Modelling the Exchange Ability of Nigerian Currency (Naira) with respect to US Dollar.

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Abstract: This paper investigates the exchange strength of Nigerian naira with respect to United States dollar and fit an appropriate model to the data using Box Jenkins approach, the data spans the period 1972 to 2014.

The result revealed that the exchange rate of naira to a U.S dollar has been relatively stable from 1972 to 1985, and then a continuous upward trend from 1985 to 2014.The series was slightly stationary after 1st difference and sufficiently stationary after 2nd difference, meaning that the series was either I (1) or I (2). Base on the selection criteria AIC and SIC, the best model that explains the series was found to be ARIMA (0, 2, 1). Test of model adequacy confirmed that the model is adequate (i.e the errors were white noise) and a forecast for period of six (6) years terms was made and the forecasted values were all within the confidence limits and it indicates if positive measure is not taken, the value of naira will continue to depreciate.

Keywords: Stationary, Forecast, ARIMA, Exchange rate, AIC and SIC

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1. INTRODUCTION

Exchange rate is the rate at which one currency exchanges for another (Jhingan, 2003). Exchange rate is said to depreciate if the amount of domestic currency require to purchase a foreign currency increases, while the exchange rate appreciates if the amount of domestic currency require to obtain a foreign currency reduces. It determines the relative prices of domestic and foreign goods, as well as the strength of external sector participation in the international trade.

In Nigeria, exchange rate has changed within the time frame from regulated to deregulated regimes. Ewa (2011) agreed that the exchange rate of the naira was relatively stable between 1973 and 1979 during the oil boom era and when agricultural products accounted for more than 70% of the nation's gross domestic products (GDP).

In 1986, Nigeria adopted a fixed exchange rate regime supported by exchange control regulations that engendered significant distortions in the economy prior to the introduction of structural adjustment programme (SAP). The country depends heavily on imports from various countries as most industries in Nigeria import their raw materials and massive importation of finished goods from foreign countries. This has caused adverse effects on domestic production, balance of payments position and the nation's external reserves level. In addition, this has made the foreign exchange market in the fixed exchange rate period to be characterized by high demand for foreign

exchange that cannot be adequately met with the supply of foreign exchange via the Central Bank of Nigeria (CBN). This inadequate supply of foreign exchange by the CBN promoted the parallel market for foreign exchange and created uncertainty in foreign exchange rates. Sanusi (2004) opined that the fixed exchange rate period was also characterized by sharp practices perpetrated by dealers and end-users of foreign exchange. A new wave came in during the period of SAP in 1986, which deregulated the foreign exchange market that led to the introduction of market determined exchange rate and managed floating rate regime. The CBN usually intervene in foreign exchange market through its monetary policy actions and operations in the money market to influence the exchange rate movement in the desired direction such that it ensures the competitiveness of the domestic economy. The CBN through its monetary policy instruments and operations intervened in the foreign exchange market by influencing the exchange rate changes in the desired direction such that it ensures the competitiveness of the domestic economy.

Today, many economy focuses attention on exchange rate policy for many reasons. As a tool of correcting internal and external imbalances as well as an instrument of improving the efficiency of resource allocation, government in many developing countries use exchange rate as an instrument for stabilization purposes. This is particularly so for imported commodities and those produced within an economy whose intermediate inputs and raw materials depend heavily on import whereas Nigerian economy is also an import dependent country. The real exchange rate measures international exchange of goods and services, the competitiveness of an economy to international trade and ensures viable balance of payment position. Mordi (2006) argued that the exchange rate movements have effects on inflation, prices incentives, fiscal viability, exports competitiveness, efficiency in resource allocation, international confidence and balance of payments equilibrium. Exchange rate policy guides investors on the best way they can strike a balance between their trading partners, and investing at home or abroad (Balogun, 2007). For the period of Structural Adjustment Programme, the following problems present in the Nigeria exchange rate require a freely floating exchange rate regime which removes any form of economic rigidity. The Nigerian economy is characterized by structural rigidities and bottlenecks. Most of the country's exports and imports are characterized by inelasticity on the demand and/or supply side, restraint on the free flow of goods and services by trading partners. The guiding rules of the CBN on the purchase of foreign currency are often burdensome causing many potential foreign exchange users being frustrated to patronize the parallel market. There is always a gap between supply and demand for foreign exchange.

In the post SAP/NEEDS era, it was discovered that most of the problems were still present. Other problems identified are investment growth, precautionary savings, credit market effects and

distributional effects. One major problem identified is exchange rate instability that created burden on the poor through unemployment, higher price of foodstuffs, pressure on the employed to accept lower or no wage increases, higher costs of borrowing, reduction in the purchasing power of financial assets and high output fluctuation. Insufficient supply of foreign exchange continues to mount pressures on the country's exchange rate from the external sector. The stringent documentation requirements in the official market crowds out some forex demands that are ultimately met in the parallel or black market. There are several reasons why research into the effect of macroeconomic volatility on exchange rate is vital for a developing resourcebased economy like Nigeria. Considering the country's macroeconomic variables, volatilities manifest in different forms ranging from changes in real growth rates, price inflation, investment per capita and government revenues per capita to fluctuations in terms of trade and real exchange rate.

The volatility of financial assets has been of growing area of research (Longmore and Robinson, 2004). The modeling and forecasting of exchange rates including volatility has important implications for many economic and financial issues. Exchange rate volatility refers to the swings or fluctuations in the exchange rates over a period of time or the deviations from a benchmark or equilibrium exchange rate (Mordi, 1993). Also, it is seen as the risk associated with unexpected movements in the exchange rate. Economic fundamentals such as the inflation rate, interest rate and the balance of payments, which have become more volatile in the 1980s and early 1990s, by themselves, are sources of exchange rate volatility (Ozturk, 2006).

Based on past scholars, determinants of the NAIRA/USD exchange rate identified in long term are commodity price level, money supply, interest rates, inflation rate and income level, investment per capita, openness of trade, foreign exchange reserves and government revenues per capita etc.

This inconsistency in policies and lack of continuity in exchange rate policies aggregated unstable nature of the naira rate (Gbosi, 2005).

Benson and Victor, (2012) and Aliyu, (2011) noted that despite various efforts by the government to maintain a stable exchange rate, the naira has depreciated throughout the 80's to date.

This research study intends to   explore the movements of the Naira/USD exchange rate and forecast the future exchange strength of our Naira per Dollar using Naira/USD exchange rate data obtained from Wikipedia (the free encyclopedia) and recorded yearly (from 1972 to 2014).

2. LITERATURE REVIEW

Several studies have taken place in the analysis of pattern and distribution of data on Nigerian Naira exchange rate per American Dollar in Nigeria. Different time series methods with

different objectives are employed to analyze the data in various literatures. In terms of using a formal time series model to forecast, the patterns and intensity of Naira exchange rate per American Dollar overtime.

Most researchers have done a great research on forecasting of exchange rate for developed and developing countries using different approaches. The approach might vary in either fundamental or technical approach.

Onasanya O. K. and Adeniji, O. E(2013), in their work titled Forecasting of exchange rate between Naira and US" they used a time domain approach to model Naira per Dollar exchange rate, using non-seasonal ARIMA model for the period January 1994 to December 2011.The result revealed that, the model ARIMA(1, 2, 1) best fit the data. So also Ette Harrison (1998), used a technical approach to forecast Nigeria naira – US dollar using seasonal ARIMA model for the period of 2004 to 2011. He reveals that the series (exchange rate) has a negative trend between 2004 and 2007 and was stable in 2008. His good work expatiates on that seasonal difference once produced a series SDNDER with slightly positive trend but still within discernible Stationarity. M.K Newaz (2008) made a comparison on the performance of time series models for International Journal of development and Economic Sustainability forecasting exchange rate for the period of 1985 – 2006. He compared ARIMA model, NAÏVE 1, NAÏVE 2 and exponential smoothing techniques to see which one fits the forecasts of exchange rate. He reveals that ARIMA model provides a better forecasting of exchange rate than either of the other techniques; selection was based on MAE (mean absolute error), MAPE (mean absolute percentage error), MSE (mean square error), and RMSE (root mean square error). Further work, Olanrewaju I. Shittu and Olaoluwa S.Y (2008) try to measure the forecast performance of ARMA and ARFIMA model on the application to US/UK pounds foreign exchange. They reveal that ARFIMA model was found to be better than ARMA model as indicates by the measurement criteria. Their persistent result reveals that ARFIMA model is more realistic and closely reflects the current economic reality in the two countries which was indicated by their forecasting evaluation tool. They found out that their result was in conferment with the work of Kwiatkowski et. al. (1992) and Boutahara. M. (2008). Shittu O. I (2008) used an intervention analysis to model Nigeria exchange rate in the presence of financial and political instability from the period (1970 -2004). He explains that modelling of such series using the technique was misleading and forecast from such model will be unrealistic, he continued in his findings that the intervention are pulse function with gradual and linear but significant impact in the naira – dollar exchange rates. S.T Appiah and I.A

Adetunde (2011) conducted a research on forecasting exchange rate between the Ghana cedi's and the US dollar using time series analysis for the period January 1994 to December 2010. Their findings reveal that the predicted rates were consistent with the depreciating trend of the observed series and ARIMA (1, 1, 1) was found to be the best model to such series and a forecast for two years were made from January 2011 to December 2012 and reveals that a depreciation of Ghana cedi's against the US dollar was found.

3.0 RESEARCH METHODS

3.1 Modelling Approach(Time domain)

This approach focuses on modelling some future value of the series as function of the current and the past. Conducting investigations using standard statistical methodologies is an essential step in the development of climatology (Polyak, 1996). In this respect, the time-domain approach of univariate time series continues to be an important topic. An intrinsic feature of the time-domain approach is that, typically, adjacent points in time are correlated and that future values are related to past and present values. Autoregressive integrated moving average (ARIMA) modeling is one of the most widely implemented methods for analyzing univariate time series data (Box and Jenkins, 1976). In order to understand the modelling procedure, it is useful to briefly introduce the following basic models.

3.1.1 Autoregressive (AR) models

Autoregressive models are based on the idea that the current value of the series, x_t can be explained as a function of p past values, $x_{t-1}, x_{t-2}. . . x_{t-p}$, where p determines the number of steps into the past needed to forecast the current value. An autoregressive model of order p, abbreviated AR (p), can be written as

$$x_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + ... + \emptyset_p x_{t-p} + w_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[1]$$

where x_t is stationary series, $\emptyset_1, \emptyset_2, \ldots , \emptyset_p$ are the parameters of the AR ($\emptyset_p \neq 0$). Unless otherwise stated, we assume that Wt is a Gaussian white noise series with mean zero and variance σ_w^2 . The highest order p is referred to as the order of the model.

The model in lag operators takes the following form:

$$\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) x_t = w_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{[2]}$$

where the lag (backshift) operator B is defined as: $B^p x_t = x_{t-p}$ p = 0,1,2,…

More concisely we can express the model as: $\emptyset(B) \, x_t = w_t$

The autoregressive operator $\emptyset(B)$ is defined to be $\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p$

The values of $\emptyset$ which make the process stationary are such that the roots of $\emptyset(B) = 0$ lie outside the unit circle in the complex plane (Chatfield, 1991). If all roots of $\square(B)$ are larger than one in absolute value, then the process is a stationary process satisfying the autoregressive equation and can be represented as: $x_t = \sum_{j=1}^{\infty} \psi_j w_{t-j}$

The coefficients ψ_j converge to zero, such that $\sum_{j=1}^{\infty} |\psi_j| < \infty$. If some roots are "exactly" one in modulus, no stationary solution exists.

A plot of the ACF of a stationary AR (p) model show a mixture of damping sine and cosine patterns and exponential decays depending on the nature of its characteristic roots.

Another characteristics feature of AR (p) models is that the partial autocorrelation function defined as PACF (j) = corr. (x_t , x_{t-j} | x_{t-1} , x_{t-2} , … , x_{t-j+1}) becomes "exactly" zero for values larger than p (Tsay, 2005).

3.1.2 Moving average (MA) Models

As an alternative to the autoregressive representation in which the x_t on the left-hand side of the equation are assumed to be combined linearly, the moving average model of order q, abbreviated as MA (q), assumes the white noise(w_t) on the right-hand side of the defining equation are combined linearly to form the observed data.)

A series x_t is said to follow a moving average process of order q, or simply MA (q) process if

$$x_t = w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \ldots + \theta_p w_{t-q} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{[3]}$$

where θ_1, θ_2, … , θ_q are the MA parameters. MA(q) models immediately define stationary, every MA process of finite order is stationary (Diebold et al., 2006). In order to preserve a unique representation, usually the requirement is imposed that all roots of $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q = 0$ are greater than one in absolute value. If all roots of (B) = 0 lie

outside the unit circle, the MA process has an autoregressive representation of generally infinite order

$\sum_{j=1}^{\infty} \psi_j x_{t-j} = w_t$ with $\sum_{j=1}^{\infty} |\psi_j| < \infty$. MA process as with an infinite order autoregressive representation are said to be invertible.

A characteristics feature of MA (q) is that their ACF, ρ_j becomes statistically insignificant after j=q. The property of the ACF should be reflected in the correlogram, which should „cut off‟ after q. The PACF converges to zero geometrically.

3.1.3 Autoregressive –Moving average (ARMA):

We now proceed with the general development of autoregressive, moving average, and mixed autoregressive moving average (ARMA), models for stationary time series. In most cases, it is best to develop a mixed autoregressive moving average model when building a stochastic model to represent a stationary time series. The order of an ARMA model is expressed in terms of both *p* and *q*. The model parameters relate to what happens in period *t* to both the past values and the random errors that occurred in past time periods. A general ARMA model can be written as follow:

$$X_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + ... + \emptyset_p x_{t-p} + w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + ... + \theta_p w_{t-q} \quad .... [4]$$

Equation (4) of the time series model will be simplified by a backward shift operator B to obtain

$\emptyset(B) x_t = \theta(B) w_t$

The ARMA model is stable i.e. It has a "stationary solution" if all roots of $\emptyset(B)=0$ are larger than one in absolute value. The representation is unique if all roots of $\emptyset(B)=0$ lie outside the unit circle and $\emptyset(B)$ and $\theta(B)$ *do* not have common roots. Stable ARMA models always have an infinite order MA representation. If all roots of $\emptyset(B)$ are larger than one in absolute value, it has an infinite order AR representation. The process is invertible only when the roots of $\emptyset(B)$ lie outside the unit circle .Furthermore, a process is said to be causal when the roots of $\emptyset(B)$ lie outside the unit circle. To have ARMA (*p,q*) model, both ACF and PACF should show a pattern of decaying to zero. The autocorrelation of an ARMA (*p, q*) process is determined at greater lags by the AR (*p)* part of the process as the effect of the MA part dies out. Thus, eventually the ACF consists of mixed damped exponentials and sine terms. Similarly, the partial autocorrelation of an ARMA (*p, q*) process is determined at greater lags

by the MA (q) part of the process. Thus, eventually the partial autocorrelation function will also consist of a mixture of damped exponentials and sine waves.

3.1.4 Autoregressive Integrated Moving Averages (ARIMA) Models:

Autoregressive integrated moving average (ARIMA) models are specific subset of univariate modeling, in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of a „white noise" error term (the moving average component). ARIMA models are univariate models that consist of an autoregressive polynomial, an order of integration (d), and a moving average polynomial.

A process (x_t) is said to be an autoregressive integrated moving average process, denoted by ARIMA (p, d, q) if it can be written as:

$$\emptyset(B)\nabla^d \, x_t = \theta(B) \, w_t \quad\text{... [5]}$$

where $\nabla^d = (1 - \mathrm{B})^d$ with $\nabla^d x_t$ and d^{th} consecutive differencing (Vandale,1983)
if $\mathrm{E}(\nabla^d x_t) = \mu$, we write the model as

$$\emptyset(B)\nabla^d \, x_t = \alpha + \theta(B) \, w_t \quad\text{…………………………………………………………[6]}$$

Where: α is a parameter related to the mean of the process $\{x_t\}$, by $\alpha = \mu \, (\emptyset_1 - \emptyset_2 - \ldots - \emptyset_p)$ and this process is called a white noise process, that is, a sequence of uncorrelated random variables from a fixed distribution (often Gaussian) with constant mean $\mathrm{E}(\ ) = \mu$,usually assumed to be "zero" and constant variance. if d=0, it is called ARMA(p,q) model while when d=0 and q=0,it is referred to as autoregressive of order *p* model and denoted by AR *(p)*. When p=0 and d=0, it is called Moving Average of order *q* model, and is denoted by MA (q).

There are three steps we will take to achieve our aims, and these are listed as (1) model identification (2) , model estimation and (3) model diagnostic and forecasting accuracy.

3.1.5 Autoregressive fractionally integrated moving average model(ARFIMA)

Autoregressive fractionally integrated moving average models are time series models that generalize ARIMA (autoregressive integrated moving average) models by allowing non-integer values of the differencing parameter. These models are useful in modeling time series

with long memory—that is, in which deviations from the long-run mean decay more slowly than an exponential decay. The acronyms "ARFIMA" or "FARIMA" are often used, although it is also conventional to simply extend the "ARIMA(p,d,q)" notation for models, by simply allowing the order of differencing, d, to take fractional values.

In an ARIMA model, the integrated part of the model includes the differencing operator $(1 - B)$ (where B is the backshift operator) raised to an integer power while In a fractional model, the power is allowed to be fractional, with the meaning of the term identified using formal binomial series expansion.

An ARFIMA model shares the same form of representation as the ARIMA(p,d,q) process, except that the "difference parameter", d, is allowed to take non-integer values.

3.2 Model identification

The first thing to do is to test for Stationarity of the series (naira and dollar exchange rate) using three different approach. The approach are (i) observing the graph of the data to see whether it moves systematically with time or the ACF and the PACF of the stochastic process (exchange rate) either to see it decays rapidly to zero, (ii) by fitting AR model to the raw data and test whether the coefficient "q " is less than using the wald test or (iii) we fit the Argumented Dickey Fuller test on the series by considering different assumptions such as under constancy, along with no drift or along a trend and a drift term. If found out that the series is not stationary at level, then the first or second difference is likely to be stationary and this is also subject to the three different approach above.

3.3 Model Estimation

Once stationary is attained, next thing is we fit different values of p and q, and then estimate the parameters of ARIMA model. Since we know that sample autocorrelation and partial autocorrelations are compared with the theoretical plots, but it's very hardly to get the patterns similar to the theoretical plots one, so we will use iterative methods and select the best model based on the following measurement criteria relatively AIC (Alkaike information criteria) and SIC (Swartz information criteria), and relatively small SEE (standard error of estimate).

3.4 Model Diagnosis

The conformity of white noise residual of the model fit will be judge by plotting the ACF and the PACF of the residual to see whether it does not have any pattern or we perform Ljung Box Test on the residuals. The null hypothesis is:

H_0: there is no serial correlation

H_1: there is serial correlation

The test statistics of the Ljung box is $LB = n(n+2) \sum_{k=1}^{m} \frac{\rho_k^2}{n-k}$ ....$\chi^2(m)$

where n is the sample size, m = lag length

and ρ is the sample autocorrelation coefficient

The decision: if the LB is less than the critical value of X2, then we do not reject the null hypothesis. These means that a small value of Ljung Box statistics will be in support of no serial correlation or i.e. the error are normally distributed. This is concerned about the model accuracy.

When steps 1-3 is achieved, we go ahead and fit the model, and thereby we will now perform a meta-diagnosis on the model fit. The meta- diagnosis will aid us to know the forecasting, reliability, accuracy ability which will be judge under the coefficient of determination or through the use of the smallest mean square error or other smallest measurement tools like MAE (mean absolute error, MAPE (mean absolute percentage error), RMSE (root mean square error), MSE(mean square error).

4.0 DATA ANALYSIS

In other to have a good result, the series was subjected to unit root test (stationary test). This was done by plotting the time plot and observing the behaviour of the series and by using Augumented Dickey-fuller (ADF) test.

Figure 1, shows that there is stable pattern between the years 1970 to 1985 and an upward trend afterwards. That is, the series has no specific pattern (the series is not stationary).

4.1 Unit root Test

Table 1 : Augumented Dickey-Fuller test results

	Test statistic	P-Value	Decision At 5% Level
Original series	-1.6205	0.7236	Do not reject H_0
After first difference	**-3.5493**	**0.04896**	Reject H_0
After second difference	**-4.9062**	< 0.01	Reject H_0

Table 1 presents the result of ADF test, which indicates that the series is slightly stationary after first difference and sufficiently stationary after second difference. Therefore the series is

either integrated at order 1 or integrated at order 2, that is series either I(1) or I(2).So we used both I value at order 1 and order 2 to compute various ARIMA models and the best model is the one with smallest AIC, SIC and standard error(SE).

4.2 Identifying the initial Model

Three items should be considered to determine a first guess at an ARIMA model: a time series plot of the data, the ACF, and the PACF. Figure 1 is the time plot of the original series. It can be observed that the exchange rate series displays a nonstationary pattern with steady and an upward trending behaviour. The PACF of the original series shows a single spike at the first lag and the ACF shows a tapering pattern. An AR (1) model is indicated.

Figure 1&2 are ACF and PACF of the first difference series, the plots shows a series that moves around a constant mean with approximately constant variance. With ADF test result p-value **0.04896** indicated a slightly stationary series. The first coefficients of the ACF of the series are statistically significant and decay as AR or ARMA models. With regard to the PACF, its first coefficient is clearly significant and large, indicating that an AR(1) model could be appropriated for the series. But given that the first coefficients show some decreasing structure and one coefficient is statistically significant, perhaps an ARMA(1,1) model should be tried as well. The ACF, PACF and the ADF test p-value (< 0.01) of the second difference series shows that the exchange rate series is highly stationary. The ACF suggested an MA (1) model.
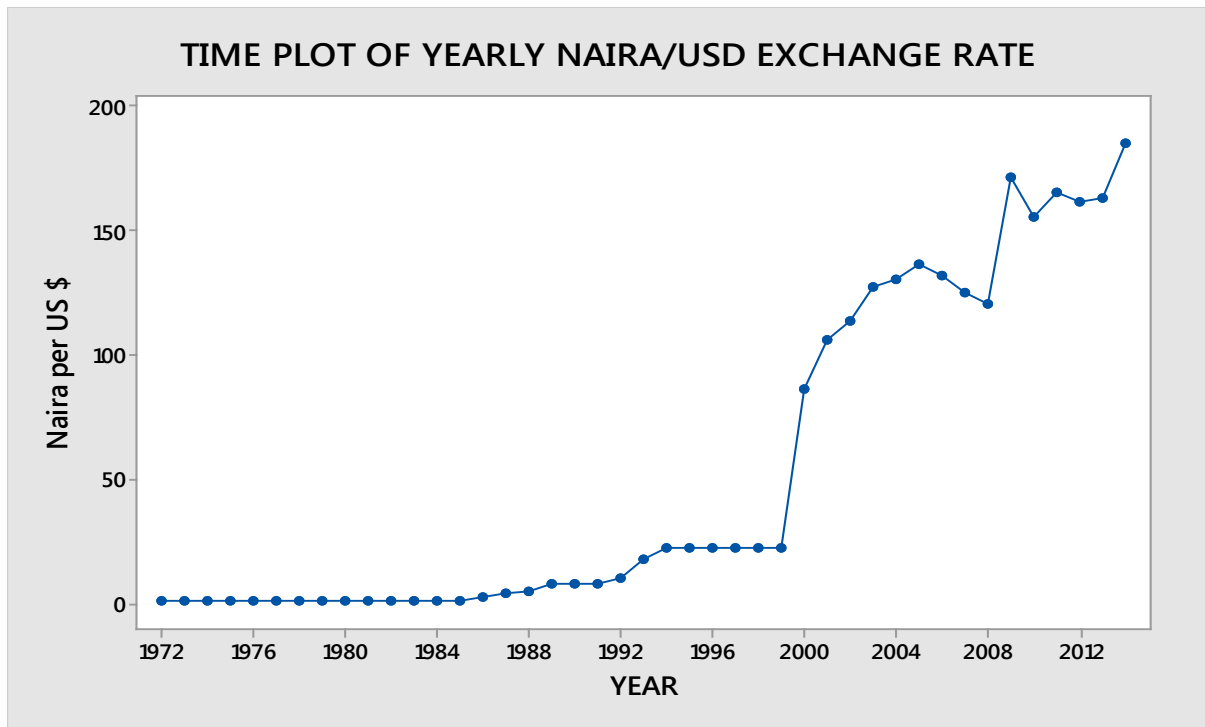
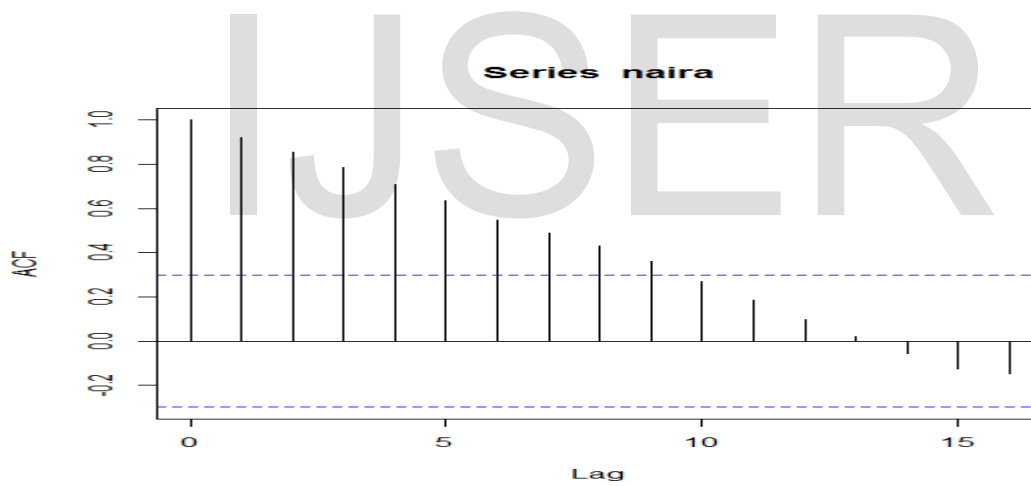Figure 1: Time plot of the yearly Naira/USD exchange rate (1972-2014)
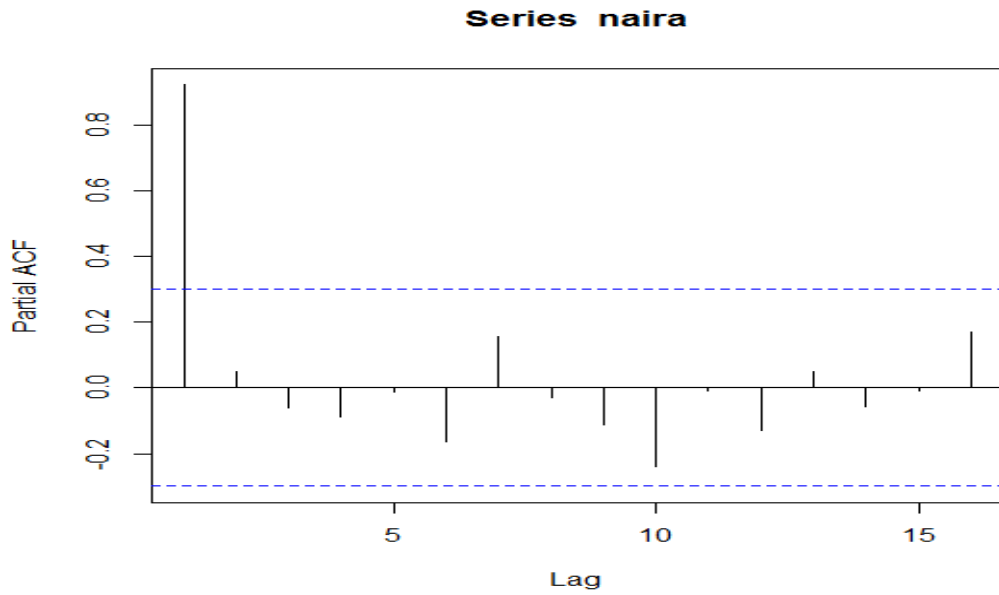

Figure 2 : ACF of the original series

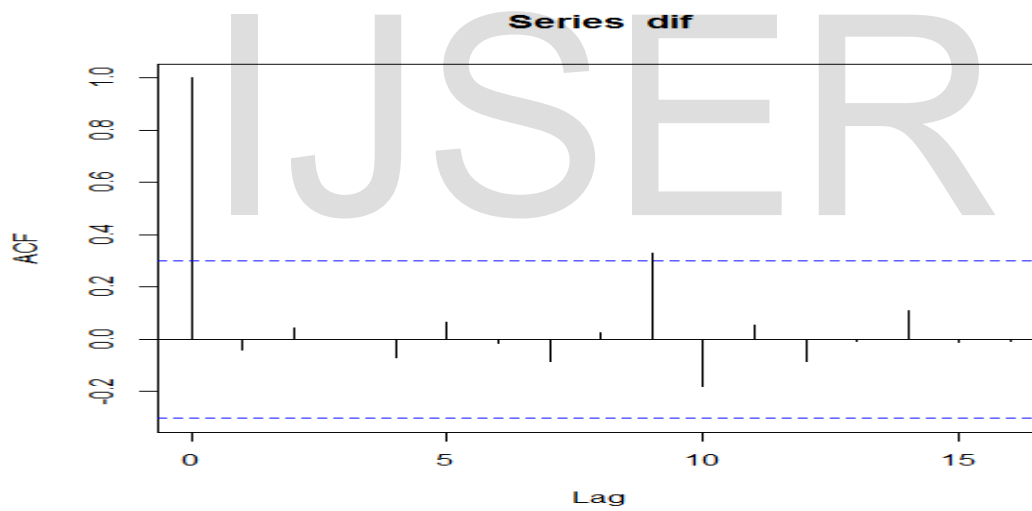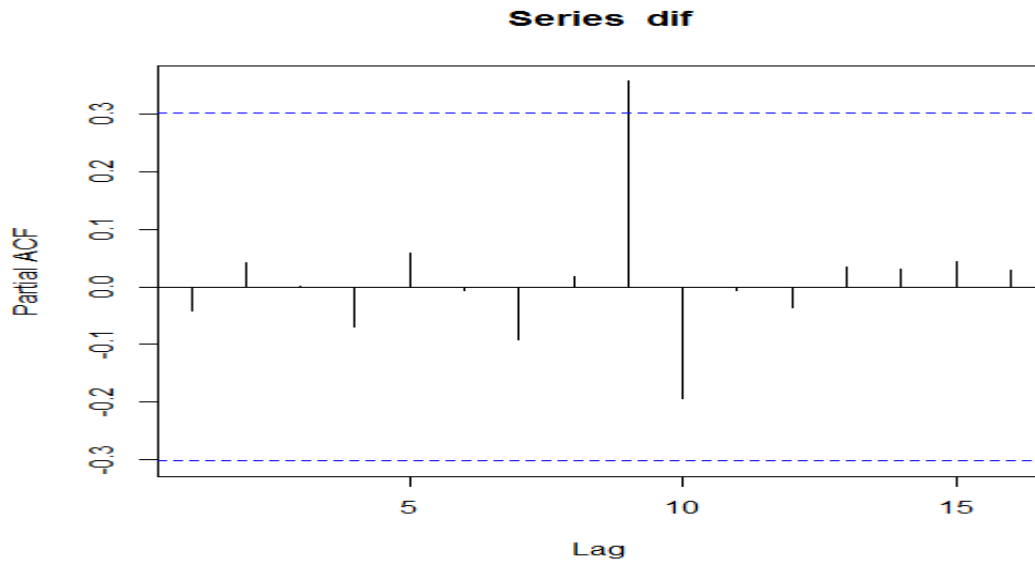Figure 3 :PACF of the original series

Figure 4 : ACF of the series after first difference

Figure 4 : PACF of the series after first difference
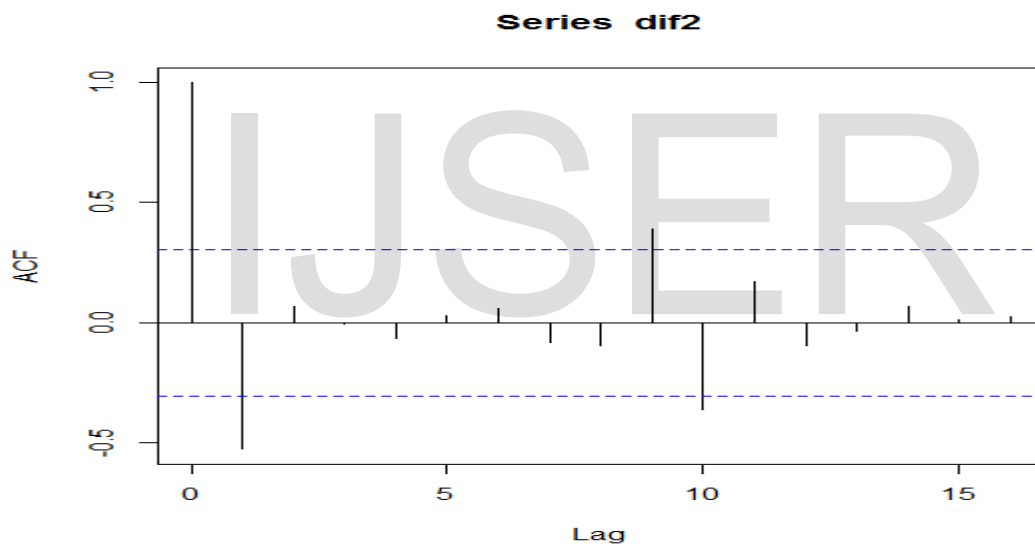

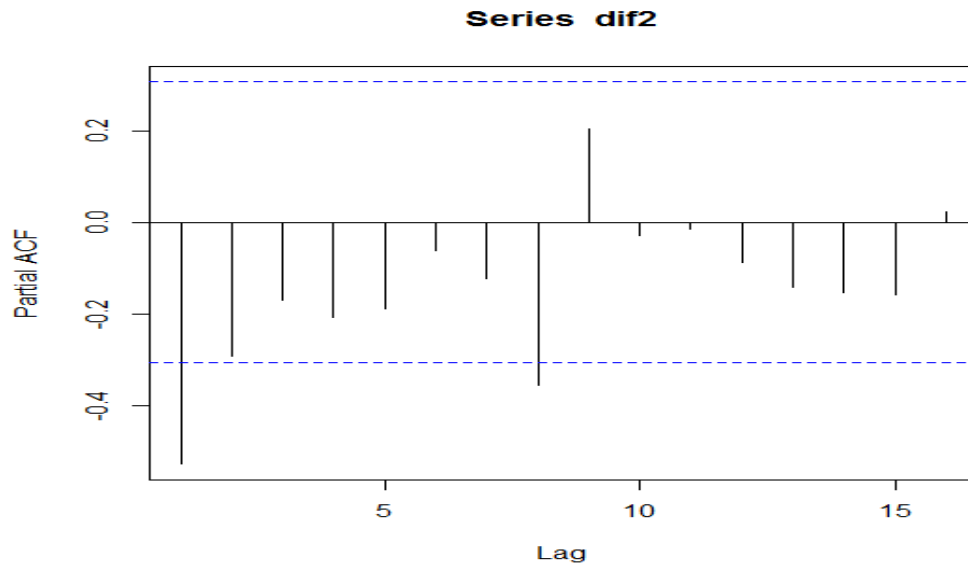Figure 6 : ACF of the series after Second difference

Series dif2

Figure 7 : PACF of the series after Second difference

4.2.1 ARIMA MODELS

It should be noted that, even if the ARIMA model has been correctly identified and gives good results, this will not mean that it is the only model that can be consider, various models should be identified and tested. We then apply the selection criteria to pick the best ARIMA model.

Table 2: Various ARIMA models

S/N	p	d	q	AIC	SIC	S.E	LOGL
1	0	1	1	343.935808	345.673477	14.350072397	−170.967904
2	1	1	0	343.914668	345.652337	14.346303343	−170.957334
3	1	1	1	343.790348	347.265687	14.108003781	−169.895174
4	1	1	2	345.616664	350.829673	14.256001268	−169.808332
5	2	1	1	345.610045	350.823054	14.254829534	−169.805023
6	2	1	2	347.602750	354.553428	14.440024004	−169.801375
7	**0**	**2**	**1**	**335.985844**	**337.699416**	**14.046389355**	−166.992922
8	1	2	0	348.410732	350.124304	16.674853564	−173.205366
9	1	2	1	337.832354	341.259498	14.199609749	−166.916177
10	2	2	0	346.214365	349.641509	16.002505543	−171.107182
11	0	2	2	337.839319	341.266463	14.200867805	−166.919659
12	1	2	2	339.638672	344.779388	13.916985031	−166.819336
13	2	2	1	339.813738	344.954454	14.381516998	−166.906869
14	2	2	2	341.812596	348.666884	14.574388225	−166.906298

Table 2, shows various ARIMA models. Using the model selection criteria that is, AIC, SIC and SE ARIMA(0, 2,1) is the best model(because it has the smallest AIC, SIC and SE)

Table 3: The Model estimates

Variable	Coefficient	Standard error(SE)	T-Stat	Prob
MA1	0.92789352	0.08037426	11.54466	0.0000

$$\text{Exchange Rate}_t = w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \dots + \theta_q w_{t-q}$$

But q =1 and $\theta_1 = 0.92789352$

The Model equals to:

$$\text{Exchange Rate}_t = w_t + 0.92789352\, w_{t-1}$$

4.2.1.1 Model Diagnostic

Table 4: Portmanteau and Ljung-Box Q-test Residual autocorrelation test results

Test Type	Test-Statistic	P-value
Ljung Box	12.3544	0.6520
Portmanteau	9.1991	0.8669

From table (3), the coefficient of ARIMA(0,2,1) model is valid and stationary condition was met and satisfied since the coefficient is less than one (0.92789352) and is also significant since the p-value is less than 0.05. This is also justified by the p-value of F value (0.000) was less than the exact probability (0.05), these means that the overall significance of the coefficient of ARIMA (0, 2, 1) was rejected and hence MA (1) thus explain the series.

The results of Ljung Box and Portmanteau were reported in Table 4; each p-values (0.6520 and 0.8669) were greater than 0.05 which confirms the absence of residuals autocorrelation.

4.2.1.2 Forecasting

Since the model (0, 2, 1) is tested adequate, next is to make forecast. The forecasted Naira per US Dollar exchange rate for the period of six (6) years is presented in Table 5.

Table 5: The predicted Naira per US Dollar exchange rate

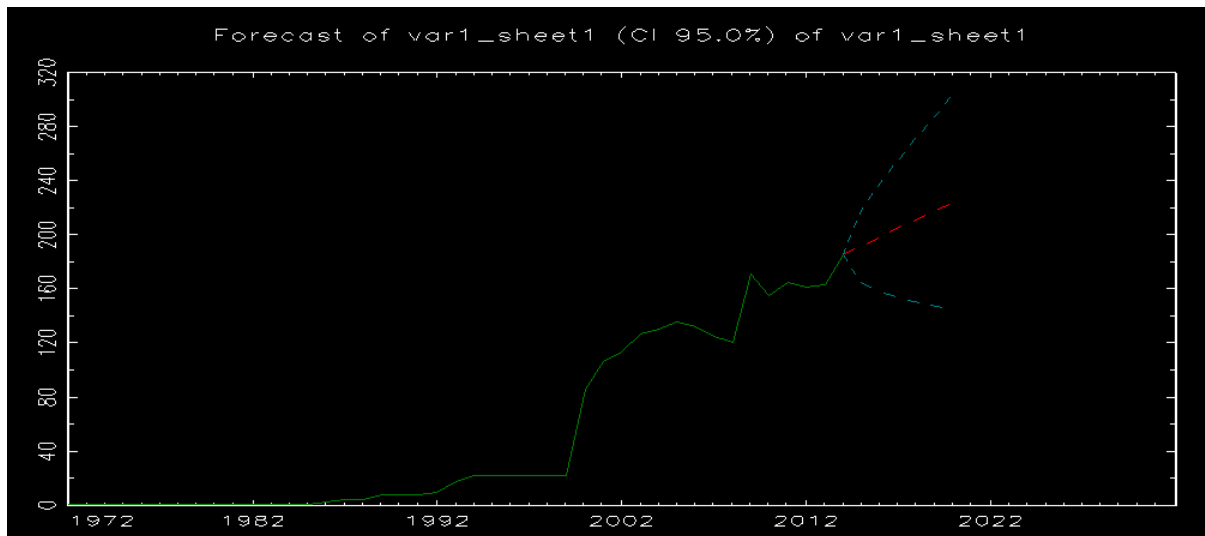| Year	Lower CI	Forecast	Upper CI	Std Error
2015	164.0608	191.5913	219.1217	14.0464
2016	157.7705	198.1325	238.4945	20.5932
2017	153.4744	204.6738	255.8732	26.1226
2018	150.0376	211.2151	272.3925	31.2136
2019	147.0395	217.7563	288.4731	36.0807
2020	144.2737	224.2976	304.3215	40.8293

Figure 8:Forecast plot

5.0 **Conclusion**

This research study examined the exchange strength of Nigerian Naira with respect to US Dollar and fit the best ARIMA model for the data using Box Jenkins approach.

As depicted in figure 1, The exchange rate of naira to a U.S dollar has been relatively stable from 1972 to 1985(i.e. the Naira had high exchange strength during the years) and an upward trend from 1986 to 2014 (i.e. the Naira depreciates)

The modeling was in three stages, the first stage was model identification stage, where the series was not non- stationary at level form based on the observed pattern of the series from the time plot and the result of Augmented Dickey-Fuller test (ADF) test. It was found that the series is slightly stationary after first difference and sufficiently stationary after second difference. Base on the selection criteria AIC and BIC, reports show that ARIMA (0, 2, 1) was selected as the best model fits the data. The second stage was the model estimation, where the parameters conforms to the stationary conditions (less than one) and finally the third stage was model diagnosis where the errors derived from the model (0,2,1) was normally distributed, random (no time dependence) and no presence of errors autocorrelation. An out sample forecast for period of 6 years was made, and this shows that the naira will continue to depreciate on US dollar for the period forecasted.

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