analysis may be used to discover the equation of a suitable trend line, and the trend values Tt can be derived from the equation. The trend line's normal equations are as follows:

$$\boxed{T_t = a + bt + \varepsilon_t} \quad (8)$$

Where a and b are the parameter to be estimated

$$\hat{b} = \frac{n\sum X_t t - \sum X_t \sum t}{n\sum X_t^2 - (\sum X_t)^2} \quad (9)$$

$$\hat{a} = \bar{T}_t - \hat{b}\bar{t} \quad (10)$$

One downside of this strategy is that it may be used to fit a linear trend into a non-linear series.

G. Auto-covariance and Autocorrelation functions

The main properties of a (weakly) stationary stochastic process are the mean μ and the auto-covariances $\gamma(k)(k \leq 0)$. The auto-covariances can be standardised by dividing them with the variance of the process. This yields the autocorrelations,

$$\gamma(k) = \frac{\gamma(k)}{\gamma(\theta)} \quad . \quad (11)$$

One useful way of summarising the time domain properties of a stationary process is by plotting the autocovariances $\gamma(k)$ against k (auto-covariance function) or the auto-correlations against k (autocorrelation function or ACF). Since $\gamma(-k) = \gamma(k)$ you do not have to extend the plots over the negative values of k. Not any function can be an auto-covariance function. To see this, consider forming a 'weighted average' $X = a_1Y_1 + \cdots + a_TY_T$ of a stationary time series Y_t, where the as are arbitrary constants. X is a random variable and therefore has a variance, which is given by

$$Var(X) = \sum_{i=1}^{T}\sum_{j=1}^{T} a_i a_j \gamma(i-j) \geq 0 \quad (12)$$

Now $Cov(Y_i, Y_j) = \gamma(i-j)$; also, since variances are never negative, the whole expression on the right-hand side must be non- negative. Therefore the auto covariance function must satisfy.

$$\sum_{i=1}^{T}\sum_{j=1}^{T} a_i a_j \gamma(i-j) \geq 0 \quad (13)$$

for any set of as, and for any T. This property is known as the positive semi-definite property of an auto covariance function.

H. Estimation of Auto Covariance

If the anticipated value of $E(^{P}{}_t) = 0$, a time series is referred to be white noise or totally random. $E(\epsilon^2) = \sigma^2 \forall\ t$ and $E(\epsilon_t \epsilon_s) = o^t\ \forall S \neq t$. If a stationary time series Xt satisfies the difference equation, it is said to follow a general linear process (GLP).

$$X_t = \mu + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + \ldots \quad (14)$$

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where $\mu = E(X_t)$ and if $\mu = 0$ we have

$$X_t = \epsilon_t + \sum_{j=1}^{\infty} \phi_j \epsilon_{t-j} \tag{15}$$

Equation 15 expresses Xt s as a weighted sum of the w.n.p's$_t$. current and previous values. We want to show that under suitable condition of X_t; X_t is weighted sum of the past value of X_t and a shock a i.e $X_t = \sum \prod_j X_{t-j} + a_r^t$ Now let

$$X_t = \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + \dots \tag{16}$$

$$X_t = \sum_{j=0}^{\infty} \phi_j \epsilon_{t-j} - - - - - (\phi_0 = 1) \tag{17}$$

$from\ eqn1\ make\ \epsilon_t\ the\ the\ subject$

$$\epsilon_t = X_t - \phi_1 \epsilon_{t-1} - \phi_2 \epsilon_{t-2} \dots \tag{18}$$

$$\epsilon_{t-1} = X_{t-1} - \phi_1 \epsilon_{t-2} - \phi_2 \epsilon_{t-2} \dots \tag{19}$$

$substitute\ for\ (16)\ in\ (17)$

$$\epsilon_t = X_t - \phi_1 (X_{t-1} \phi_1 \epsilon t - 2 - \phi_2 \epsilon_{t-3}) - \phi_2 \epsilon_{t-2} \tag{20}$$

$$\epsilon_t = x_t - \phi_1 x_{t-1} + \phi^2 \epsilon_{t-2} + \phi_1 \phi_2 \epsilon_{t-3} - \phi_2 \epsilon_{t-2} \tag{21}$$

$$\epsilon_t = X_t - \phi_1 x_{t-1} - (\phi_2 - \phi_j^2) \epsilon_{t-2} + \phi_1 \phi_2 \epsilon_{t-3} \tag{22}$$

(23)

$$\epsilon = x_t + \prod_i X_{t-1} + \prod_2 X_{t-2} \tag{24}$$

$$\epsilon_t = \sum_{j=0}^{\infty} \prod_j X_{t-j} \tag{25}$$

$$x_t = \sum_{j=0}^{\infty} \phi_j \epsilon_{t-j}\ (using\ the\ back\ ward\ shitoperator) \tag{26}$$

$$x - t = \sum_{j=0}^{\infty} B^j \epsilon_t = (\sum_{j=0}^{\infty} B^j) \epsilon_t \tag{27}$$

$$x_t = \Phi_{(B)} \epsilon_t$$

$$\epsilon = x_t \Phi^{-1}_{(B)\dots} \tag{28}$$

from the above equation

$$\epsilon_t = \sum_{j=0}^{\infty} \prod_j x_{t-j} \tag{29}$$

$$= \sum_{j=0}^{\infty} \prod_j B^j x_t = \left(\sum \prod_j B^j \right) x_t \tag{30}$$

$$\epsilon_t = \prod_{(B)} x_t \tag{31}$$

$$\prod_{(B)} x_t = \Phi^{-1}_{(B)} x_t \tag{32}$$

$$\prod_{(B)} = \Phi^{-1}_{(B)}\ proved \tag{33}$$

I. Auto covariance Generating Function of a Linear Process

The linear process' auto covariance generating function is defined by $\Gamma B = \sum_{K=N}^{\infty} Y_K B^K$

$$\begin{aligned}
Recall\ that\ \gamma_k &= E(x_t-\mu)(x_{t+k}-\mu) && (34)\\
If\ \mu &= 0\\
\gamma_k &= E(x_t \quad X_{t+k}) && (35)\\
Recall\ that\ X_t &= \sum_{i=w}^{\infty}\phi_i X_{t-i} && (36)\\
X_{t+k} &= \sum_{j=w}^{\infty}\phi_j X_{t+k-j} && (37)\\
\gamma &= E\left(\sum_{i=0}^{\infty}\phi_i X_{t-i}\sum_{j=0}^{\infty}\phi_j X_{t+k-j}\right) && (38)\\
&= \sum_{i=0}^{\infty}\phi_i\sum_{j=0}^{\infty}\phi_j E(X_{t-i}X_{t+k-j}) && (39)\\
Let\ t-i &= t+k-j && (40)\\
j &= k+i\\
&= \sum_{i=0}^{\infty}\phi_i\sum_{k+i=0}^{\infty}\phi_{k+i}E(X_{t-i}\ X_{t+k-k-i}) && (41)\\
&= \sum_{i=0}^{\infty}\phi_i\sum_{k+i=0}^{\infty}\phi_{k+i}E(X_{t-i}\ X_{t-i}) && (42)\\
&= \sum_{i=0}^{\infty}\phi_i\sum_{k+i=0}^{\infty}\phi_{k+i}E(X_{t-i}^2) && (43)\\
Recall\ that\ \sigma^2 &= (\epsilon_t^2) && (44)\\
\gamma_k &= \sigma^2\sum_{i=0}^{\infty}\phi_i\sum_{k+i=0}^{\infty}\phi_{k+i} && (45)\\
\Gamma B &= \sum_{k=0}^{\infty}\gamma_k B^k && (46)\\
&= \sigma^2\sum_{i=0}^{\infty}\phi_i\sum_{k+i=0}^{\infty}\phi_{k+i}B^k && (47)\\
Let\ h &= k+i \quad k=h-i && (48)
\end{aligned}$$

$$\begin{aligned}
&= \sigma^2\sum_{i=0}^{\infty}\phi_i\sum_{h-i=0}^{\infty}\phi_{h-i+i}B^{h-i} && (49)\\
& && (50)\\
&= \sigma^2\sum_{i=0}^{\infty}\phi_i\sum_{h-i=0}^{\infty}\phi_h B^h B^{-i} && (51)\\
& && (52)\\
&= \sigma^2\sum_{i=0}^{\infty}\phi_i B^{-i}\sum_{h=0}^{\infty}\phi_(h)B^h && (53)\\
&= \sigma^2\Phi_{(B^{-1})}\Phi(B) && (54)
\end{aligned}$$

J. Autoregressive Model (p)

An autoregressive (AR) model is a representation of a type of random process; as such, it describes certain time-varying processes in nature, economics, etc. The autoregressive model specifies that the output variable depends linearly on its own previous values and on a stochastic term (an imperfectly predictable term); thus, the model is in the form of a stochastic difference equation.

It is a special case and key component of the more general ARMA and ARIMA time series models, which have a more complicated stochastic structure; it is also a special case of the vector autoregressive model (VAR), which consists of a system of more than one stochastic difference equation, along with the moving-average (MA) model.

- *Definition*

A real valued stochastic process (X_t) is said to be an autoregressive process of order p, if there exist $\varphi_1,\varphi_2,\ldots,\varphi_p \in \Re<$ with $\varphi_p \neq 0$ and a white process (ε_t) such that

$$X_t=\varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \ldots + \varphi_p X_{t-p} + \varepsilon_t = \sum_{K=1}^{p} \phi_k X_{t-k} + \varepsilon_t \tag{55}$$

where tz and $\varepsilon_t \sim N(0,\sigma_\varepsilon^2)$ This can be equivalently written using the backshift operator B Where $X_{t-1} = BX_t, X_{t-2} = B^2X_t, X_{t-3} = B^3X_t,\ldots,X_{t-p} = B^pX_t$, it can be written as

$$\left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right) X_t = \varepsilon_t \tag{56}$$

And this implies

$$(\Phi)(B)X_t = \varepsilon_t \tag{57}$$

where $\Phi(B)$ is a polynomial in B. For stationarity the roots of $\Phi(B)$ must lie outside the unit circle i.e., $|B| > 1$.

- The process value at time t, X_t, is a weighted linear mixture of the process values from the preceding p time points plus a shock or innovation term et at time t in this model.
- We suppose that et, the innovation at time t, is unaffected by the process variables $X_{t1},Y_{t2},\ldots$.
- $E(Y_t) = 0$ is still the assumption. By substituting X_t with X_t, a nonzero mean might be introduced to the model (for all t). The stationarity characteristics would be unaffected.
- This process is a specific instance of the generic linear process (assuming it is stationary).

K. Yule-Walker Equation

The Yule-Walker equations are a set of equations named after Udny Yule and Gilbert Walker. The equations are obtained from a p-order autoregressive model. In the case of an AR(p) process,

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \ldots + \varphi_p X_{t-p} + \varepsilon_t \tag{58}$$

Multiplying equation above with X_{t-k} and taking the expectation, we have

$$\gamma_k = \varphi_1 \gamma_k + \varphi_2 \gamma_{k-2} + \varphi_2 \gamma_{k-2} \ \ldots + \varphi_p X_{t-p} + \varepsilon_t \tag{59}$$

Since $E(X_{t-k},X_t) = \gamma_k$ and $E(X_{t-k},\epsilon_t) = \sigma^2 \ \forall \ k = 0$ but $E(X_{t-k},\epsilon_t)$ vanish when $k > 0$

When K=1 $$\gamma_1 = \varphi_1 \gamma_0 + \varphi_2 \gamma_1 + \varphi_2 \gamma_2 + \varphi_3 \gamma_3 \ldots + \varphi_p X_{p-1} \tag{60}$$

When K=2 $$\gamma_2 = \varphi_1 \gamma_1 + \varphi_2 \gamma_0 + \varphi_2 \gamma_0 + \varphi_3 \gamma_1 \ldots + \varphi_p \gamma_{p-2} \tag{61}$$

... ...

... ...

when k = p $$\gamma_p = \varphi 1\gamma p-1 + \varphi 2\gamma p-2 + \varphi 3\gamma p-3 + \ldots + \varphi p\gamma 0 \tag{62}$$

The above equations (the Yule-Walker equations) provide several routes to estimating the parameters of an AR(p) model, by replacing the theoretical covariances with estimated values.

When equation 62 is divided by γ_0 it gives:

$$\rho k = \varphi 1\rho k{-}1 + \varphi 2\rho k{-}2 + \varphi 3\rho k{-}3 + \ldots + \varphi p\rho k{-}p \qquad k > 0 \tag{63}$$

$$\text{when } k = 1 \qquad \rho_1 = \varphi_1\rho_0 + \varphi_2\rho_1 + \varphi_3\rho_2 + \ldots + \varphi_p\rho_{p-1} \tag{64}$$

$$\varphi_1\rho_1 + \varphi_2\rho_0 + \varphi_3\rho_1 + \ldots + \varphi_p\rho_{p-2} \ldots \tag{65}$$

$$\text{when } k = p \qquad \rho_p = \varphi_1\rho_{p-1} + \varphi_2\rho_{p-2} + \varphi_3\rho_{p-3} + \ldots + \varphi_p\rho_0 \tag{66}$$

The above equation can be written in matrix form as:

$$\begin{bmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \rho_\rho \end{bmatrix} = \begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdots & \rho_{\rho-1} \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{\rho-2} \\ \vdots & \vdots & \vdots & \vdots & \cdots \\ \rho_{\rho-1} & \rho_{\rho-2} & \rho_{\rho-3} & \cdots & 1 \end{bmatrix} \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_\rho \end{bmatrix} \quad (67$$

In this research work, Autoregressive or order two (2) will be consider

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \epsilon_t \tag{68}$$

L. 3.12. Estimating the Parameter of AR(2) using Yule Walker

$$\begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix} = \begin{bmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{bmatrix} \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} \qquad (69) \;\&\; (70)$$

$$\begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} = \begin{bmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix} \qquad (71) \;\&\; (72)$$

$$\begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} = \frac{1}{1-\rho_1^2} \begin{bmatrix} 1 & -\rho_1 \\ -\rho_1 & 1 \end{bmatrix} \begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix} \qquad (73) \qquad (74)$$

$$\begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} = \frac{1}{1-\rho_1^2} \begin{bmatrix} \rho_1 - \rho_1\rho_2 \\ -\rho_1^2 + \rho_2 \end{bmatrix} \tag{75}$$

$$\therefore \quad \hat{\phi}_1 = \frac{\rho_1 - \rho_1\rho_2}{1-\rho_1^2} \tag{76}$$

$$\hat{\phi}_2 = \frac{\rho_2 - \rho_1^2}{1-\rho_1^2} \tag{77}$$

Where $\rho_1 = \frac{Cov(X_t, X_{t-1})}{\sqrt{Var(X_t)Var(X_{t-1})}}$ and $\rho_2 = \frac{Cov(X_t, X_{t-2})}{\sqrt{Var(X_t)Var(X_{t-2})}}$

M. Moving Average (q)

The moving-average (MA) model is a typical strategy for modelling univariate time series in time series analysis. According to the moving-average model, the output variable is linearly dependent on the present and various historical values of a stochastic (imperfectly predicted) factor.

The moving-average model, like the autoregressive (AR) model, is a specific example and fundamental component of the more general ARMA and ARIMA time series models, which have a more sophisticated stochastic structure. The MA model, unlike the AR model, is always stationary. If a stochastic process X_t fulfils the difference equation, it is said to be a moving average process of order (q).

$$X_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \quad (78)$$

where $\{\varepsilon_t\}$ is a white noise process with variance σ^2, then

$$X_t = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right)\varepsilon_t = \theta(B)\varepsilon_t \quad (79)$$

Where

$$\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \quad (80)$$

If $\Theta^{-1}(B)$ exist, then we can write

$$\Theta^{-1}(B) = \varepsilon_t \quad (81)$$

The roots of the characteristic equation $\Theta(B) = 0$ must fall outside the unit circle, which is the requirement for invertibility

N. The Auto-covariance and Autocorrelation of the General qth Order Moving Average MA(q) Process

Equation (50) describes the generic qth order moving average process, which can be rewritten as:

$X_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \cdots - \theta_q\varepsilon_{t-k}$

where ε_t is a w.n.p.

$$E(X_tX_{t-k}) = (\varepsilon_t - \theta_1\varepsilon_{t-1} - \cdots - \theta_q\varepsilon_{t-k})(\varepsilon_{t-k} - \theta_1\varepsilon_{t-k-1} - \theta_2\varepsilon_{t-k-2} - \cdots - \theta_q\varepsilon_q) \quad (82)$$

$$\gamma_k = \sigma_\varepsilon^2(-\theta_k + \theta_1\theta_{k+1} + \theta_2\theta_{k+2} + \cdots + \theta_q\theta_{q+k})$$
$$= -\theta_k + \theta_1\theta_{k+1} + \theta_2\theta_{k+2} + \cdots + \theta_q\theta_{q+k} \quad (83)$$

setting $k = 1, 2...$, we have,

$$\gamma_1 = \sigma_\varepsilon^2(-\theta_1 + \theta_1\theta_2 + \theta_2\theta_3 + \cdots + \theta_q\theta_1\theta q\theta q{+}1) \quad (84)$$

$$\gamma_2 = \sigma_\varepsilon^2(-\theta 2 + \theta 1\theta 3 + \theta 2\theta 4 + \cdots + \theta q\theta q{+}2) \quad (85)$$

$$\gamma_0 = \sigma_\varepsilon^2(\theta_1^2 + \theta_2^2 + \cdots + \theta_q^2) \quad (86)$$

The above are equivalence of the Yule-Walker equations in the AR model. However, for the MA model, these equations are no longer linear in the parameter, optimization technique is required. This makes the MA(q) models fitting more difficult.

However, the ACF of the $MA(q)$ mode is summarized as:

$$\gamma_k = \begin{cases} \{-\theta_k + \theta_1\theta_{k+1} + \cdots + \theta_{q+k}\theta_q & \text{for k } = 1,2,\ldots,\text{q} \\ 0; & for\ k > q \end{cases}$$

$\gamma_o = \sigma_\varepsilon^2 \sum_{j=0}^{q} \theta_i^2$

Hence, the autocorrelation function becomes

$$\rho_k = \begin{cases} \frac{\{-\theta_k + \theta_1\theta_{k+1} + \cdots + \theta_{q+k}\theta_q}{\theta_1^2 + \cdots + \theta_q^2}; & for\ k = 1,2,\ldots q \\ 0; & for\ k > q \end{cases} \quad (87)$$

Note that a given time series is generated by a moving average process if the ACF cuts off after lag q.

O. Autoregressive Moving Average (ARMA)

AR(1) may be written as an $MA(\infty)$and MA(1) can be written as an $AR(\infty)$. As a result, in order to have the fewest number of parameters, it is natural to represent a time series model as a mix of AR and MA processes, referred to as an autoregressive moving average process (ARMA) model.

$$X_t - \varphi_1 X_{t-1} - \cdots - \varphi_p X_{t-p} = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_p \varepsilon_{t-p} \quad (88)$$

where ε_t is a w.n.p with$Var(\varepsilon_t = \sigma_\varepsilon^2)$.

Equation (88) can be expressed as

$$\Phi(B)X_t = \Theta(B)\varepsilon_t \quad (89)$$

where $\Phi(B) = (1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p)$.

The root of the characteristic equation $\Phi(B) = 0$ must lie outside the unit circle for stationarity, and the roots of the characteristic equation $\Theta(B) = 0$ must also be outside the unit circle for invertibility.

To obtain the autocovariance function of ARMA (p, q), we multiply equation 88 by X_{t-k} and take expectation to obtain

$$\gamma_k = \phi_1\gamma_{k-1} + \phi_2\gamma_{k-2} + \cdots + \phi_q\gamma_{k-q} - \theta_1\gamma_{12\{k-1\}} - \theta_2\gamma_{12\{k-2\}} - \ldots - \theta_q\gamma_{12\{k-q\}} \quad (90)$$

where $\gamma_{12}(k) = E(X_{t-k}\varepsilon_t)$.

Since X_{t-1} depends only on $\varepsilon_{t-k}, \varepsilon_{t-k-1}, \ldots$, we have $\gamma_{12}(k) = E(X_{t-k}\varepsilon_t) = 0 for k > 0$ and $\gamma_{12}(k) = 0$. Therefore, we have

$$\gamma_k = \phi_1\gamma_{k-1} + \phi_2\gamma_{k-2} + \cdots + \phi_q\gamma_{k-q} \text{ for } k \geq q+1 \quad (91)$$

P. Model Identification

Even after a thorough examination of the time plot, determining the suitable model for a time series data is not always straightforward. The two model identification tools must also be examined. The Autocorrelation function (ACF) and the Partial autocorrelation function (PACF) are the two functions.

Suppose we have N-observations on $\{X_t\}$ say $X_1, X_2, \ldots, X_N$ and if the series is stationary, then the problem is how to determine the order of the appropriate model to fit to the data. The classic Box Jenkins strategy, which combines the ACF and PACF functions, is the original way to tackling this problem. Using the Box Jenkins (1976) approach, you critically observe the ACF and PACF for possible decline of the curves or a cut off on either of the two curves.

A series is said to be generated by an AR(p) decays if the (ACF) ρ_k decays exponentially to zero and φ_{kk} (PACF) cuts off at lag p. The cut off point of φ_{kk} determines appropriate order of the AR model to be fitted.

On the other hand, a time series is said to be generated by an MA process of order q if the ACF k ρ_k cuts off at a particular lag and the φ_{kk} PACF decays exponentially to zero. The point at which ρ_k; k = 1,2,$\cdots$, cuts-off (q) determines the lag of the Moving Average model to fit. If neither ACF nor the PACF cuts off, it suggests an **ARMA**

(p, q) model. The order (p, q) is sometimes difficult to determine by mere inspection of the ACF and PACF. However by practice, it easy to determine.

	AR(p)	MA(q)	ARMA(p,q)
ACF	Tail off	Cut off after lag q	Tail off
PACF	Cut off after lag p	Tail off	Tail off

Table 1: The Behaviour of the ACF & PACF for AR(p), MA(q) and ARMA(p,q) Models

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Q. Order Determination or Model Selection

The following are the most current ways that have been utilized as criterion for selecting the order of a model without going through hypothesis testing:

- Final Prediction Error (FPE)
- Akaike Information Criterion (AIC)
- Bayesian Information Criterion (BIC)
- Schwartz's BIC Criterion [SBIC]
- Parzen's CAT Criterion (Criterion for Autoregressive transfer function).

R. Unit Root

The Unit Root test is widely used to evaluate stationarity in a univariate time series. The test begins by posing the null hypothesis that a certain time series has a unit root, implying that it is non stationary, and then determines whether the null hypothesis is statistically rejected in favour of the alternative hypothesis that the time series is stationary. To determine if a time series is non-stationary, assume the following connection between the current value (in time t) and the last value (in time t-1).

$$x_t = \phi x_{t-1} + \epsilon_t \quad (92)$$

where xt is a time-dependent observation value and t is a white noise process. A first-order autoregressive process is represented by this model. If $|\varphi| < 1$, the time series xt converges to $x \rightarrow \infty$, a stationary time series as x. If $|\varphi| = 1$ *or* > 1, the xt series is not stationary, and the variance of xt is time dependent (Diebold et al., 2006). The series has a unit root, to put it that way.

The following one-sided hypothesis is then put to the Unit Root test. H0 is a zero.

$H_0 : \varphi = 1$ (has a unit root)

$H_1 : \varphi < 1$ (has root outside the unit circle)

S. Augmented Dickey- Fuller Test

For the model $x_t = \alpha_{t-1} + ut$ in which ut is white noise, Dickey and Fuller established a test of the null hypothesis that $\alpha = 1$ versus an alternative hypothesis that 1 for the model xt = t1 +ut. The augmented Dickey-Fuller test (Said and Dickey, 1984) is a broader test that permits the differenced series ut to be any stationary process rather than white noise and approximates the stationary process using an AR model. The adf. test function in the tseries package implements the technique in R. For our simulated random walk x, the null hypothesis of a unit root cannot be rejected.

T. Phillips- Perron test

The Phillips-Perron test (Perron, 1988) is an alternative to the enhanced Dickey-Fuller test that is implemented in the R function pp. Test. The Phillips-Perron approach calculates the autocorrelations in the stationary process u_t directly (using a kernel smoother) rather than assuming an AR approximation, which is why the Phillips-Perron test is defined as semi-parametric. The test statistic's critical values are computed using either asymptotic theory or lengthy simulations.

IV. RESULTS AND DISCUSSION

A. Trend Plot

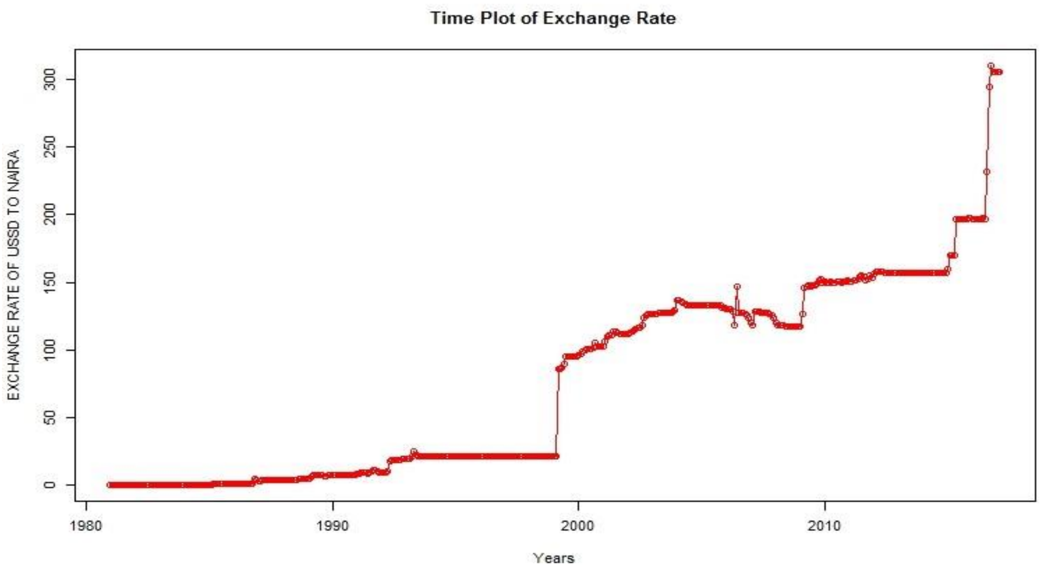


Fig 4.1 Time Plot of Exchange Rate

Fig 4.1: displays the time plot of record of Nigerian Naira to US Dollar exchange rate for the period of 33 years. The plot shows that there is an upward movement of trend from (1981-2013), since this series contain trend that is there is a systematic shift or change in it mean over time. It can also be shown from the graph that around 2006 there is a downward and upward movement in the series.

In this study, we're looking to see if the values for successive years are connected so that the value for one year can aid in anticipating the next year's exchange rate.

B. Test For Stationary with Augmented Dickey-Fuller Test

H_o: The data is not stationary.
H1: The data is stationary.
α = 1%,5%,10%

Table 4.1: ADF Test

Dickey -Fuller	-0.8259
Lag order	7
p-value	0.9591
alternative hypothesis:	stationary

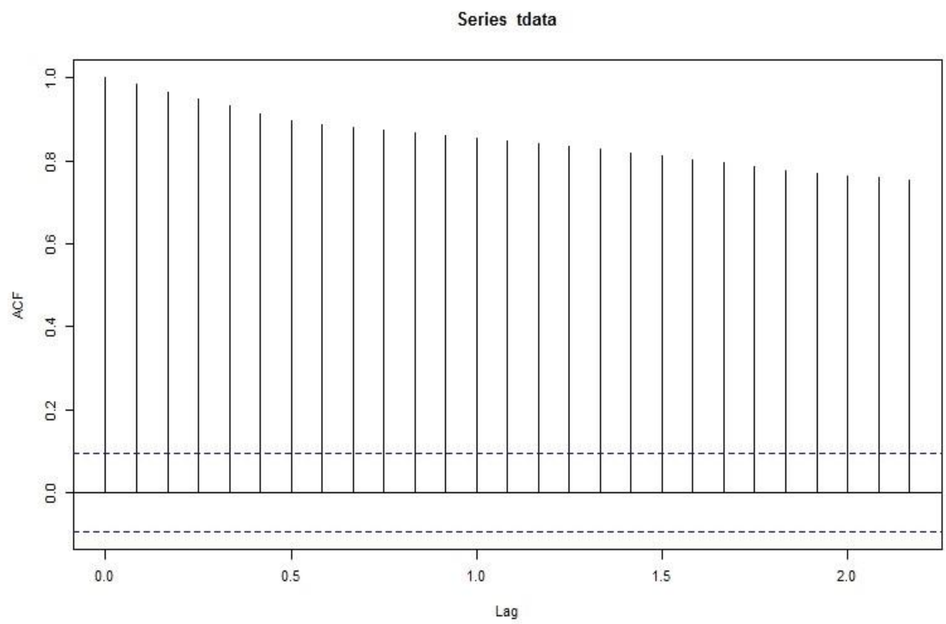
C. Phillips-Perron Unit Root Test

Table 4.2: Phillips's perron Unit Root Test

Dickey-Fuller Z(alpha)	-3.7448
Truncation lag parameter	5
p-value	0.9006
alternative hypothesis	stationary

Since the p-value 0.9006(ADF Test) and 0.9591(Phillips Perron Unit Toot test) are greater than the level of significant we fail to reject the null hypothesis and conclude that the data is not stationary.

D. Plot of ACF and PACF of the Data



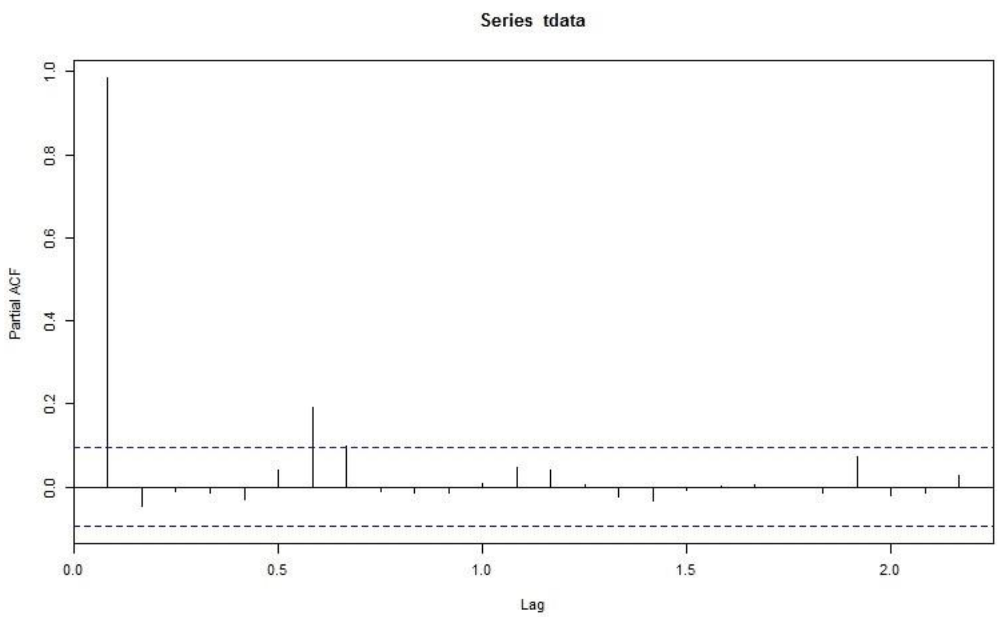


Fig 4.2 : ACF and PACF of Nigerian Naira to US Dollar Exchange Rate

The ACF decays exponentially slowly and this is a trace of non-stationary while the PACF cut off after a particular lag

E. Decomposition of additive time series

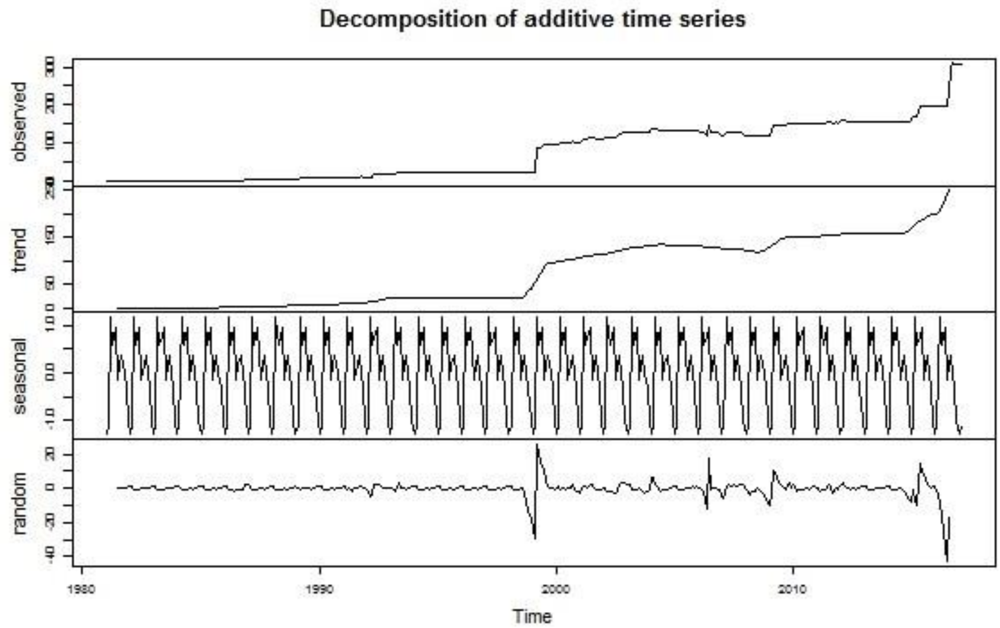
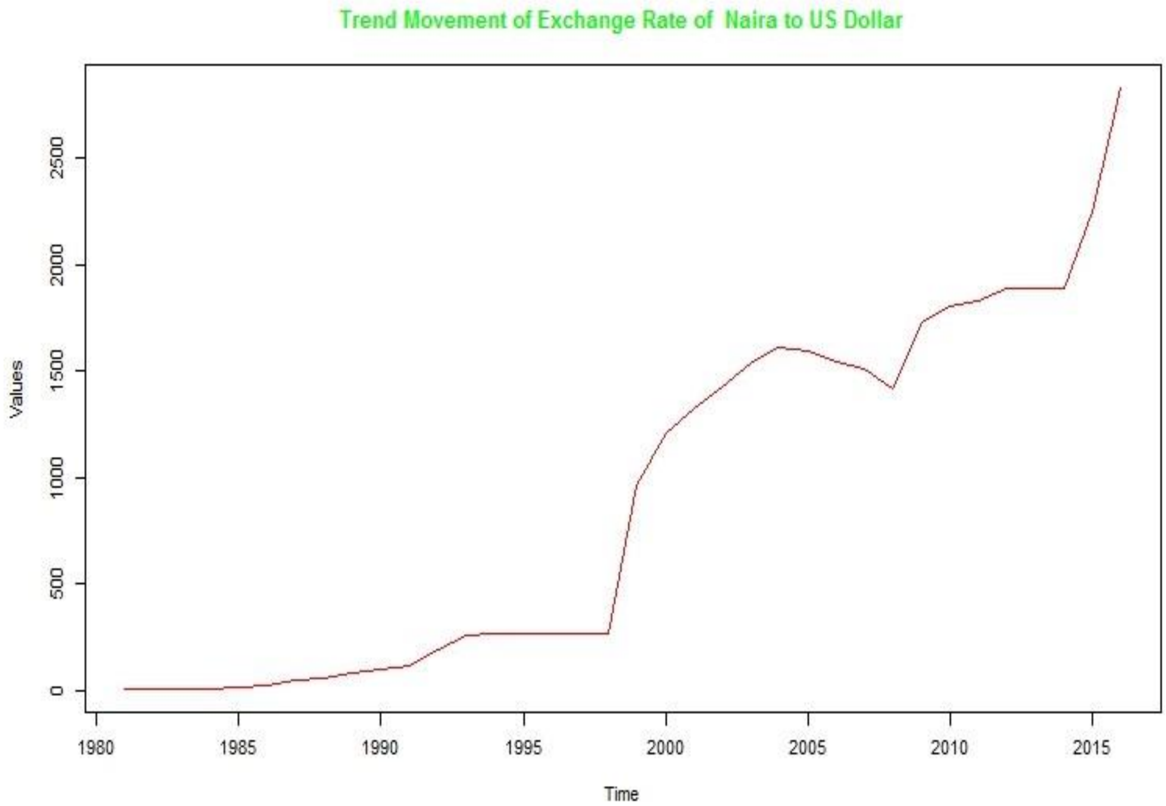


Fig 4.3 Decomposition of Nigerian Naira to US Dollar Exchange Rate

It can be seen that there is an upward movement along the trend line. It can also be observed that there is a constant rate over time from 2003 to 2004 this we can say that the exchange rate maintains a certain price over this period. Hence the process is not stable, the instability can be related to some factors affecting the exchange rate these factors can also to either assignable causes of variation or natural causes as the case may be.



It can be observe that the trend as an upward movement

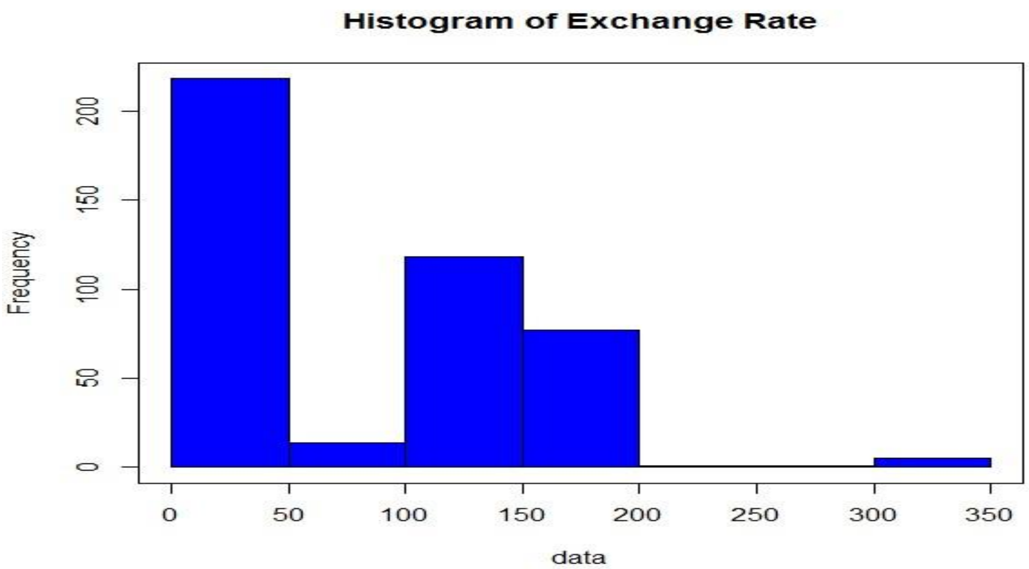
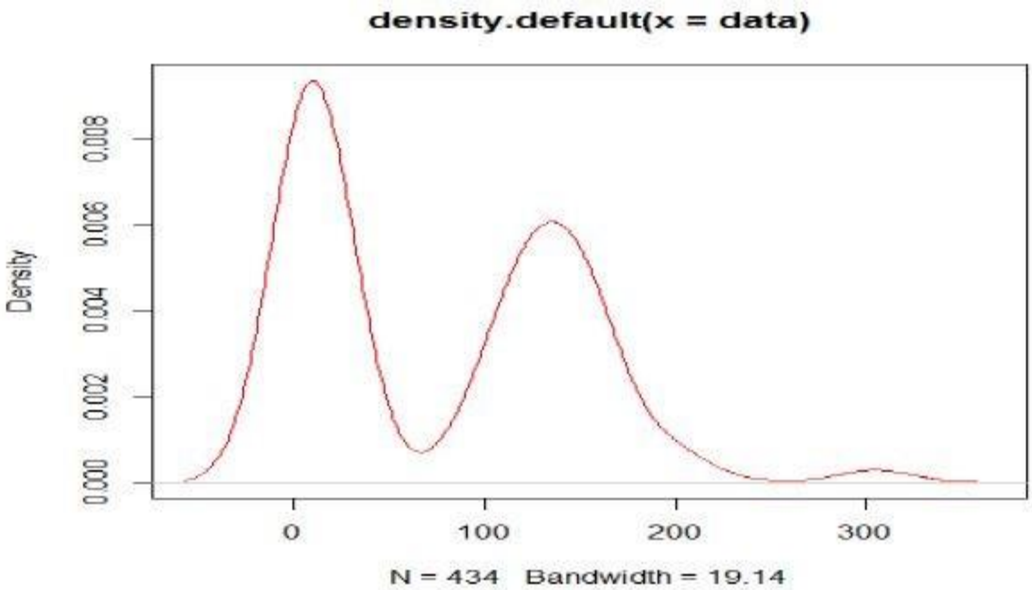


Fig 4.4: Histogram Plot of Exchange Rate

The data is not normally distributed, as seen by the histogram. The distribution is not bell-shaped but positively skewed, since most of the data point are in the lower half.



the density shows a bi modal form Figure 4.5: Density Plot

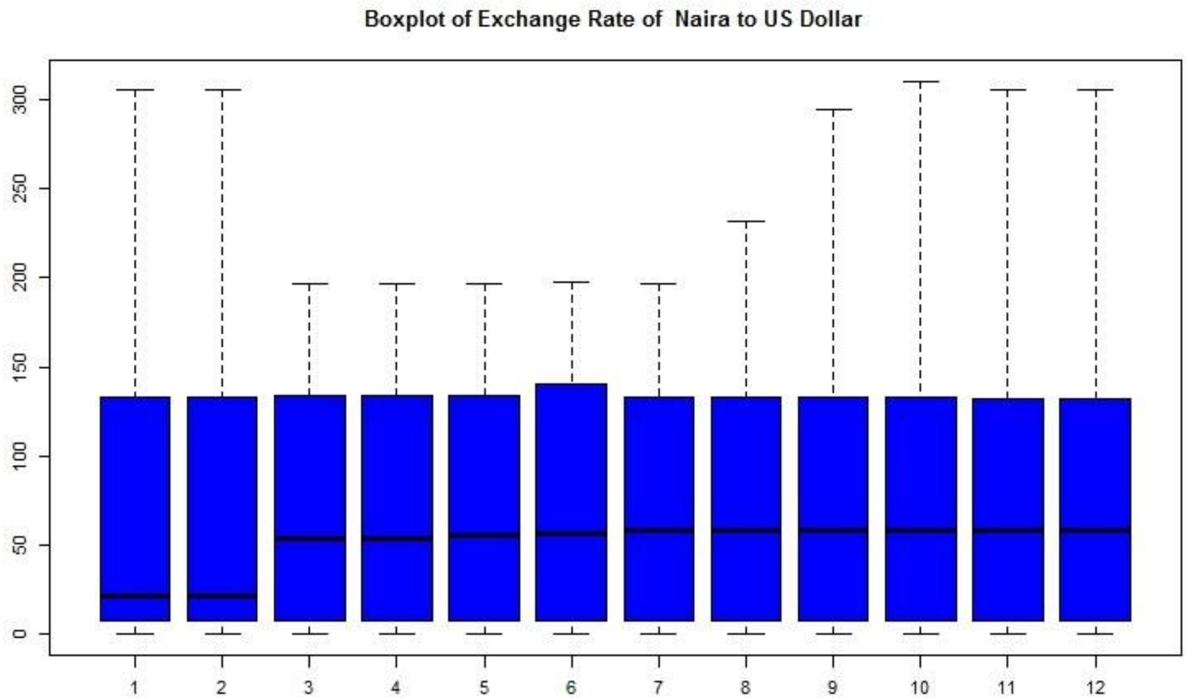


Fig 4.6: BOX Plot of Exchange Rate

The Box Whisker plot reveals that there are no outliers in the data and that the majority of it is above the median.

F. Estimation of Trend Using Least Square Estimate

The total number of observations is 434, the summation of the time series data which is X_t=33084.7, and the respective squares $\sum t^2 = 27154729$, $(\sum t)^2 = (93961)^2$

$$X_t = a + bt + \epsilon_t \tag{93}$$

$$\hat{X}_t = \hat{a} + \hat{b}(t) \quad (94)$$

$$\hat{b} = \frac{n\sum X_t t - \sum X_t \sum t}{n\sum t^2 - (\sum t)^2} \quad (95)$$

$$\hat{b} = \frac{(433 \times 10803435) - (93961 \times 33084.7)}{(433 \times 27154729) - (93961)^2} \quad (96)$$

$$= \left(\frac{1569215858}{2929328136}\right) \quad (97)$$

$$= 0.535691 \quad (98)$$

$$\hat{b} \approx 0.53569 \quad (99)$$

$$\bar{a} = \bar{X}_t - \hat{b}\bar{t} \quad (100)$$

$$\bar{X}_t = \frac{\sum X_t}{N} = \frac{33054.7}{433} \quad (101)$$

$$\bar{t} = \frac{\sum t}{n} = \frac{93961}{433} \quad (102)$$

$$\therefore \bar{a} = \frac{33054.7}{433} - (0.535691)\frac{93961}{433}$$

$$= 74.408083 - (0.535691)(217) \quad (103)$$

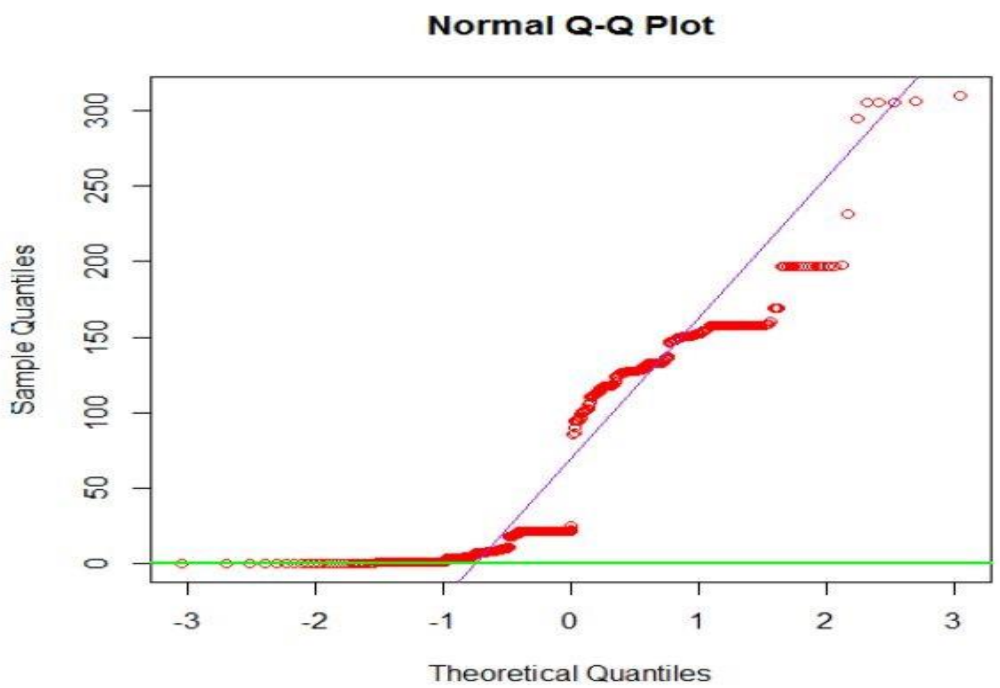
$$\hat{a} = 74.408083 - 116.2450314 \quad (104)$$

$$\hat{a} = -39.83686386 \quad (105)$$

$$\hat{a} \approx -39.83686386 \quad (106)$$

The trend Equation is

$$\hat{T}_t = -39.83686386 + 0.535691t \quad (107)$$



Interpretation: qqnorm, qqline and Density plot of Nigerian Naira to US Dollar Exchange Rate
Fig: 4.7 Normal QQ Plot

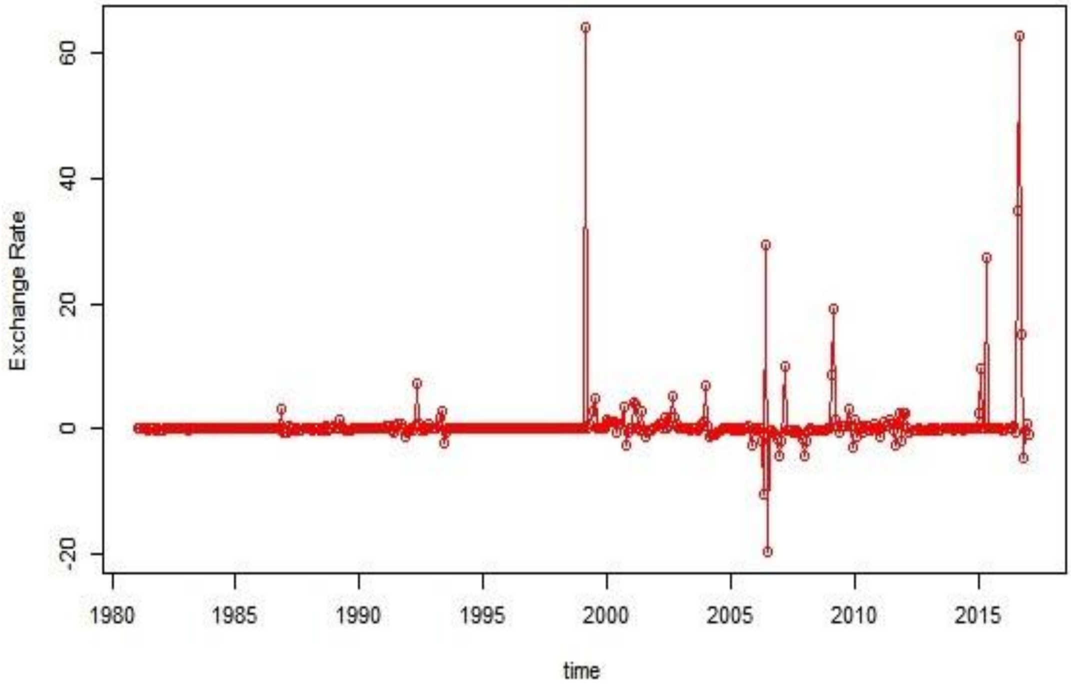


Fig 4.8 Plot of First Difference of Exchange Rate Data

➢ *Interpretation:*

Above shows that the trend of non-stationarity in 4.1 has now disappeared due to the fact that first differencing has taken place then we have real stationarity picture but with presence of strong seasonality

G. Stationarity Test for First Difference of Exchange Rate

H_o : The data is not stationary H_1 The data is stationary α = 5%,10%

Table 4.3 ADF test

Augmented Dickey-Fuller Test	
Dickey-Fuller	6.6018
Lag order	7
p-value	0.01

Since the p-value (0.01) is less than the level of significant 5%, 10%, hence we fail to accept the null hypothesis and conclude that the series is stationary

Table 4.4 Phillips-Perron Unit Root Test

Phillips-Perron Unit Root Test	
Dickey-Fuller Z(alpha)	-350.1992
Truncation lag parameter	5
p-value	0.01

Since the p-value (0.01) is less than the level of significant 5%, 10%, hence we fail to accept the null hypothesis and conclude that the series is stationary

H. Model Identification

Table 2: Summary of Model Identification

Order	Model	AIC	Log likelihood	σ2
0	**ARIMA (1,1,0)**	**2642.74**	**-1318.37**	**28.74**
	ARIMA (2,1,0)	2719.52	-1355.76	36.36
	ARIMA (0,1,1)	2644.91	-1318.46	28.74
1	ARIMA (1,1,1)	2644.69	-1318.35	28.73
	ARIMA (1,1,0)	2717.68	-1355.84	36.37
	ARIMA (1,1,1)	2719.55	-1355.77	36.36
2	ARIMA (1,1,1)	2695.55	-1342.77	34.01
	ARIMA (1,1,1)	2646.68	-1318.34	28.73
	ARIMA (1,2,1)	2653.3	-1321.65	28.49
3	ARIMA (2,1,4)	2654.15	-1318.08	28.67
	ARIMA (3,1,4)	2652.64	-1316.32	28.28
	ARIMA (4,1,4)	2652.63	-1316.32	28.27

According to the table above, ARIMA (1,1,0) is the best model since it has the lowest AIC=2642.74.02 and Log Likelihood=-1318.37 with σ^2 = 28.74.

I. Diagnostics Test

Here are some diagnostic tests of the model to see if it accurately represents the data.

J. Residual Analysis

These are a set of tests that determine if the model fits the data well or not. This is done to avoid fitting the erroneous model specification for the data.

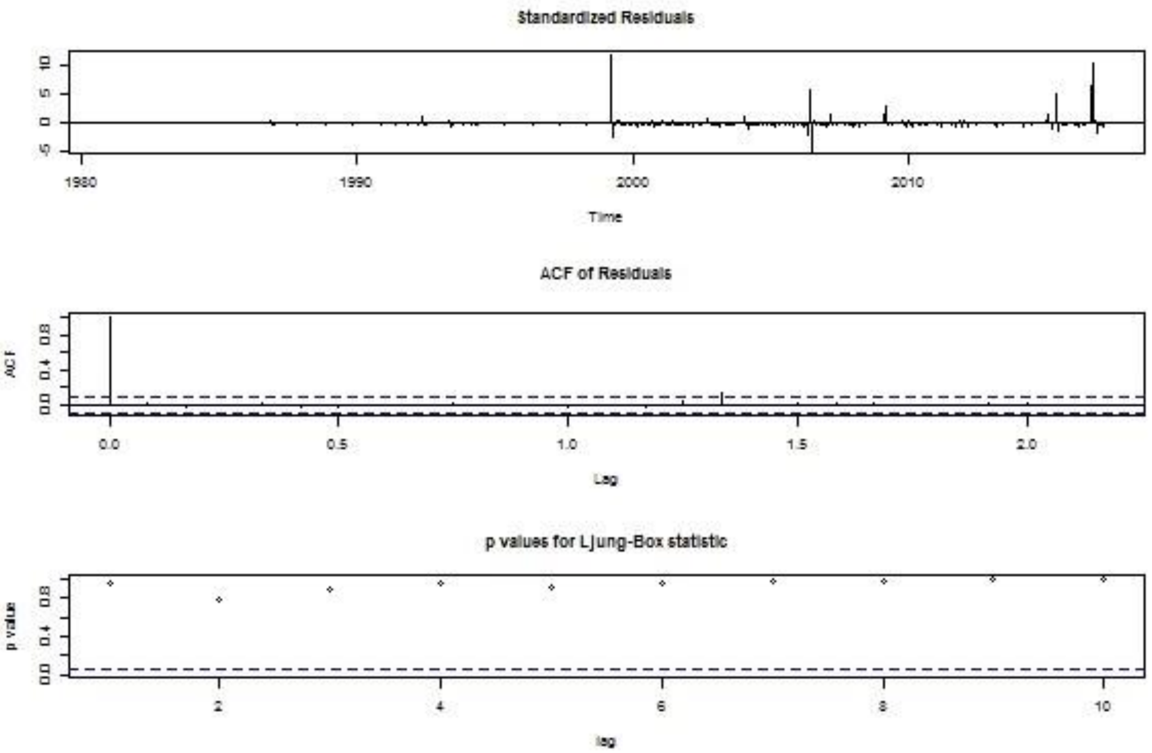


Fig 4.5 : Residual Analysis

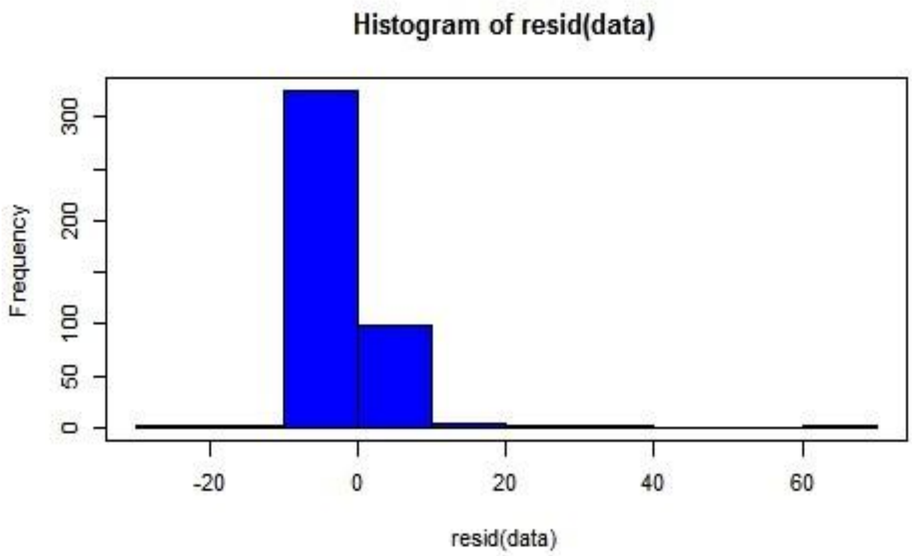


Fig 4.6 Histogram of Residual

Box-Pierce Test

Box-Pierce Test		
X-squared	df	p-value
22.317	20	0.3236

At lag 1, the Ljung-Box test statistics is 3.8999, and the p-value is 0.04829. The Null of independently distributed residuals is investigated using this test. It is based on the assumption that the residuals of a well described model are dispersed independently. If they aren't, the residuals are from a model that was mis specified. As a result, the residuals are spread out evenly.

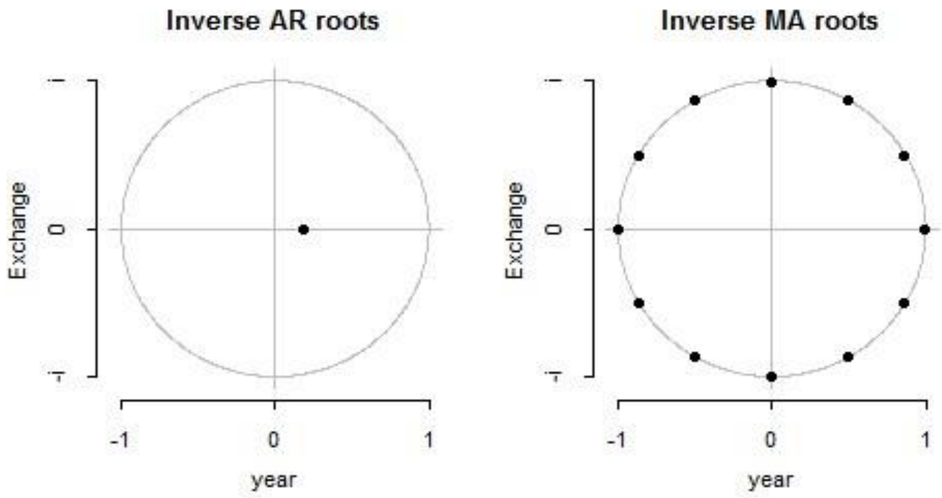


Fig 4.7: Unit Root Test

To maintain stationarity, $\Phi(B)$ must converge for $|B| \leq 1$, which implies that parameter φ_1 of the AR (1) process must meet the condition$|\varphi_1| < 1$, which is similar to saying that the root of $1 - \varphi_1$ B=0 must be outside the unit circle.

K. Parameter Estimation

Table 4.6: Estimation of the relevant model's coefficient and its related standard error

Variable	Coefficient	Standard error
φ_1	0.1884	0.0480

0.1 Model Identification

Consider the ARMA (p,q) define as

$X_t - \phi_1 X_{t-1} \dots \phi X_{t-p} = \epsilon_t - \theta_1 \epsilon_{t-1} \dots \theta_q \epsilon_{t-q}$

ARMA(1,1)

$$\begin{aligned} X_t - \phi_1 X_{t-1} &= \epsilon_t - \theta_1 \epsilon_{t-1} \\ X_t - \phi_1 B x_t &= \epsilon_t - \theta_1 B \epsilon_t \\ (1-\phi_1 B) X_t &= (1-\theta_1 B)\epsilon \\ \Phi(B) X_t &= \Theta(B)\epsilon_t \end{aligned}$$

Now to find our model

$$\begin{aligned} \phi_p(B)(1-B)^d X_t &= \theta_q(B)\epsilon_t \\ but\ since\ the\ model\ favours\ AR\ we\ have & \\ (1-\phi_1 B)(1-B)^1 X_t &= 0 \\ By\ expanding\ the\ equation\ we\ have & \\ (1-\phi_1 B - B + \phi_1 B^2) X_t & \\ by\ rewriting\ the\ backward\ shift\ operator & \\ X_t = (1-\phi_1 X_{t-1}) & \\ where\ \phi_1 = 0.1884 & \\ \therefore\ the\ final\ model\ is & \\ X_t &= 1 - 0.1884 X_{t-1} \end{aligned} \tag{108}$$

L. Forecast

The forecast has been calculated for a period of 48 times in the future. It's worth noting that this corresponds to only four years in the future.

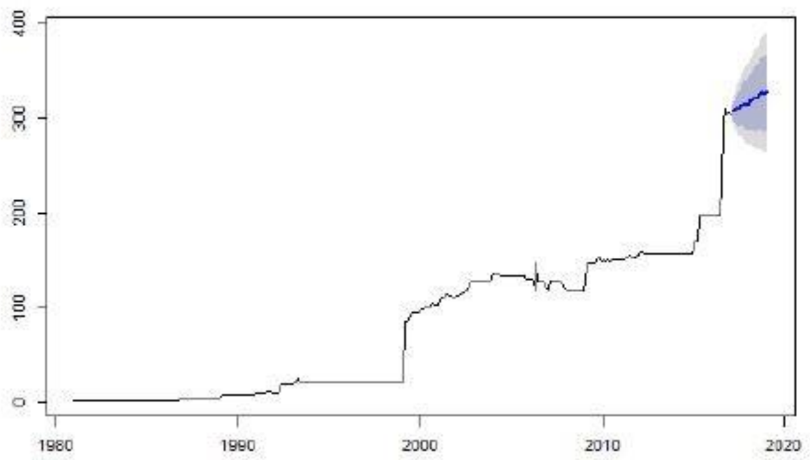


Fig 4.7: Forecast Graph

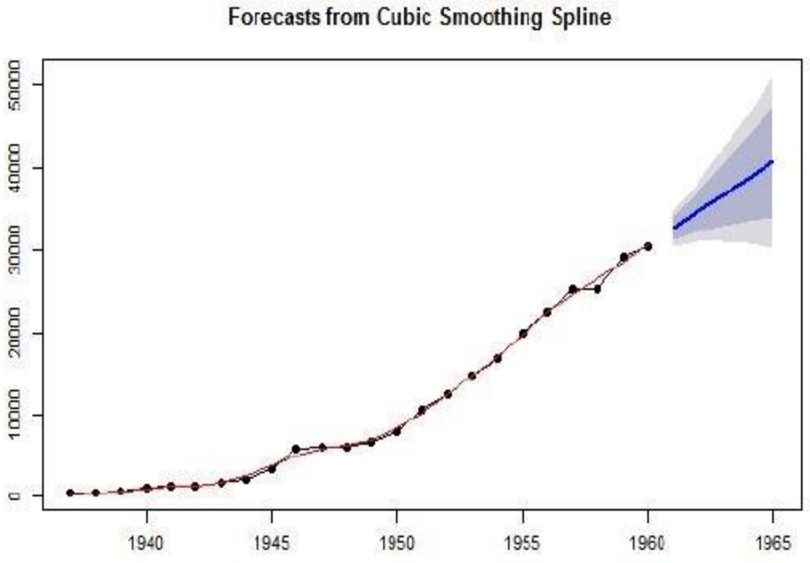


Fig 4.7: Cubic Smoothing Graph

V. SUMMARY AND CONCLUSION

A. *Summary*

The notion of time series analysis on raw data has been clearly discussed in this study. The goal and objectives specified at the start of the research project were met. The data under scrutiny was obtained from the Nigerian Central Bank.

The data was plotted in time for visual inspection, and non-stationarity was discovered. In the time plot, there was a leap and upward movement, which was described using an additive model. The p-value (0.9591) was more than the significant level (0.05) in an ADF test, indicating that the data is not stationary. The data was subjected to exploratory data analysis, and the box plot revealed that there are no outliers in the data, but the histogram plot revealed that the data is not normally distributed. The trend of the series was estimated using the Least Square approach. With the trend equation $\hat{T}_t = -39.83686 + 0.535691_t$, the least square indicated that the exchange rate of Naira to Dollar has increased throughout the years, implying that the exchange rate would continue to rise as time passes.

The data was differenced and the ADF test was performed on the differenced data, which revealed that the data was stationary with a p-value (0.01) less than the significance threshold (0.05). To identify the order (p,d,q) of the model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the differenced data were observed using a correlogram.

The series' model identification was confirmed, and parameter estimation for the relevant model was also calculated. The technique was carried out in order to generate AIC and the order of the model; the model with the lowest AIC value is the most suited for the series. As a result, the Exchange Rate statistics are based on ARIMA (1,1,0), which is likewise ARMA (1,1) and has an AIC of 2642.74. A diagnostics test was performed on the chosen model to determine its correctness. The Ljung box test was completed, and the results demonstrate that the model chosen was appropriate. Finally, the series forecast was created using the model chosen 5.2 Conclusion.

B. *Conclusion*

The partial auto-correlation function (PACF) plot and estimated auto-correlation function (ACF) plot assisted in the building of the several probable models. The ARIMA (1,1,0) model appears to have the lowest Akaike Information Criterion (AIC)=2642.7, with a log likelihood value of (-1318.37). The residual analysis of the model shows that it passes the residual test. The data distribution is essentially normal, as seen by the histogram. As a result, we may infer that the model is suitable for the data.

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