TIME SERIES ANALYSIS OF CHINESE YUAN TO NIGERIA NAIRA EXCHANGE RATES

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Abstract

This paper presents a detailed empirical study focusing on modelling and forecasting time series data of the daily exchange rates between theChinese Yuan and the Nigerian Naira. The study uses data from two reliable websites, https://www.exchangerates.org.uk/CNY-NGexchange-rate-history.html, covering a period ranging from Sunday,20 February 2022, to Thursday, 4 August 2022. The study's primary objective is to determine the most appropriate model for accurately predicting the daily exchange rates between the two currencies. The study utilizes the Box-Jenkins time series analysis method to predict theexchange rates of the Chinese Yuan to the Nigeria Naira. The results show that the ARIMA (2,1,1) model is the most suitable for this purpose. The model successfully identifies the underlying trends and patterns inthe data and provides dependable forecasts for the exchange rates. Overall, this *method proves to be practical in analyzing time series data. The study also examines the accuracy of the forecasts generated by the ARIMA (2,1,1) model. The fourteen-day forecasts produced by the model are compared with the actual exchange rates, and the results show that the forecast compares favourably with the original exchange rates. This finding suggests that the ARIMA (2,1,1) model is reliable for predicting the daily exchange rates between the Chinese Yuan and Nigerian Naira.*

Key word: ARIMA, Exchange Rate, Forecasting, Stationary,

Introduction

The currency exchange rate is one of the most critical determinants of a country's relative level of economic health. A higher-valued currency makes a country's imports less expensive and its exports more expensive in foreign markets. Modern macroeconomics relies hugely on foreign exchange rate dynamics. The exchange rate reflects the ratio at which one currency can be exchanged with another currency, namely the ratio of currency policies. A correct or appropriate exchange rate has been one of the most critical factors for economic growth in the economies of most developed countries.

In contrast, a high volatility or inappropriate exchange rate has been a major obstacle to the economic growth of many African Countries, of which Nigeria is inclusive. It is good to note that the value of a country's currency with the highest trade volume in Nigeria significantly impacts the consumer's price index in Nigeria. So, predicting the bilateral exchange with such countries is essential to Nigeria's economy. Over a decade now, the trade volume between China, India and Nigeria has increased drastically, especially in crude earnings for Nigeria, drugs and medical services earnings for India, and electronics and fabrics earnings for China. However, the volume of trade between these countries affects the exchange rate. Hence, modelling the Rupee/Nigeria exchange rate and Yuan/Nigeria exchange rate is crucial to policy implication, exchange rate forecast and risk management.

Time series forecasting models are based on the analysis of historical data. These methods support the assumption that past patterns in data can be used to forecast future data points. (Meyler, 1998) used the Arima model for forecasting inflation in Ireland (Mondal, 2014) used Arima model for forecasting stock price. Arima is also used for predicting the stock price in the research (Jarrett, 2011) (Adebiyi, 2014) (and Isenah, 2014). It is also used for forecasting the price of gold (Guha & Bandyopadhyay, 2014). Arima is also a good solution for prediction; some authors used it for forecasting, such as (Appiah & Adetunde, 2011), Nwankwo, 2014), (Tlegenova, 2014). (Amaefula, 2022) used the Arima Model in forecasting NREXR).

Methodology

The data obtained from the websites https//www.exchangeratrs.org.uk/CNY-NGN exchange-rate-histroy.html comprise the daily accurate foreign exchange rates from Sunday, 20 February 2022, to Thursday, 4 August 2022, are used forthe analysis.

The time series method of using the Box and Jenkins in methodology was adopted, and its accompanying assumptions, like meeting thestationarity condition, were adequately justified.

There are four components of a time series: A skeletal trend, seasonal variation, cyclical variation, and irregular variation.

The Box-Jenkins Method

The Box-Jenkins method is a methodology which uses a variable's past behaviour to select the forecasting model from a general class of models. Three stages are involved in this methodology; these include identifying the tentative model, determining the model's parameters, and applying the model.

They are identifying the tentative model involved in making sure that the variables are stationary and using plots of the dependent time series's autocorrelation and partial autocorrelation functions to decide which (if any) auto-regressive or moving average component should be used in the model.

Model Identification

The identification stage involves the determination of tentative values of p,d,q and the P,D,Q sets using the linear least squares method. In the

Identification stage, a stationary or a weakly stationary situation is obtained by differencing and transformation of the data if needed. Then, the ACF and PACF plots are used to suggest possible models by determining the orders p and q in the seasonal ARIMA *(p,d,q)(P,D,Q)* model. The goodness of best models could be evaluated using the mean square error (Residuals) MSE or using the Akaike Information Criterion.

Autocorrelation Function (ACF)

It is the similarity between observation as a function of the time separation between

$$\rho_k = \frac{E[(X_t-\mu)(X_{t+k}-\mu)]}{\sqrt{E[(X_t-\mu)^2 E[(X_{t+k}-\mu)^2]}}$$

$$= \frac{Cov\,(X_t, X_{t+k})}{\sqrt{Var\,(X_t)Var\,(X_{t+k})}}$$

$$= \frac{Cov\,(X_t, X_{t+k})}{\sigma_x^2}$$

Therefore, $\rho_k = \frac{r_k}{r_0} = \frac{R_k}{R_0}$

Where $\sigma_x^2 = r_0 = R_0$ for stationary process, thus the autocorrelation at lag K is

$$\rho_k = \frac{r_k}{r_0}$$

Where $\rho_0 = 1, 2, \ldots$ k = 0 $\pm$ 1 $\pm$ 2 $\pm$ 3 $\pm$

Partial Autocorrelation Function (PACF)

Given a process $X_t, t \in Z$, the partial autocorrelation function is said to be the correlation between X_t and X_{t+k}. After removing their mutual dependency on the intermediate or intervening variables $X_{t+1}, X_{t+2}, \ldots, X_{t+k-1}$. This is denoted as $\emptyset_{kk}$ and it is defined as:

$$\phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1}\phi_{k-1}\rho_{k-j}}{1-\sum_{j=2}^{k-1}\phi_{k-1},\rho_{k-j}}\, k = 2,3$$

and $\emptyset_k.j = \emptyset_{k-1}, j - \emptyset_{kk}\emptyset_{k-1,k-1}$ $\qquad j = 1,2,3, \ldots, k-1$

- **Autoregressive Integrated Moving Average Model (Arima)**

In practice, most time series are non-stationary. In order to fit a stationary model, the method of differencing is applied. This method is particularly useful for removing trend in the series. For non-seasonal data, first order differencing is usually sufficient to attain apparent stationarity. Here a new series say $(Y_1, Y_2, \dots, Y_N)$ is formed from the original observed series say $(X_1, X_2, \dots, X_N)$ by;

$$Y_t = X_t - X_{t-1} = \nabla x_t \text{ for } t = 1,2,3, \dots N$$

Occasionally, second order differencing is required.
Giving the ARIMA model

$$X_t = \emptyset_1 X_{t-1} + \cdots + \emptyset_P X_{t-P} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} + e_t$$

By backshift, the equation becomes

$$\emptyset(B)X_t = \theta(B)e_t$$

If X_t is replaced by $\nabla^d X_t$then we have a model capable of describing certain types of non-stationary series, such a model is called an integrated model because the stationary model that is fitted to the differenced data has to be summed or integrated to provide a model for the original non-stationary data written as

$$W_t = \nabla^d X_t = (1 - B)X_t$$

The d^{th} difference of X_t is said to be an ARIMA process of order (p,d,q).

Choice of Model and Order Through ACF and PACF

- **AR(1):** ACF decays exponentially and PACF cuts-off or spikes at lag 1. The model is given as

$$X_t = \emptyset_i X_{t-1} + e_t$$

- **AR(2):** ACF has a sine-wave pattern or a set of exponentially decays, PACF cuts-off or spikes at lag 1 and lag 2 and no correlation for other lag.

$$X_t = \sum_{t=1}^{P} \emptyset_i X_{t-i} + e_t$$

i.e. $X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + e_t$

- **MA(1):** ACF cuts-off at lag 1 and no correlation for other lags and PACF decays exponentially, the model is

$$X_t = e_t - \theta_i e_{t-1}$$

- **MA(2):** ACF cuts-off at lag 1 and 2 and no correlation for other lags and PACF exhibits a set of sine-wave pattern or exponentially decays.

$$X_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2}$$

This involves finding the appropriate values of (p,d,q) for the ARIMA process for the series. This can be achieved by the use of Auto-correlation Function (ACF) Correlogram and Partial Auto-correlation Function (PACF) Correlogram. The table below summarizes how sample ACF could be used for model identification.

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Summary of Sample ACF for Model Identification

S/No	Shape	Indicated Model
1	Exponential decaying to zero	AR model, use the PACF plot to identify the order of the AR model.
2	Alternating positive and negative decaying to zero	AR model, use the PACF plot to identify the order
3	One or more spikes, rest are essentially zero	MA model, order identified by where plot becomes zero
4	Decay, starting after a few lags	Mixed AR and MA model
5	All zero or close to zero	Data is essentially random
6	High values at fixed	Include seasonal AR term
7	No decay to zero	Series is not stationary

Estimation and Diagnostic Checking

Having identified p and q values, the parameters of autoregressive and the moving average was estimated using Minitab software. After choosing a particular ARIMA model, the next thing is to check whether the model chosen fits the data appropriately. Since there is a possibility of choosing another ARIMA model that might do the same work as well.

A simple test of the adequacy of the chosen model is to see if the residual estimated from the model are white noise. If the residuals are not white noise, then there is a need to start over again in the identification and specification of another model. So the iteration continues until a right model is fitted to the data.

If the fitted model is adequate, the residuals should be approximately white noise. So, we should check if the residuals have zero mean and if they are uncorrelated. The key instruments are the time plot, the ACF and PACF of the residuals. The theoretical CF and PACF of white noise processes take value zero for lags

$$Q = n\sum_{j=1}^{T} Pj^2$$

The critical region is given by $\sim \chi^2_{a.T-p-q}$ where T is the default number of lags in the ACF of the residual p=AR parameter, q=MA parameter $\hat{P}_j$=Correlogram.

Diagnostic Checking:

This is concerned with checking the statistical significance of the model. The derived model must be checked for adequacy by considering the properties of the residuals whether the residual from an ARIMA model is normally and randomly distributed. The histogram and pq plots of the residuals can be used to assess the normality assumption visually. An overall check of the model adequacy is provided by Ljung-Box Q statistics. The test statistics Q is given in the equation below:

$Q_m = n(n+2)\sum_{k-i}^{n} \quad (n-k)^{-1} r_k^2 \approx X_{m-r}^2$.

Where:

r_k^2= The residual autocorrelation at lag k

n = The number of residuals

m = The number of time lags included in the test

Q = The modified Lung – Box test statistics

If the p-value associated with the Q Statistics is small (p-value < α), the model is considered inadequate. The analysis should consider a new or modified model and continue the analysis until a satisfactory model has been determined.

3. RESULTS AND DISCUSSION

The Box-Jenkins methodology for forecasting requires the series to be stationary. The data was found to be non-stationary. An examination of Fig.1 clearly revealed that non-stationarity is inherent in the data. Stationarity was achieved after differencing the time plots once as seen in fig. 2.

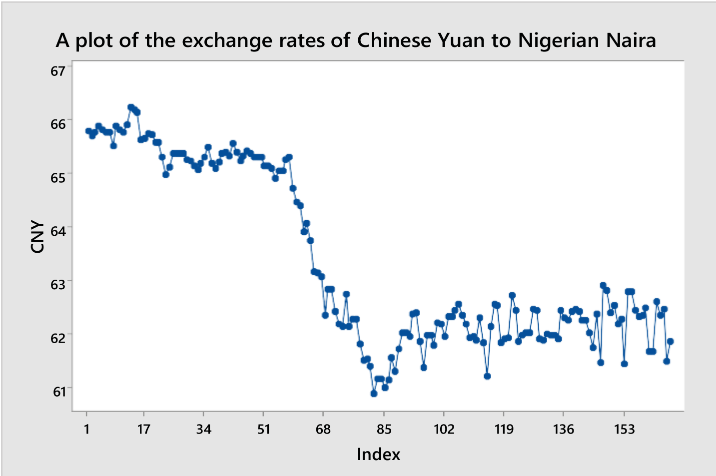

Fig. 1: Time Plot of the Exchange rates of Chinese Yuan to Nigerian Naira

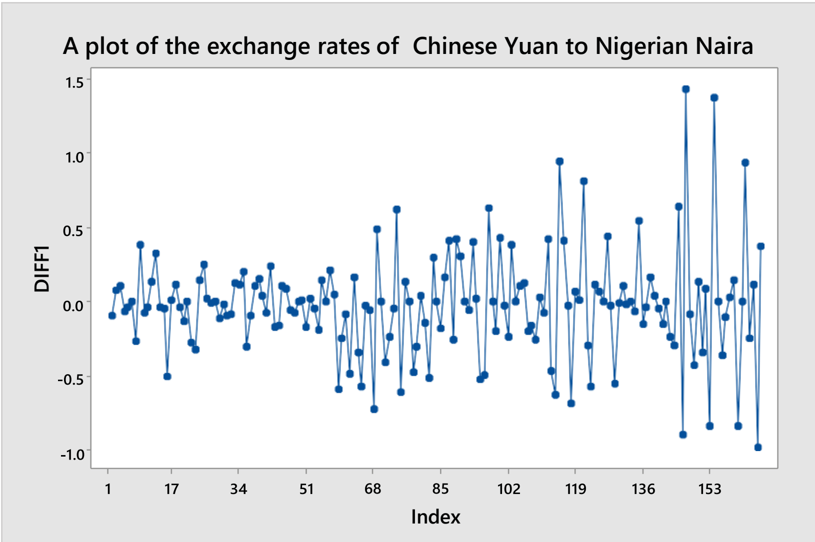

Fig. 2: Plot of the 1st difference Exchange rates of Chinese Yuan to Nigerian Naira

Model Identification

Identification of ARIMA models is basically in the pattern of ACF and PACF as presented in Fig. 3, Fig. 4.

The plot of autocorrelation function in fig. 3 cut off at lag one and no correlation for other lags in ACF, but there is a cut off at lag 2 and no correlation for other lags in PACF in fig. 4. Hence, ARIMA (2,1,1) is identified as the model.

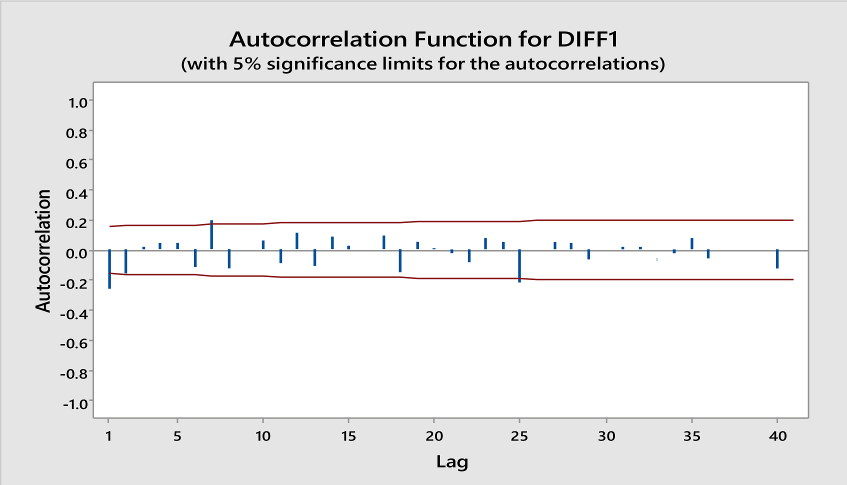

Fig. 3: Plot of the 1st difference ACF of Chinese Yuan/Nigerian Naira Exchange Rate

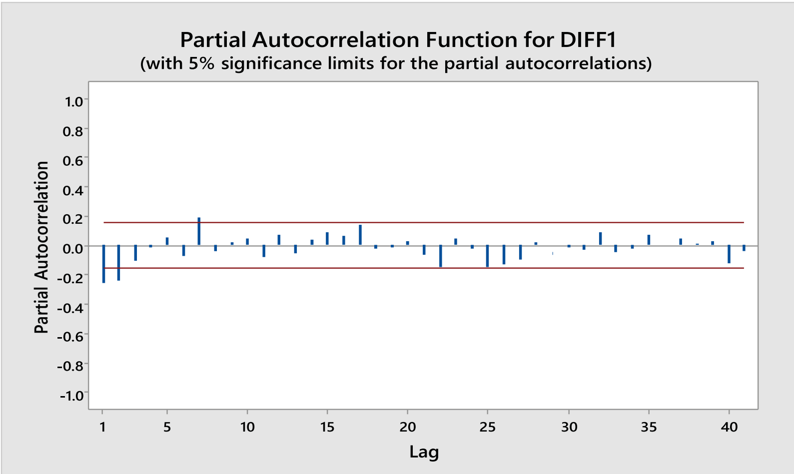

Fig. 4: Plot of the 1st difference PACF of Chinese Yuan/Nigerian Naira Exchange Rate

Estimation of Parameters for Chinese Yuan/Nigerian Naira Exchange Rate

Table 1: Final Estimates of Parameters

Type	Coef	SE Coef	T	P
AR 1	-0.9566	0.2253	-4.25	0.000
AR 2	-0.3105	0.0794	-3.91	0.000
MA1	-0.6900	0.2296	-3.01	0.003

Differencing: 1 regular difference
Number of observations: Original series 166, after differencing 165
Residuals: SS = 18.8144 (backforecasts excluded)
MS = 0.1161 DF = 162

The result from table 1 of the final estimates of parameters revealed that the estimates are statistically significant aft4er accessing from their p-values, which al are less than 0.05.

Hence, the model

$\Delta Xt = -0.9566\,(\Delta X_{t-1}) - 0.3105\,(\Delta X_{t-2}) - 0.69\mu_t$

$= -09566\,[X_{t-1} - X_{t-2}] - 0.3105\,[X_{t-2} - X_{t-3}] - 0.69\mu_t$

$= -09566\,X_{t-1} + 0.9566\,X_{t-2} - 0.3105X_{t-2} + 0.3105X_{t-3} - 0.69\mu_t$

$\Delta Xt = [X_t - X_{t-1}]$

$X_t = -0.9566X_{t-1} + X_{t-1} +$

$X_t = -0.0434X_{t-1} + 0.6461X_{t-2} + 0.3105X_{t-3} - 0.69\mu_t$

Table 2: Modified Box-{ierce (Ljung-Box) Chi-square Statistic

Lag	12	24	36	48
Chi-square	13.8	22.2	38.3	54.5
DF	9	21	33	45
P-Value	0.130	0.387	0.241	0.157

Diagnostic test using Ljung-Box chi-square statistic

The result in table 2 shows that there is no autocorrelation up to 48th lag in the fitted model residuals. This is observed from the p-value when compared to the significance level for each chi-square statistic.

Fig. 5 ACF plot of the fitted model residual. The ACF of the fitted model residual in fig. 5 shows absence of autocorrelation residuals. Hence, ARIMA (2, 1, 1) model fitted for Chinese Yuan to Nigerian Naira exchange rate is adequate for making forecast.

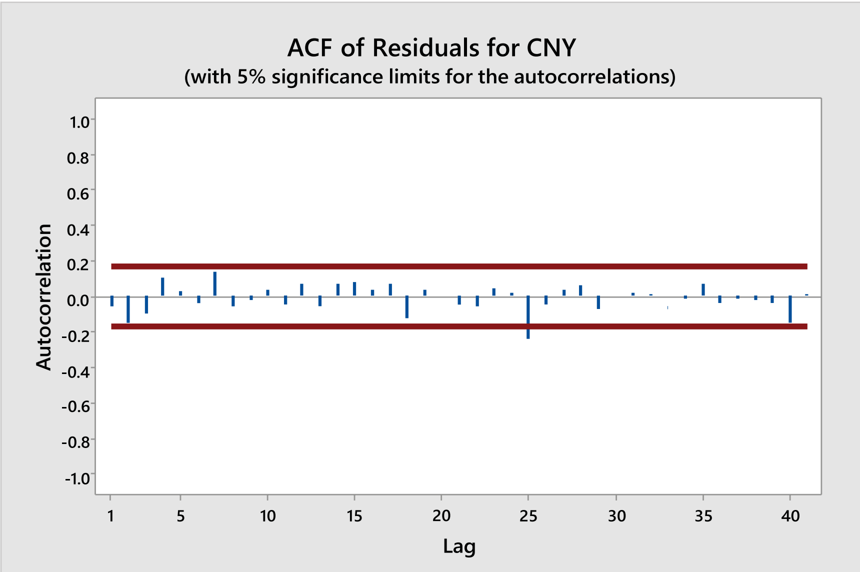

Fig. 9: Plot of the ACF of the fitted residual for Chinese Yuan/Nigeria Naira Exchange Rate

Fig. 6, which is the histogram fulfilled the assumption of normality and fig. 7 which is the normal probability plot of the residuals shows departure from normality at the tails due to the others that occurred. All these prove that the selected ARIMA model in an appropriate model.

Frequency

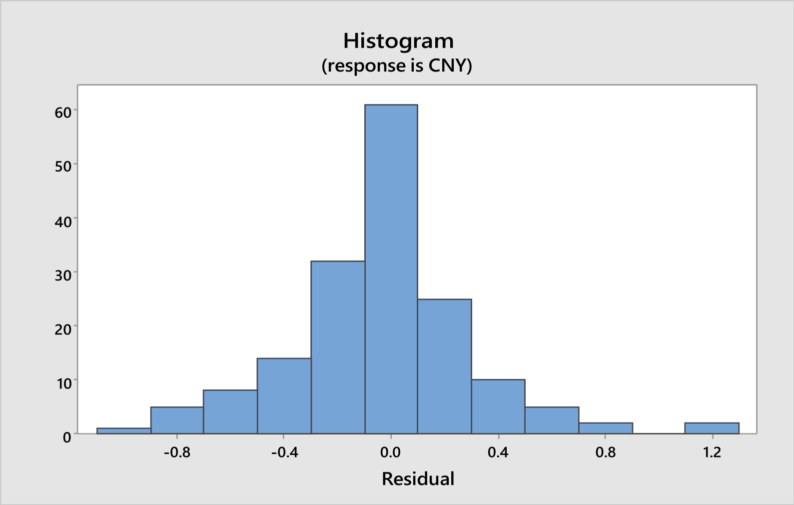

Fig. 6: Histogram plot of residual for Chinese Yuan/Nigerian Naira exchange rate

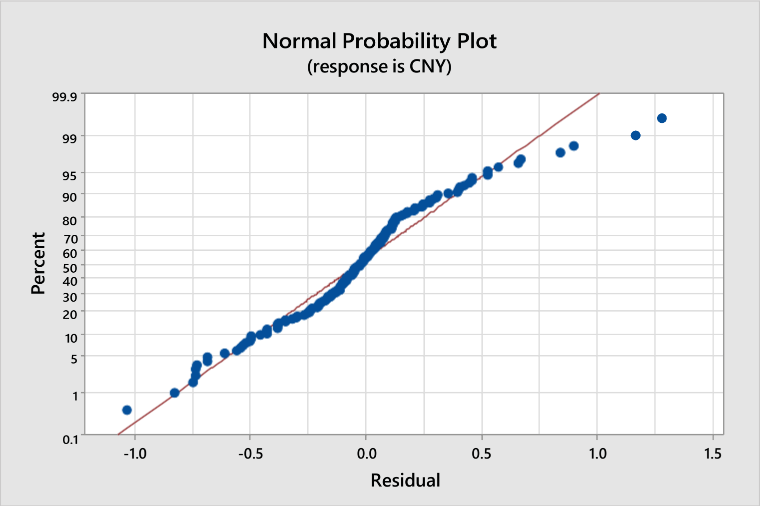

Fig. 7: Normal probability plot for Chinese Yuan/Nigerian Naira exchange rate

Forecast for China Yuan/Nigerian Naira exchange rate

Table 3: Two-Sample T-Test and CI: Train, Forecast

Two-sample T for Train vs Forecast

	N	Mean	StDev	SE Mean
Train	14	62.060	0.364	0.097
FORECAST	14	61.8384	0.0411	0.011

Difference = μ (Train) - μ (Forecast)
Estimate for difference: 0.2212
95% CI for difference: (0.0201, 0.4223)
T-Test of difference = 0 (vs ≠): T-Value = 2.26 P-Value = 0.032 DF = 26
Both use Pooled StDev = 0.2588.

Using Theil coefficient of evaluating performance accuracy, U_2

$$U_2 = \frac{\sqrt{\sum_{t=1}^{n-1}\left\{\frac{(f_{t+1} - y_{t+1})}{y_t}\right\}^2}}{\sqrt{\sum_{t=1}^{n-1}\left\{\frac{(y_{t+1} - y_t)}{y_t}\right\}^2}}$$

$$= \frac{\sqrt{0.000620613}}{\sqrt{1.00034}} = 0.0249$$

The result from two-sample T-test in table 3 shows that the small p-value, the stronger the evidence is that the two population ie, the train and forecast have difference means.

Also, using their coefficient of evaluating performance accuracy in which the closer the value of U_2 is to zero, the better the forecast method. With our U_2 value being close to zero, an evidence for the accuracy of our forecasting model.

Table 4: Train and Forecast for Chinese Yuan/Nigerian Naira Exchange Rate

Train	**FORECAST**
61.750	61.9283
61.613	61.7417

61.670	61.8968
61.621	61.8064
61.583	61.8447
62.180	61.8361
62.136	61.8324
62.172	61.8386
62.172	61.8338
62.813	61.8365
62.147	61.8354
62.298	61.8356
62.436	61.8358
62.244	61.8356

Summary

This study analyzed the daily exchange rate data of the Chinese Yuan to Nigerian Naira from 20th February 2022 to 4th August 2022. Our analysis revealed that the time plots of the data showed non-stationarity, which was addressed by differencing it once to make it stationary. We used the classical Box and Jenkins Time Series methodology and its indicative ACF and PACF identification guide to prepare the data. Our analysis concluded that the ARIMA (2, 1, 1) model was the most suitable for forecasting the accurate daily data for 14 days. We conducted a diagnostic test to evaluate the reliability of the fitted model and the forecasts generated. The test results indicated that the model was adequate, and the forecasts were very close to the actual values. Therefore, the fitted model is reliable and adequate for accurately forecasting the exchange rate data.

Conclusion

According to the study's results, the ARIMA (2, 1, 1) model is a significant and ideal approach for analyzing the exchange rate between the Chinese Yuan and Nigerian Naira. Additionally, the model can offer valuable insights into investment risk aversion, economic development, and bilateral trade between the two nations by predicting exchange rates.

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