# TIME SERIES MODELING OF MONTHLY AVERAGE EXCHANGE RATE OF NIGERIAN- NAIRA AND UNITED STATES-DOLLAR


## ABSTRACT

This work considered the time series modelling of monthly average exchange rate of the Nigeria -Naria (NGN) and United States -Dollar (USD). The data for this work was obtained from the Central Bank of Nigeria spanning from 2003 to 2024. The time plot of the monthly average exchange rate of both currencies indicated an upward rise in the Dollar and a relatively reduction in the Naira. The reason for this paper was mainly to model the monthly average exchange rate of the Nigerian - Naira and the United States - Dollar and to forecast thefuture exchange rate in 2025. To achieve this aim, a powerful timeseries forecasting model known as autoregressive integrated moving average(ARIMA) was employed.

The Exchange rate data was non stationary at level but achieved stationarity after first difference using augmented dickey-fuller (ADF) unit root test via E-views 12.

The strategies for model specification or identification as recommended by Box and Jenkins (1976) were adhered to in this work and ARIMA (8,1,2) was selected as the most parsimonious model among the other six potential or tentative estimated models. This ARIMA (8,1,2) satisfied the residual diagnostic test because of its invertibility and covariance stationary behaviors hence it was  considered as the best forecasting power.



**Keywords: Time series, Exchange rate & ARIMA model**




## 1.0 INTRODUCTION

Exchange rate is the rate at which a country's currency is exchanged for other currencies at international market.

Nigeria is characterized with a mixed exchanged rate system where Naira (₦) is matched to the US-Dollar (USD) and the rate at which the local currency (Naira) is exchanged for other currencies has noticeable effect on the economy of the country especially for a country like Nigeria that is solely dependent on foreign products.

There was a significant volatility in the exchange rate of Nigeria-Naira and US-Dollar between 2014 to 2024 as a result of economic and political events in both domestic and global levels, this was evident in 2014 oil crash which resulted to a sharp decline in global oil prices and consequently impacted on Nigeria's foreign exchange earnings and spontaneous depreciation of the local currency. The depreciation of the Naira has a far-reaching effect on Nigeria 's economy such as pushing up inflation, increasing production cost, reducing foreign investment and worsening of the country's debt burden. The above factors contributedto a higher cost of living of the citizenry, reduced economic growth and limited industrial development.

To curb out these ugly scenarios, a study of this nature is needed to warrant a strategic approach capable of strengthening the indigenous or local production, encouraging diversification and embarking on policy implementation with a view to enhancing the stability of the local currency.

Hence, this study employed a detailed statistical analysis that would reveal the presence of trend (short term or long term) including patterns in the series than a mere observation of the day- to- day changes for a proper comprehension of the dynamics of the exchange rate.

The analysis of the exchange rate's trends and volatility will help in planning and stabilizing macroeconomic components of the county such as the External Reserve, Public Debt, interest rate, unemployment, Gross Domestic Product, Inflation and monetary Policy.

The study will help the policy makers to comprehend the underlying trends and factors responsible for fluctuations of the exchange rate in other to aid them in formulating effective monetary and fiscal policies.

The framework of this study is in segments: segment 1.0 is the introductory part, segment 1.1 has a review of related works, segment 2.0 has the methods and materials adopted, segment 2.1shows the working of ARIMA model,3.0 has the assumptions of ARIMA model, 3.1 explains the stages of forecasting using ARIMA while 4.0 has results and discussionsand lastly segment 4.1 covers the conclusion and possible suggestions.

## 1.1 RELATED WORK

Many research studies have been done on modelling exchange rate between the Nigeria - Naira and the US - Dollar in the time past. These studies aim at understanding the dynamics of exchange rate fluctuation, identifying the major influencing factors and providing relevant and accurate forecasts. Amongthe related studies done by other researchers are:

**Adebiyi, et al (2014):**In their paper titled *"Forecasting Exchange Rate Between Naira and US Dollar Using ARIMA Model"*. They applied ARIMA model to predict the NGN/USD exchange rate and found that the ARIMA model was effective for short-term exchange rate forecastingwith reasonable accuracy.

**Udoka, et al (2017)** studied*"ARIMA Model for Forecasting Exchange Rates in Nigeria: A Case Study of Naira to Dollar"*, Udoka et al. employed the ARIMA model to forecast the NGN/USD exchange rate over a specific period. The study used time series data from 2000 to 2016 and applied Box-Jenkins's methodology to identify an appropriate ARIMA model. The authors concluded that ARIMA models weresuitable for exchange rate forecasting in the short term, but that the model's performance declined with longer-term forecasts due to the exchange rate's high volatility.

In a research paper by**Ogundipe, et al (2017)** titled*"Macroeconomic Determinants of Exchange Rate in Nigeria:* A vector autoregressive (VAR) Approach was used by Ogundipe et al to study the relationship between the exchange rate and macroeconomic variables such as inflation, interest rates, and GDP. This multivariate approach allowed them to capture the interactions between these factors and the NGN/USD exchange rate. They found that inflation and interest rate differentials had significant impacts on the exchange rate, and the VAR model was able to capture these interactions better than univariate models like ARIMA.

**Emenike (2010)** also worked on *"Modeling Exchange Rate Volatility in Nigeria Using GARCH Models"*, Emenike explored the use of GARCH models to capture the volatility clustering in the NGN/USD exchange rate. The study subjected Naira to high levels of volatility due to Nigeria's dependence on oil exports and the impact of global market fluctuations. Emenike's research demonstrated that GARCH models outperformed linear models like ARIMA in terms of capturing periods of high volatility in exchange rates. His findings also included that GARCH models were superior to ARIMA in handling volatility clustering in exchange rates and thatthe Naira's volatility was closely tied to external factors, such as global oil prices. ConclusivelyGARCH models provided better insights into the risks associated with exchange rate fluctuations, making them valuable for risk management. His work remained an important reference for those studying the volatility of the NGN/USD exchange rate.

**Oyemade et al (2019)** carried out a study *"A Hybrid Model for Forecasting Nigeria's Exchange Rate with the US Dollar"*.Oyemade et al. combined the ARIMA model with Artificial Neural Networks (ANNs) to develop a hybrid approach to exchange rate forecasting. Their results showed that the hybrid model outperformed individual models (ARIMA and ANN) in terms of accuracy. The ARIMA model captured the linear patterns in the data, while the ANN handled the non-linear relationships, resulting in an improved forecast accuracy.

**Nwosu and Ugwoke (2020),** in their paper *"Modeling Structural Breaks in Nigeria's Exchange Rate Using Regime-Switching Models"*, Nwosu and Ugwoke focused on the impact of structural breaks on the **NGN/USD** exchange rate. They applied regime-switching models to capture the sudden shifts in the exchange rate caused by policy interventions by the Central Bank of Nigeria (CBN) and external shocks such as oil price fluctuations. Their research showed that traditional time series models like ARIMA often fail to account for these breaks, resulting in poor predictive performance. They also found that regime-switching models provided better accuracy by adjusting for these breaks andStructural breaks have a significant impact on exchange rate forecasting.

Regime-switching models outperform traditional time series models by accounting for policy interventions and external shocks.The study highlighted the importance of considering policy-related structural breaks when forecasting exchange rates.

Obiora, C.A. &Ofoegbu, O.K. (2022) In their work ***"Application of Time series Models in Forecasting Exchange Rates in Nigeria,"***Obiora and Ofoegbu explored the application of ***Time series*** models to forecast the Naira-Dollar exchange rate using historical data spanning several years. They found that ***Time series*** models provided reliable short-term forecasts but struggled with long-term accuracy. The study also recommended incorporating other external variables, such as interest rates and inflation, to improve forecast precision.

**Akinola and Olaniyan (2020)** In their study *"Modeling the Impact of Global Financial Shocks on the Naira/Dollar Exchange Rate: A GARCH Approach"*, Akinola and Olaniyan explored how global financial stocks, such as the 2008 financial crisis and the COVID-19 pandemic, affected the NGN/USD exchange rate. Using GARCH models, they were able to capture the increased volatility during these periods. Their findings demonstrated that the Naira was specifically sensitive to global economic events, and that GARCH models were well-suited for forecasting exchange rate volatility during such crises.

Adeyemi, S.B., &Olanrewaju, O.B. (2019) Research, ***"Time Series Analysis of the Naira-Dollar Exchange Rate Using ARIMA and Neural Networks,"*** compared the ARIMA model with artificial neural networks (ANN) to determine which approach provided better forecasts. While ARIMA performed well in short-term predictions and captured trends in the historical data, ANN outperformed ARIMA in periods of high volatility, showing superior accuracy when significant external shocks were present. The study concluded that combining ARIMA with more sophisticated machine learning techniques could enhance forecasting accuracy, particularly in turbulent economic environments.

**Ogundele, T.S. & Ibrahim, M.A. (2023)** conducted a study titled *"Empirical Forecasting of Naira-Dollar Exchange Rate Using ARIMA and Monte Carlo Simulations."* They found that ARIMA models provided a good fit for historical exchange rate data, particularly in capturing trends and seasonality. However, they noted that ARIMA could not effectively handle random shocks and unforeseen economic events. By integrating Monte Carlo simulations, they were able to improve the accuracy of long-term forecasts by incorporating random variability into their projections, which ARIMA models alone could not account for

Ogunleye and Adeyeye (2015) In their work titled ***"Modeling Exchange Rate Dynamics in Nigeria: Application of GARCH Models"***, Ogunleye and Adeyeye explored various Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models to analyze the volatility of the NGN/USD exchange rate. They applied both symmetric and asymmetric GARCH models, such as EGARCH (Exponential GARCH) and TGARCH (Threshold GARCH), to capture the exchange rate volatility's time-varying nature. Their findings suggested that asymmetric models better captured the volatility clustering and leverage effects, where negative stocks had a larger impact on volatility than positive ones.

**Obi, et al (2020)** In their study *"Modeling Naira Exchange Rate Using Markov-Switching Models"*, Obi et al. focused on regime-switching models to analyze the structural breaks and sudden shifts in the NGN/USD exchange rate. They argued that the exchange rate undergoes different regimes due to policy interventions by the Central Bank of Nigeria (CBN), oil price stocks, and political instability. The Markov-Switching model captured these shifts by identifying different regimes (high and low volatility periods). Their results indicated that regime-switching models provided more accurate forecasts during periods of structural change than linear models such as ARIMA.

Ezeabasili, et al (2011) In their paper ***"An Empirical Analysis of Exchange Rate Volatility in Nigeria"***, applied ARCH and GARCH models to study the volatility of the NGN/USD exchange rate over a 20-year period. Their analysis showed that the exchange rate exhibited significant volatility clustering, largely driven by oil price fluctuations and monetary policy decisions. They found that the GARCH (1,1) model was the most appropriate for capturing the time-varying volatility in the exchange rate. Their study contributed to the growing understanding of the exchange rate volatility drivers in oil-dependent economies like Nigeria.

Yahaya et al (2019). In their study ***"Forecasting Naira to Dollar Exchange Rate Using ARIMA and Holt-Winters Smoothing Models"***, Yahaya et al. compared the performance of ARIMA and the Holt-Winters exponential smoothing model for forecasting the NGN/USD exchange rate. They found that while ARIMA performed well for short-term forecasting, the Holt-Winters model was more effective for medium-term forecasts, especially when there were seasonal components. The study concluded that using a combination of models could offer a better forecasting approach depending on the time horizon.

Adesina, O.S. (2017) researched on***"ARIMA Modeling for Forecasting Exchange Rate in Nigeria"***. Theyutilized ARIMA models to analyze and predict the Naira-Dollar exchange rate over a decade. The study found that ARIMA models were effective in capturing the time-dependent nature of the exchange rate, showing that past data could be a reliable predictor of short-term future trends. Adesina noted that while ARIMA performed well in predicting short-term exchange rate movements, it was less reliable for long-term predictions due to external economic factors not captured by the model.

Udoh, F.S. &Essien, B.S. (2019).In the study ***"Forecasting the Naira/Dollar Exchange Rate: A Comparison of ARIMA and Exponential Smoothing Models."***Udoh and Essien applied ARIMA to examine the dynamics of the Naira-Dollar exchange rate. They compared ARIMA with other models and found that the ARIMA model provided more accurate short-term forecasts. The study revealed that the ARIMA model's ability to handle linear time series data made it a suitable option for analyzing the Naira-Dollar exchange rate, but they recommended hybrid models for better long-term predictions.

Adigun, M.A. &Okafor, B.O. (2020). Adigun and Okafor, in their paper ***"Time Series Analysis of Exchange Rate Movements in Nigeria Using ARIMA Models,"*** evaluated the performance of different ARIMA specifications in modeling the Naira-Dollar exchange rate. Their analysis showed that ARIMA models performed reasonably well in predicting the exchange rate within a short forecasting horizon. They emphasized the importance of accurate identification of ARIMA parameters (p, d, q) to improve forecasting accuracy and noted that external shocks like oil price fluctuations still posed challenges to model accuracy.

Adeniran, et al (2014) In their study titled ***"The Impact of Exchange Rate Fluctuations on the Nigerian Economic Growth: An Empirical Investigation,*** *"*Adeniran and colleagues applied ARIMA models to forecast the Naira-Dollar exchange rate and assess its impact on the broader economy. The study found that exchange rate volatility negatively impacted economic growth, with ARIMA successfully capturing the short-term fluctuations in the exchange rate. They emphasized that while ARIMA could handle the inherent seasonality and trends in the exchange rate data, the model faced challenges in predicting the effects of external stocks such as global oil price changes, which heavily influenced the Nigerian economy.

Eze, O.R. &Okoye, O.N. (2016), worked on a paper titled ***"Modeling the Naira/USD Exchange Rate Using ARIMA Model."*** They explored the suitability of ARIMA models in exchange rate prediction, particularly in the context of Nigeria's floating exchange rate regime. Their research demonstrated that ARIMA models were effective for short-term predictions but struggled in periods of significant economic instability or political uncertainty. They recommended enhancing ARIMA forecasts by integrating external factors such as oil prices, inflation rates, and global economic conditions into the model to account for Nigeria's dependence on crude oil exports.

## 2.0 MATERIALS AND METHODS

The work employed a powerful time series forecasting model known as autoregressive integrated moving average (ARIMA) which has been widely used by many time series researchers.

The ARIMA approach which was introduced by Box-Jenkins can also be referred to as Box Jenkins model and consisted of autoregressive term(AR) and moving average term(MA).The 'I' that separates the AR term and MA term indicates the number of times that the series would be integrated to achieve stationarity. Hence the key parameters for anARIMA model are (p, d, q) with' p' denoting a time series that is dependent on past values of itself, 'd' the number of times differencing has to be done to achieve a stationary seriesand 'q' being the past random errors. The strategies for modelling ARIMA include identification stage, estimationstage , diagnostic checking and forecasting stage and these stages were fully adhered in thiswork.

## 2.1 THE WORKING OF ARIMA MODEL

Autoregressive Integrated Moving Average popularly known as the Box Jenkins (1976) methodology is a method used in forecasting variables using the information obtained from the variables to forecast their trends. This means that the variables are regressed on their own past values.

ARIMA model requires knowing and analyzing the stochastic properties of the variable and it is specifically designed to forecast future movements.

In ARIMA (p, d, q), the AR models are models in which the value of a variable in one period is related to its value in the previous periods. The AR(p) is an autoregressive model with lags:

$Y_t = \mu + \sum_{i=1}^{p} Y_i \, y_{t-1} + \varepsilon_t$ ……………………… (1)

where $\mu$ is a constant and $y_p$ is the coefficient for the lagged variable in time $t-p$

AR (1) model is expressed as:

$Y_t = \mu + Y y_{t-1} = \varepsilon_t$……………………………………………………………….. (2)

The MA(q) is the moving average model which accounts for the possibility of a relationship between variable and the residuals from previous periods. It is a moving average model with q lags:

$Y_t = \mu + \mu_t + \theta_i \varepsilon_{t-1}$ ……………………………………………………………………(3)

where $\theta_q$ is the coefficient for the lagged error term in time $t-p$

MA (1) model is expressed as: $Y_t = \mu + \varepsilon_t + \theta \varepsilon_{t-1}$……………………………………(4)

An ARIMA (Autoregressive Integrated Moving Average) model is a time series model usually used to predict future values or occurrences based on their past values. ARIMA model generally combines AR (Autoregressive) component, MA (Moving Average) model and,I (the number of differencing done before the series becomes stationary).

Considering an autoregressive model of order p best written as AR(p) and expressed as:

$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t$………………………………… (5)

**APPLYING A BACKWARD SHIFT OPERATOR**, equation (5) becomes

$(1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_p B^p) Y_t = \varepsilon_t$…………………………………………….. (6)

A moving average of order q is given by the formular:

$Y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$…………………………………… (7)

If we apply the same backshift operator, then we shall have:

$\varpi(B) = 1 + \eta_1 B + \eta_2 B^2 + \cdots + \eta_q B^q = 0$…………………………… (8)

A combination of equations (5) and (6) yields an ARMA (p, q) model as below:

$Y_t - Y_{t-1} - \phi_2 Y_{t-2} - \cdots - \phi_p Y_{t-p} = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$ ………………(9)

In the above equations, $\varepsilon_t$ denotes a white noise process that is considered as normally distributed with a zero mean and variance ( $\sigma^2$). We can further express equation (5) as below:

$\Psi(B) Y_t = \Phi(B) \varepsilon_t$…………………………………………………………… (10)

Where $\Psi(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_p B^p)$

This makes it easier for ARIMA (p, d, q) to be formulated as below:

$Y_t = X_t - X_{t-1} = (1 - B) X_t$………………………………………………….. (11)

$Y_t - Y_{t-1} = X_t - 2X_{t-1} + X_{t-2} = (1 - B)^2 X_t$……………………………… (12)

## 3.0 THE ASSUMPTIONS OF THE MODEL

The time series data must be stationary for (AR models). A series is said to be stationary if it enables mean reversion, if it has a finite and time-invariant variance and lastly if its theoretical correlogram diminishes as the lag length increases. The invertibility assumption (for MA model) states that the series can be represented by a finite order of MA or convergent autoregressive process, the series can use autoregressive function (ACF) and partial autoregressive function (PACF) for identification and the series can be approximated by autoregressive model.

## 3.1 THE STAGES OF FORECASTING USING ARIMA MODEL

The Box and Jenkins (1976) methodology identified four steps by which forecasting can be done which include; identification, estimation, Diagnostic Checking and Forecasting

In identification procedure, the autocorrelation function (ACF) and the partial autocorrelation (PACF) known as the correlogram of the series are examined. The ACF reveals the order of the moving average (MA) terms while the PACF reveals the order of the autoregressive (AR) terms.

The ACF helps to understand how each data point in our time series relates to its past values while the lag max parameter specifies the maximum number of time lags to consider.

The PACF indicates the relationship between a data point and its past value while removing the influence of other time lags. Basically, it is the correlation between $Y_t$ and $Y_{t-k}$ after removing the effect of the intermediate Y's (the marginal impact).

The model Estimation is usually done by ordinary least square (OLS) method. The estimation is done using the stationary specified model. The model with the smallest number of parameters is usually the best to be used for forecasting. this means that parsimonious models give better forecast than over - parameterized model.

In model diagnostic procedure, the correlogram of the tentative best model is checked for any uncaptured information in the model. If all the lags fall within the 95-confidence interval or within the threshold lines (error bands), the model passes the residual diagnostic test.

The forecasting can now be done using the model that satisfied the residual diagnostic test hence the correlogram for the adjusted ARIMA model has to be flat and confirmed by Ljung Box test.

## 4.0 RESULTS AND DISCUSSIONS



**FIGURE 1: TIME PLOT OF NAIRA -DOLLAR EXCHANGE RATE**

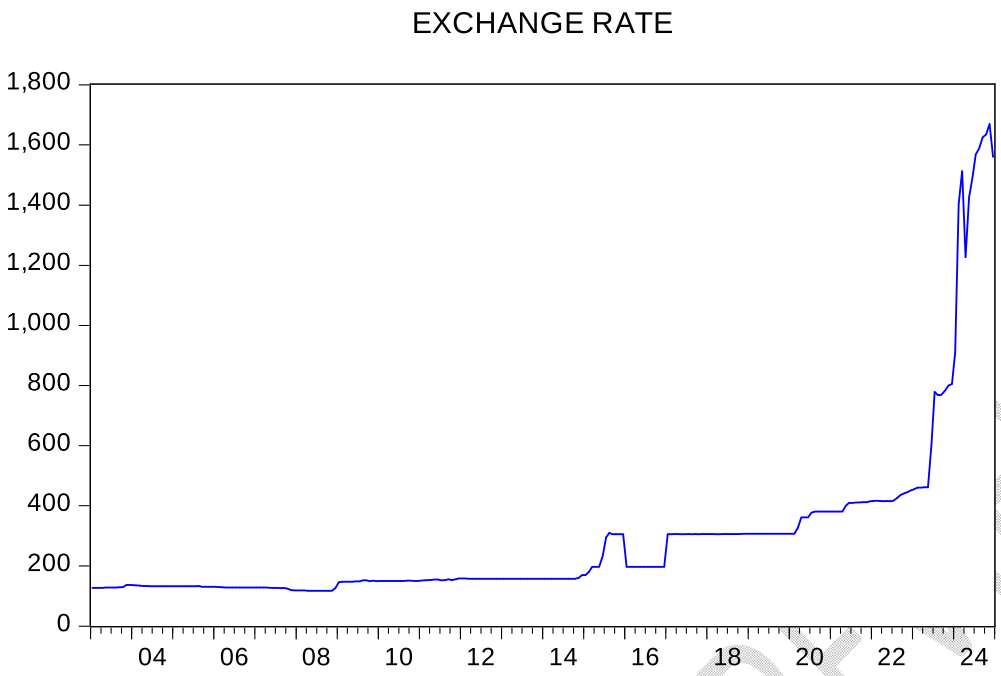
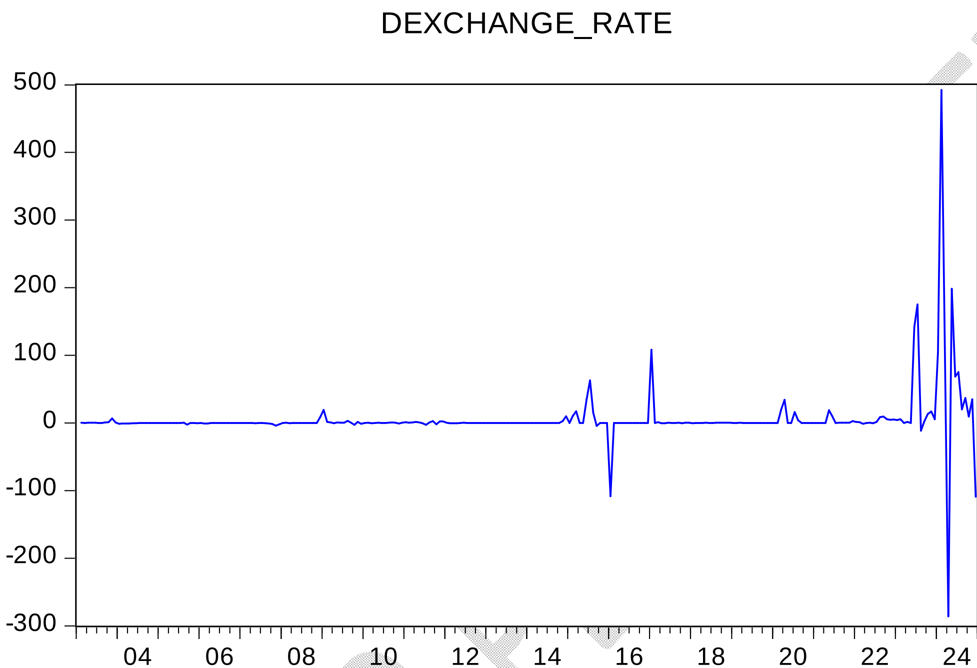

EXCHANGE RATE
1,800
1,600
1,400
1,200
1,000
800
600
400
200
0
04
06
08
10
12
14
16
18
20
22
24

**FIGURE 2:PLOT OF DIFFERENCED SERIES**



## FIGURE 3: CORRELOGRAM OF SERIES AT LEVELS


| Lag | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | 0.953 | 0.953 | 242.42 | 0.000 |
| 2 | 0.897 | -0.121 | 457.96 | 0.000 |
| 3 | 0.847 | 0.051 | 651.06 | 0.000 |
| 4 | 0.795 | -0.071 | 821.75 | 0.000 |
| 5 | 0.741 | -0.033 | 970.73 | 0.000 |
| 6 | 0.687 | -0.038 | 1099.3 | 0.000 |
| 7 | 0.636 | 0.002 | 1209.8 | 0.000 |
| 8 | 0.585 | -0.041 | 1303.7 | 0.000 |
| 9 | 0.539 | 0.029 | 1383.6 | 0.000 |
| 10 | 0.477 | -0.211 | 1446.6 | 0.000 |
| 11 | 0.425 | 0.106 | 1496.6 | 0.000 |
| 12 | 0.398 | 0.208 | 1540.8 | 0.000 |
| 13 | 0.377 | 0.009 | 1580.7 | 0.000 |
| 14 | 0.356 | -0.006 | 1616.2 | 0.000 |
| 15 | 0.335 | -0.024 | 1647.8 | 0.000 |
| 16 | 0.314 | -0.042 | 1675.7 | 0.000 |
| 17 | 0.293 | -0.009 | 1700.0 | 0.000 |
| 18 | 0.271 | -0.036 | 1721.0 | 0.000 |
| 19 | 0.260 | 0.140 | 1740.3 | 0.000 |
| 20 | 0.256 | 0.047 | 1759.1 | 0.000 |
| 21 | 0.252 | -0.097 | 1777.4 | 0.000 |
| 22 | 0.248 | 0.032 | 1795.2 | 0.000 |
| 23 | 0.243 | 0.051 | 1812.4 | 0.000 |
| 24 | 0.239 | 0.007 | 1829.2 | 0.000 |
| 25 | 0.235 | 0.011 | 1845.5 | 0.000 |
| 26 | 0.232 | -0.018 | 1861.3 | 0.000 |
| 27 | 0.228 | 0.005 | 1876.7 | 0.000 |
| 28 | 0.224 | -0.048 | 1891.6 | 0.000 |
| 29 | 0.221 | -0.018 | 1906.3 | 0.000 |
| 30 | 0.219 | 0.109 | 1920.6 | 0.000 |
| 31 | 0.216 | 0.029 | 1934.7 | 0.000 |
| 32 | 0.214 | -0.037 | 1948.5 | 0.000 |
| 33 | 0.211 | 0.001 | 1962.0 | 0.000 |
| 34 | 0.207 | -0.004 | 1975.1 | 0.000 |
| 35 | 0.204 | 0.006 | 1987.8 | 0.000 |
| 36 | 0.200 | -0.004 | 2000.2 | 0.000 |

**FIGURE 4: CORRELOGRAM OF D(EXCHANGE- RATE)**

Date: 01/07/25 Time: 09:52
Sample: 2003M01 2024M12
Included observations: 263

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.113 | 0.113 | 3.3905 | 0.066 |
| | | 2 | -0.229 | -0.245 | 17.392 | 0.000 |
| | | 3 | 0.131 | 0.205 | 21.979 | 0.000 |
| | | 4 | 0.149 | 0.043 | 27.925 | 0.000 |
| | | 5 | 0.053 | 0.114 | 28.691 | 0.000 |
| | | 6 | 0.040 | 0.041 | 29.132 | 0.000 |
| | | 7 | 0.173 | 0.187 | 37.245 | 0.000 |
| | | 8 | 0.276 | 0.248 | 58.067 | 0.000 |
| | | 9 | -0.070 | -0.099 | 59.421 | 0.000 |
| | | 10 | -0.124 | -0.038 | 63.667 | 0.000 |
| | | 11 | 0.053 | -0.102 | 64.442 | 0.000 |
| | | 12 | 0.021 | -0.082 | 64.561 | 0.000 |
| | | 13 | 0.024 | -0.002 | 64.724 | 0.000 |
| | | 14 | 0.013 | -0.053 | 64.775 | 0.000 |
| | | 15 | 0.013 | -0.015 | 64.819 | 0.000 |
| | | 16 | 0.017 | -0.020 | 64.905 | 0.000 |
| | | 17 | -0.019 | 0.071 | 65.010 | 0.000 |
| | | 18 | -0.011 | 0.047 | 65.043 | 0.000 |
| | | 19 | 0.007 | 0.022 | 65.056 | 0.000 |
| | | 20 | -0.003 | 0.013 | 65.059 | 0.000 |
| | | 21 | 0.002 | -0.022 | 65.060 | 0.000 |
| | | 22 | 0.002 | 0.003 | 65.062 | 0.000 |
| | | 23 | -0.002 | -0.013 | 65.063 | 0.000 |
| | | 24 | 0.000 | -0.014 | 65.063 | 0.000 |
| | | 25 | 0.010 | -0.004 | 65.093 | 0.000 |
| | | 26 | 0.004 | -0.008 | 65.098 | 0.000 |
| | | 27 | -0.006 | 0.010 | 65.109 | 0.000 |
| | | 28 | -0.006 | -0.000 | 65.119 | 0.000 |
| | | 29 | -0.002 | 0.004 | 65.120 | 0.000 |
| | | 30 | -0.002 | -0.006 | 65.121 | 0.000 |
| | | 31 | -0.002 | -0.003 | 65.122 | 0.000 |
| | | 32 | 0.010 | 0.012 | 65.153 | 0.000 |
| | | 33 | 0.018 | 0.013 | 65.246 | 0.001 |
| | | 34 | -0.005 | -0.001 | 65.255 | 0.001 |
| | | 35 | -0.006 | 0.005 | 65.266 | 0.001 |
| | | 36 | 0.009 | 0.007 | 65.292 | 0.002 |

**TABLE 1: ESTIMATION OF ARIMA (1,1,1)**

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:15
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 104 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.309870 | 4.458553 | 1.190940 | 0.2348 |
| AR(1) | -0.494913 | 0.058911 | -8.401068 | 0.0000 |
| MA(1) | 0.768714 | 0.048719 | 15.77843 | 0.0000 |
| SIGMASQ | 1700.498 | 48.95067 | 34.73902 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.083937 | Mean dependent var | 5.449430 |
| Adjusted R-squared | 0.073326 | S.D. dependent var | 43.16707 |
| S.E. of regression | 41.55431 | Akaike info criterion | 10.30780 |
| Sum squared resid | 447231.0 | Schwarz criterion | 10.36213 |
| Log likelihood | -1351.475 | Hannan-Quinn criter. | 10.32963 |
| F-statistic | 7.910527 | Durbin-Watson stat | 2.070111 |
| Prob(F-statistic) | 0.000046 | | |

| | |
|---|---|
| Inverted AR Roots | -.49 |
| Inverted MA Roots | -.77 |

**TABLE 2: ESTIMATION OF ARIMA (2,1,2)**

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:23
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 159 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.544323 | 5.232529 | 1.059588 | 0.2903 |
| AR(2) | -0.855228 | 0.069278 | -12.34491 | 0.0000 |
| MA(2) | 0.703710 | 0.077959 | 9.026715 | 0.0000 |
| SIGMASQ | 1728.591 | 57.63194 | 29.99363 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.068803 | Mean dependent var | 5.449430 |
| Adjusted R-squared | 0.058017 | S.D. dependent var | 43.16707 |
| S.E. of regression | 41.89615 | Akaike info criterion | 10.32455 |
| Sum squared resid | 454619.5 | Schwarz criterion | 10.37888 |
| Log likelihood | -1353.678 | Hannan-Quinn criter. | 10.34638 |
| F-statistic | 6.378884 | Durbin-Watson stat | 1.688779 |
| Prob(F-statistic) | 0.000347 | | |

| | | |
|---|---|---|
| Inverted AR Roots | -.00+.92i | -.00-.92i |
| Inverted MA Roots | -.00+.84i | -.00-.84i |

## TABLE 3: ESTIMATION OF ARIMA (3,1,3)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:29
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 76 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.392766 | 5.083356 | 1.060867 | 0.2897 |
| AR(3) | 0.210618 | 0.661738 | 0.318280 | 0.7505 |
| MA(3) | -0.078489 | 0.653968 | -0.120020 | 0.9046 |
| SIGMASQ | 1823.164 | 43.29361 | 42.11162 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.017856 | Mean dependent var | 5.449430 |
| Adjusted R-squared | 0.006480 | S.D. dependent var | 43.16707 |
| S.E. of regression | 43.02698 | Akaike info criterion | 10.37683 |
| Sum squared resid | 479492.1 | Schwarz criterion | 10.43116 |
| Log likelihood | -1360.553 | Hannan-Quinn criter. | 10.39867 |
| F-statistic | 1.569630 | Durbin-Watson stat | 1.720007 |
| Prob(F-statistic) | 0.197154 | | |

| | | | |
|---|---|---|---|
| Inverted AR Roots | .59 | -.30-.52i | -.30+.52i |
| Inverted MA Roots | .43 | -.21+.37i | -.21-.37i |

## TABLE 4: ESTIMATION OF ARIMA (1,1,3)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:37
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 118 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.300933 | 6.228846 | 0.851030 | 0.3955 |
| AR(1) | 0.137914 | 0.034354 | 4.014468 | 0.0001 |
| MA(3) | 0.145265 | 0.028701 | 5.061310 | 0.0000 |
| SIGMASQ | 1793.070 | 30.53204 | 58.72750 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.034068 | Mean dependent var | 5.449430 |
| Adjusted R-squared | 0.022880 | S.D. dependent var | 43.16707 |
| S.E. of regression | 42.67039 | Akaike info criterion | 10.36030 |
| Sum squared resid | 471577.5 | Schwarz criterion | 10.41463 |
| Log likelihood | -1358.379 | Hannan-Quinn criter. | 10.38213 |
| F-statistic | 3.044936 | Durbin-Watson stat | 1.889811 |
| Prob(F-statistic) | 0.029362 | | |

| | | | |
|---|---|---|---|
| Inverted AR Roots | .14 | | |
| Inverted MA Roots | .26-.46i | .26+.46i | -.53 |

## TABLE 5: ESTIMATION OF ARIMA (1,1,8)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 11:04
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 141 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.628698 | 4.633222 | 1.214856 | 0.2255 |
| AR(1) | 0.088575 | 0.022019 | 4.022641 | 0.0001 |
| MA(8) | 0.342966 | 0.028162 | 12.17834 | 0.0000 |
| SIGMASQ | 1666.747 | 33.83501 | 49.26103 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.102119 | Mean dependent var | 5.449430 |
| Adjusted R-squared | 0.091718 | S.D. dependent var | 43.16707 |
| S.E. of regression | 41.13986 | Akaike info criterion | 10.29076 |
| Sum squared resid | 438354.5 | Schwarz criterion | 10.34509 |
| Log likelihood | -1349.235 | Hannan-Quinn criter. | 10.31259 |
| F-statistic | 9.818933 | Durbin-Watson stat | 1.951856 |
| Prob(F-statistic) | 0.000004 | | |

| | | | | |
|---|---|---|---|---|
| Inverted AR Roots | .09 | | | |
| Inverted MA Roots | .81-.33i | .81+.33i | .33+.81i | .33-.81i |
| | -.33+.81i | -.33-.81i | -.81-.33i | -.81+.33i |

**TABLE 6: ESTIMATION OF ARIMA (8,1,2)**

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/09/25 Time: 10:41
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 164 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.979039 | 6.249366 | 0.956743 | 0.3396 |
| AR(8) | 0.332846 | 0.021901 | 15.19770 | 0.0000 |
| MA(2) | -0.204073 | 0.023701 | -8.610246 | 0.0000 |
| SIGMASQ | 1604.855 | 42.21892 | 38.01271 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.135460 | Mean dependent var | 5.449430 |
| Adjusted R-squared | 0.125446 | S.D. dependent var | 43.16707 |
| S.E. of regression | 40.36881 | Akaike info criterion | 10.25297 |
| Sum squared resid | 422077.0 | Schwarz criterion | 10.30730 |
| Log likelihood | -1344.266 | Hannan-Quinn criter. | 10.27480 |
| F-statistic | 13.52707 | Durbin-Watson stat | 1.690102 |
| Prob(F-statistic) | 0.000000 | | |

| | | | | |
|---|---|---|---|---|
| Inverted AR Roots | .87 | .62-.62i | .62+.62i | -.00-.87i |
| | -.00+.87i | -.62+.62i | -.62+.62i | -.87 |
| Inverted MA Roots | .45 | -.45 | | |

**FIGURE 5: CORRELOGRAM OF THE SELECTED MODEL**

Date: 01/09/25 Time: 11:02
Sample: 2003M01 2024M12
Included observations: 263
Q-statistic probabilities adjusted for 2 ARMA terms

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.152 | 0.152 | 6.1452 | |
| | | 2 | -0.036 | -0.060 | 6.4908 | |
| | | 3 | 0.139 | 0.158 | 11.683 | 0.001 |
| | | 4 | 0.133 | 0.087 | 16.448 | 0.000 |
| | | 5 | 0.064 | 0.049 | 17.558 | 0.001 |
| | | 6 | 0.170 | 0.155 | 25.353 | 0.000 |
| | | 7 | 0.174 | 0.113 | 33.638 | 0.000 |
| | | 8 | 0.026 | -0.015 | 33.829 | 0.000 |
| | | 9 | -0.103 | -0.145 | 36.746 | 0.000 |
| | | 10 | -0.043 | -0.092 | 37.266 | 0.000 |
| | | 11 | 0.058 | 0.010 | 38.198 | 0.000 |
| | | 12 | 0.015 | -0.013 | 38.264 | 0.000 |
| | | 13 | 0.032 | 0.040 | 38.541 | 0.000 |
| | | 14 | 0.007 | -0.003 | 38.555 | 0.000 |
| | | 15 | -0.051 | -0.010 | 39.291 | 0.000 |
| | | 16 | -0.046 | 0.008 | 39.882 | 0.000 |
| | | 17 | -0.005 | -0.001 | 39.888 | 0.000 |
| | | 18 | 0.013 | -0.006 | 39.935 | 0.001 |
| | | 19 | 0.014 | -0.002 | 39.990 | 0.001 |
| | | 20 | 0.012 | 0.015 | 40.029 | 0.002 |
| | | 21 | 0.004 | 0.021 | 40.033 | 0.003 |
| | | 22 | 0.004 | 0.026 | 40.038 | 0.005 |
| | | 23 | -0.002 | 0.002 | 40.039 | 0.007 |
| | | 24 | -0.004 | -0.022 | 40.043 | 0.011 |
| | | 25 | 0.000 | -0.021 | 40.043 | 0.015 |
| | | 26 | -0.002 | -0.019 | 40.045 | 0.021 |
| | | 27 | -0.007 | -0.013 | 40.058 | 0.029 |
| | | 28 | -0.009 | -0.008 | 40.085 | 0.038 |
| | | 29 | -0.003 | 0.006 | 40.087 | 0.050 |
| | | 30 | -0.008 | 0.004 | 40.106 | 0.065 |
| | | 31 | -0.007 | 0.010 | 40.119 | 0.082 |
| | | 32 | 0.008 | 0.019 | 40.139 | 0.102 |
| | | 33 | 0.016 | 0.018 | 40.218 | 0.124 |
| | | 34 | -0.007 | -0.009 | 40.233 | 0.151 |
| | | 35 | -0.007 | -0.007 | 40.248 | 0.180 |
| | | 36 | 0.012 | 0.006 | 40.293 | 0.212 |

**FIGURE 6 :GRAPH OF THE FORECASTED VALUES**

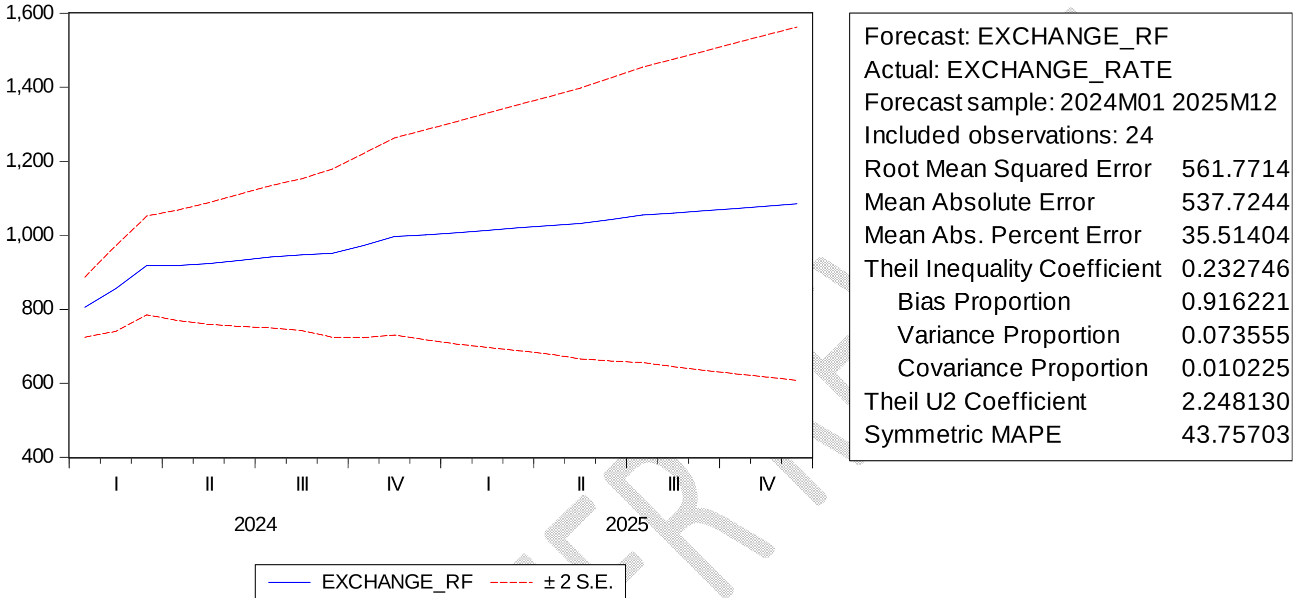


**FIGURE 7: CONFIRMATION OF INVERTIBILITY AND COVARIANCE STATIONARY PROPERTY.**

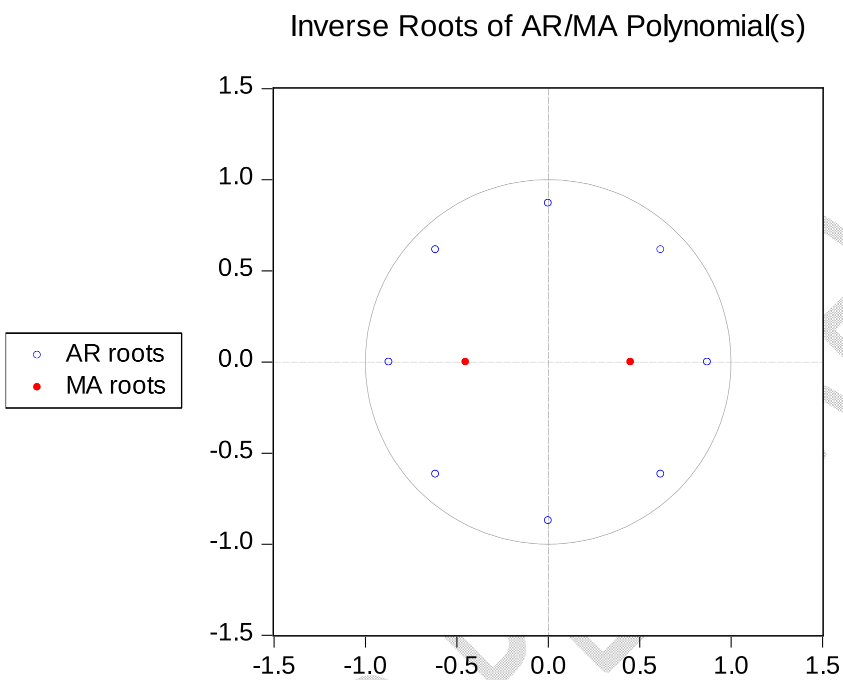


**FIGURE 8:GRAPH OF THE FORECASTED VALUES AGAINGST THE ACTUAL**

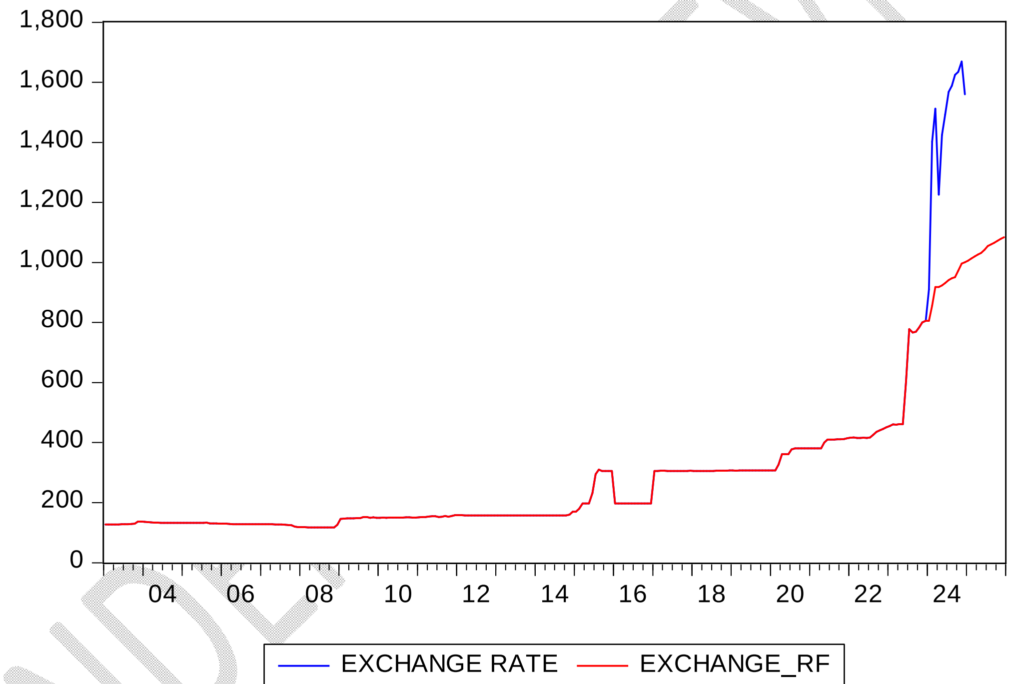


**TABLE 7: SUMMARY STATISTICS TABLE OF THE SIX TENTATIVE MODELS**

| TENTATIVE MODELS | ARIMA (1,1,1) | ARIMA (2,1,2) | ARIMA (3,1,3) | ARIMA (1,1,3) | ARIMA (1,1,8) | ARIMA (8,1,2) |
|---|---|---|---|---|---|---|
| SIGMA | 1700.498 | 1728.591 | 1823.164 | 1793.070 | 1666.747 | 1604.855 |
| C | 3 | 3 | 1 | 3 | 3 | 3 |
| ADJ.R-SQ. | 0.073326 | 0.058017 | 0.006480 | 0.022880 | 0.091718 | 0.125446 |
| AIC | 10.30780 | 10.32455 | 10.37683 | 10.36030 | 10.29076 | 10.25297 |

## DISCUSSION

The time plot of the series showed a relatively steady rate until 2015 till 2024 when it showed an upward trend and could not revert to its mean indicating nonstationary behavior but later achieved stationarity after one time differencing. The correlogram of the differenced series was taken followed by model identification procedures as specified by Box and Jenkins. Six possible tentative models were estimated and the most parsimonious one was considered as the best forecasting power and subsequently used in the forecasting.

From summary statistics table above the most parsimonious model was ARIMA (8,1,2) because it had the lowest volatility, highest adjusted R-value, least Akaike's information criteria with three of its coefficients statistically significant.

A visual inspection of figure one showed that the time plot of the average exchange rate had an upward trend and a time varying variance making the series nonstationary as was also confirmed by the ADF test in table two but after a one time differencing the series became stationary as shown in table four and the correlogram in table 3, so the correlogram of the stationary structure was used to identify the AR and MA components. The PACF was used to determine the AR order while the ACF was used to determine the MA orders. After ensuring stationary behavior of the series, the model was specified as revealed in table one and estimated accordingly in tables 5,6,7,8 and 9. The most parsimonious model ARIMA (4,1,1) was selected but residual diagnostic test showed that there was some uncaptured information in lags 16 for both AR and MA terms because the bars were exactly on threshold lines suggesting ARIMA (16,1,16) but after estimating ARIMA(16,1,16), the result still presented ARIMA(4,1,4) as the chosen model as shown in the summary statistics table above with least AIC, lowest SIGMA(volatility) and highest Adjusted R-Squared value.

ARIMA (4,1,4) had the better forecasting power thus was used in the forecast equation as the best model among the four other tentative models. The forecasted values intercepted the actual values at more than one point indicating a good forecast.

**CONCLUSION**

This work had allowed for a detailed statistical analysis revealing the presence of trend and patterns in the series capable of giving proper comprehension of the dynamics of exchange rate. The work also analyzed the exchange rate's volatility which will help in stabilizing macroeconomic components of Nigeria. However, we recommend that future research should base on hybrid model where ARIMA model can be combined with other forecasting models.

From the performances of the models in summary statistics table, it was observed that ARIMA models were directional and forecasted values were closely related to actual exchange rate values in table ten hence we recommend that ARIMA models be used for short term forecasting and that future research should focus on using hybrid forecasting models.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.



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