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ARIMA Modeling of the Exchange Rate of the Nigerian Naira to the US Dollar with Covid-19 Pandemic Event in Focus

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RESEARCH ARTICLE

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Abstract

We modelled the average monthly exchange rate between the Nigerian Naira and the USDollar using univariate time series analysis. With a data set covering January 2002 to June 2022, we divided the data set into three distinct periods, vis-à-vis; the Pre COVID-19 pandemic period, the COVID-19 period, and the Combined period (combination of both pre-COVID-19 and COVID-19 periods). This was done with a view to examining the effect of COVID-19 pandemic on the generation mechanism of the Naira/USDollar exchange rate. The Naira/USDollar exchange rate data was found to be non-stationary and was appropriately differenced to attain stationarity. Subsequently, we fitted ARIMA models for each of the three scenarios using Box Jenkins methodology. Finally, the estimated models were used for forecasting. While the estimated models for both the Pre COVID-19 and the Combined periods yielded forecast values that suggest future depreciation of the Naira against the USDollar, that of the COVID-19 period yielded forecast values that suggest future appreciation of the Naira against the USDollar.

Keywords: Exchange Rate, Nigeria Naira, US Dollar, ARIMA Model, Covid-19 Pandemic, Time Series Analysis, Foreign Exchange Market, Forecasting.

1. Introduction

Exchange rates are crucial in regulating the foreign exchange market's dynamics (Akhtar, et al., 2022). The Nigerian foreign exchange market as a segment of the financial market plays an important role in the money market of a country. The market, essentially being a spot market, facilitate short-term transactions. The sale of foreign exchange inherently mops up domestic liquidity from the banking system. To this extent, the Central Bank of Nigeria (CBN) has used it to complement its monetary control tools. The foreign exchange market has become very active with unintended adverse developments. (Mordi, et al., 2010). The stability of the exchange rate of any country is central to the stability of its economic development and growth. In managing the exchange rate appreciation, the trade-off in relation to interest rate and inflation management must be carefully balance in order to prevent economic crisis in the country. The strategy for achieving effective exchange rate is the promotion of a competitive market where foreign currencies are freely traded under the forces of demand and supply (Mordi, et al., 2010).

On the movement of the official Naira/US Dollar exchange rate, from an average exchange rate of N0.8938/US$1 in 1985, the naira exchange rate depreciated by 55.9 per cent to N2.0206/US$1 in

1986, and further depreciation to N4.0179/US$1 in 1987. By 1989, the pressure on the foreign exchange market intensified, owing to shortfall in foreign exchange supply and excess liquidity in the financial system. As a result, the official rate averaged N7,3916/US$1 in 1989. With the large and growing premium between the parallel and the official exchange market, the official exchange rate became progressively overvalued, thus putting increased pressure on the official exchange rate. The rete depreciated in 1993 to N22.0468/US$1 (Central Bank of Nigeria: Statistical Bulletin, (various issues)). Prior to the introduction of Inter-Bank Foreign Exchange Market (IFEM) in 1999, the average exchange rate at the AFEM was N91.80/US$1for the period January to October 1999. After the commencement of IFEM operations on October 25, 1999, the exchange rate depreciated to N97.42/US$1 in December, 1999, It further depreciated to N111.94/US$1 in 2001. In order to stem the depletion of external reserves and realign the naira exchange rate, the Dutch Auction System (DAS) of foreign exchange management was re-introduced in July 2002 and by end-December 2002 the official exchange rate depreciated to N120.97/US$1. In 2005, the foreign exchange market received a boost as the exchange rate appreciated to N132.2/US$1 in 2005 and N128.65/US$1 in 2006. In 2007, the average exchange rate appreciates to N125.83/US$1. Subsequently, the average monthly exchange rate has consistently appreciated. From N116.48/US$1 in December 2007, to N148.56/US$1 in December 2010, N196.49/US$1 in December 2015, N306.42/US$1 in December 2018, N306.45/US$1 in December 2019, N379.50/US$1 in December 2020, and N411.13/US$1 in December 2021 (Central Bank of Nigeria: Statistical Bulletin, (various issues)).

The CBN has over the year through its various foreign exchange policies and market interventions worked on realigning the exchange rate of the naira, conserving foreign exchange, enhancing the market transparency and curbing capital flight. In July 2002, the CBN re-introduced the Dutch Auction System (DAS). The Wholesale Dutch Auction System (WDAS) was introduced in February 2006. Other complementary policy measures were introduced including: Special foreign exchange auction offered to Deposit Money Banks, Direct sales of foreign exchange to licensed Bureaux De Change operators effective April 2006, increase in Basic Travelling Allowance, from US$2,500 biannually to US$5,000 per quarter and Personal Travelling Allowance from US$2,000 biannually to US$4,000 per quarter (Mordi, et al., 2010).

In spite of the perennial efforts of the CBN to ensure a stable foreign exchange market, the naira exchange rate has been volatile. Knowledge about exchange rates will be an added advantage to handle the large-scale exports and imports industries more effectively and to develop the most prudent monetary and fiscal policies for the country (Weerasinghe and Rathnayake, 2006). Nigerian foreign exchange market is made up of two principal segments, the official and the parallel segments of the market. The focus of this study is on the official segment of the Nigeria foreign exchange market.

Many researchers in modeling of foreign exchange rate of major currencies adopted the Autoregressive Integrated Moving Average (ARIMA) process for estimation of univariate time series of the currencies. Prominent amongst these are Ayekple, et al., (2015), Urrutia, et al. (2015), Ahmed and Keya (2019), Akhtar, et al., (2022), Weerasinghe and Rathnayake, (2006), Nwaigwe, et al., (2018), and Sheng, et al., (2021). Hence, ARIMA process is predominantly applied in practice for univariate time series modeling.

Ayekple, et al., (2015), studied the relative efficiency of Autoregressive Integrated Moving Average (ARIMA) and Random walk model for predicting the dynamics of the exchange rate (using mid-rate data) of the Ghana cedi to the US dollar over a 10year 2months period. They found modest differences between these two models based on the out-of-sample forecast. Forecast values shows that the exchange rate of the Ghana cedi to the American dollar will increase continuously in the next three (3) years. On the other hand, Andreou, et al., (2000), used the theory of chaos and nonlinear dynamical systems, to perform a time-series analysis on four major currencies against the Greek Drachma. Also, Kamble and Honrao, (2014), modelled the foreign exchange rate volatility of Indian rupee against US Dollar using GARCH (1,1) model. The empirical analysis was carried out for the period between Jan 2011 and Sep 2013. Other studies like Hanna (1991), were conducted to assess the relative contributions of the determinants of exchange rate of major currencies.

The COVID-19 pandemic induced chaos and turbulence in financial markets (Samet Gunay 2020). This cross continental pandemic came with its attendant disruption to the socio, cultural and economic activities of the whole world. Businesses were paralyzed and social and cultural life were greatly brought to a halt. Many studies in literature considered the event of COVID-19, its effect and on the foreign exchange rate of the major world currencies. Example are, Aslam et al., (2020), Sikarwar (2021), Samet Gunay (2020), Xu and Lien (2022), Hofmann et al., (2020), Wei et al., (2020), Hoshikawa and Yoshimi (2021), Beckmann and Czudaj (2022), and Fang and Zhang (2021). As expected, virtually all of these studies reported negative impacts of the COVID-19 event on the foreign exchange rates of the currencies considered.

In this study, we used a secondary data on the Naira/US Dollar exchange rate obtained from the CBN Statistical Bulletin. The data covers the period January 2002 to June 2022. Taking into account the COVID-19 pandemic event, we modeled a time series ARIMA processes of the monthly average central official exchange rate of the Naira to the US Dollar over the following periods of time: January 2002 to June 2019 representing the pre-COVID-19 pandemic period, July 2019 to June 2022 representing the COVID-19 pandemic period, and January 2002 to June 2022 representing the combination of both the pre COVID-19 pandemic and the COVID-19 pandemic periods. This is with a view to evaluating the impact of the COVID-19 shock on the generation mechanism of the Naira/US Dollar exchange rate.

The rest of the paper is organized into 3 sections. Section 2 contains the Materials and Methods of the study. The findings from our study are presented in Section 3 while Section 4 presents the Conclusions.

2. Materials and Methods

2.1 Theoretical Framework

Let Y_t represent the Naira/USDollar exchange rate at time t. Y_t follows an autoregressive integrated moving average ARIMA (*p, d, q*) process if it is modeled as

$$Y_t = \theta + \alpha_1 Y_{t-1} + \beta_0 u_t + \beta_1 u_{t-1} \quad (1)$$

where, *p*, which is equal to 1 in equation 1, denotes the number of autoregressive terms; d is the number of times the series has to be differenced before it becomes stationary; *q*, which is equal to 1 in equation 1, denotes the number of moving average terms; θ represents a constant term and $u \sim N(0,\ \sigma^2)$

The general ARIMA(*p, d, q*) process is

$$A(L)Y_t = B(L)u_t \quad (2)$$

where

$$A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \alpha_3 L^3 - \ldots\ldots\ldots - \alpha_p L^p \quad (3)$$

$$B(L) = 1 - \beta_1 L - \beta_2 L^2 - \beta_3 L^3 - \ldots\ldots\ldots - \beta_q L^q \quad (4)$$

Stationarity requires the roots of A(L) to lie outside the unit root circle, and inevitability places the same condition on the roots of B(L). Given these conditions, the ARIMA(*p, d, q*) process may alternatively be expressed as a pure AR process of infinite order or as a pure MA process of infinite order namely,

$$B^{-1}(L)A(L)Y_t = u_t \quad or \quad Y_t = A^{-1}(L)B(L)u_t \quad (5)$$

2.2 Empirical Strategy

The generics of the ARIMA model are Autoregressive model (AR), the Moving Average (MA) and the process being integrated of order d representing the order of the differencing effected on the series. For non-stationary series, we used differencing to transform the series to stationarity. The classical Box-Jenkins methodology shall be used to investigate the stationarity of our series. We used the sample autocorrelation function (SACF) and sample partial autocorrelation function (SPACF) to identify a Box-Jenkins model which adequately describes the stationary time series, achieved by implementing the Box-Jenkins model selection methods. We analyzed the times series data of the exchange rate of the Naira to the US Dollar in order to investigate the underlying relationships and trend between the two currencies and then based on the analysis build an appropriate model to forecast future values of the series.

This study was conducted on the time series of the Nigeria Naira/US Dollar Exchange Rates for the period January 2002 to June 2022. The series consist of monthly central Exchange Rate for the period under review. Our data was obtained from the Central Bank of Nigeria website. We used the Box-Jenkins Model Selection methodology on Naira/USDollar secondary data set for the period under review with due consideration of the COVID-19 pandemic event as highlighted above. The Box-Jenkins Model Selection methodology involves: 1. Model Identification **-** The identification process practically will result in identification of one or more competing ARIMA models. These competing models are to be subjected to model selection criteria to enable us settle with the overall best that will be appropriate for forecasting purposes. 2. Estimation and Model Selection **-** The model is estimated using the least square method and further evaluated for selection of the best among the competing models using: the significance test of the parameters, Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC) Sigma SQ, and the Log Likelihood of the estimation results. 3. Diagnostic Checks **-** Evaluation of the goodness of fit of the selected models using graphical analysis of the residuals, Portmanteau test and Unit Root Circle test (for covariance stationarity of AR parameters and invertibilty of MA parameters). 4. Forecasting **-** We used the best models from diagnostic tests to forecast future values of the Nigeria inflation rate for each of the three scenarios.

3. Results and Discussion

3.1 Trend Analysis

The time plots of the three periods under consideration are presented in Figures 1 to 3.

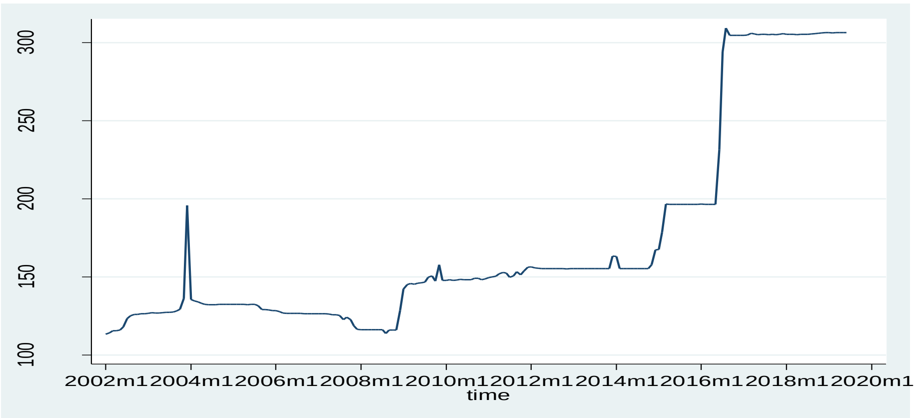

Figure 1: Time Plot for the Pre COVID-19 Series (January 2002 – June 2019)

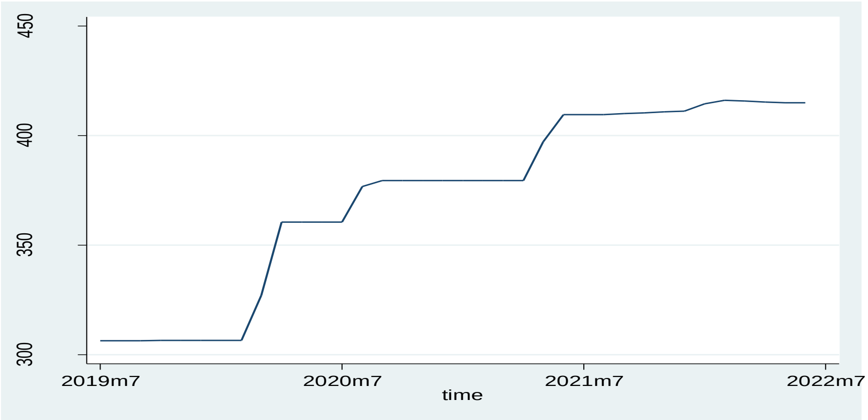

Figure 2: Time Plot for the COVID-19 Period Series (July 2019 – June 2022)

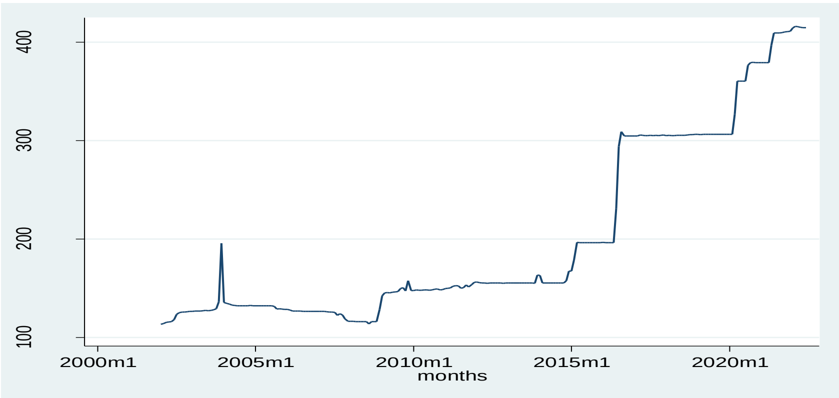

Figure 3: Time Plot for the Combined Period Series (January 2002 – June 2022)

3.2 ACF and PACF Plots for Level Data

Figure 4 to 9 presents Autocorrelation Function and Partial Autocorrelation Function plots of the level data for the Naira/USDollar exchange series of the three scenarios under consideration.

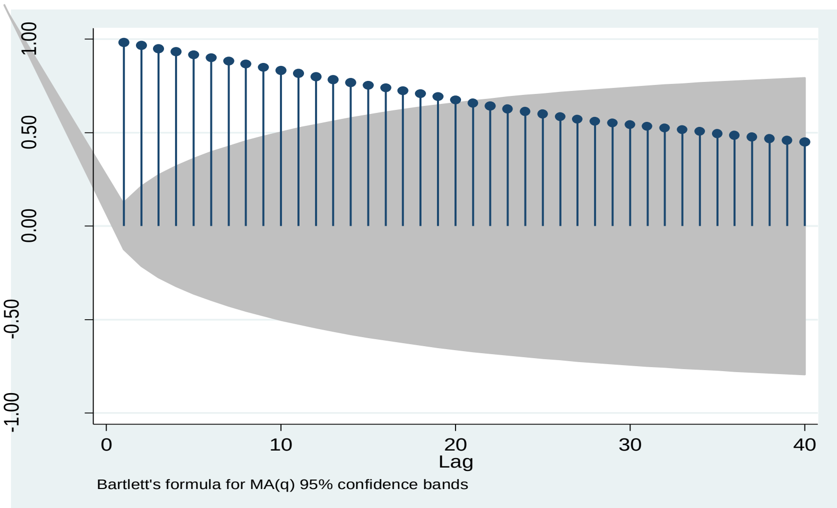

Figure 4: ACF Plot of Level Data for Pre-Covid-19 Period Series

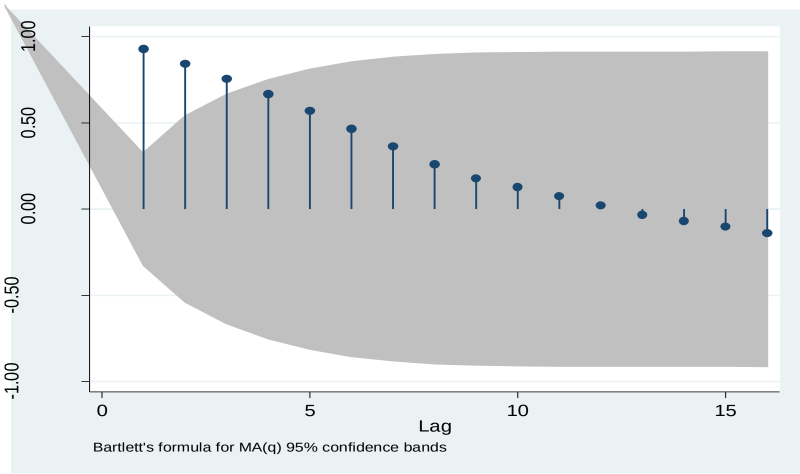

Figure 5: ACF Plot of Level Data for Covid-19 Period Series

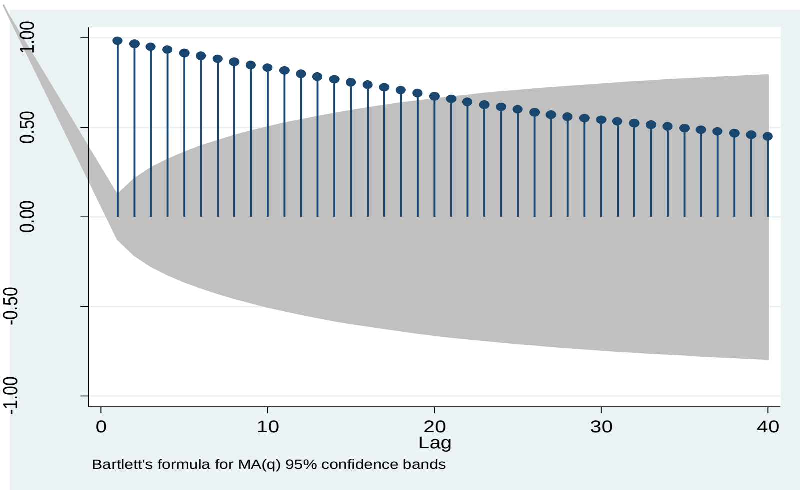

Figure 6: ACF Plot of Level Data for Combined Period Series

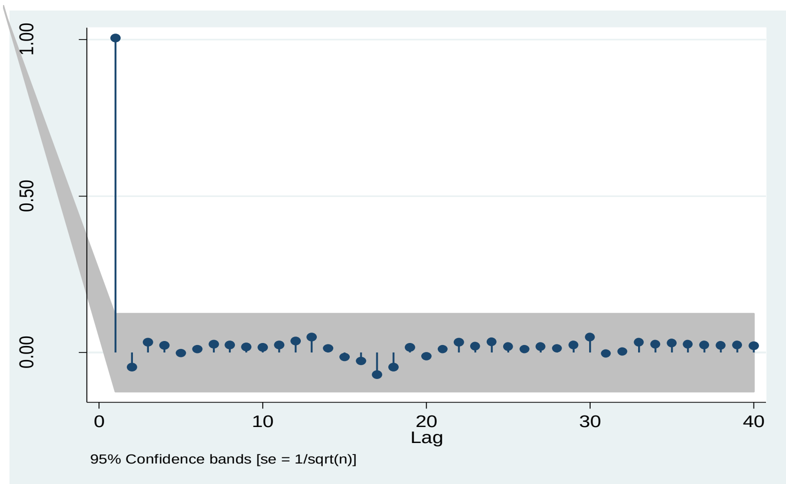

Figure 7: PACF Plot of Level data for Pre-Covid-19 Period Series

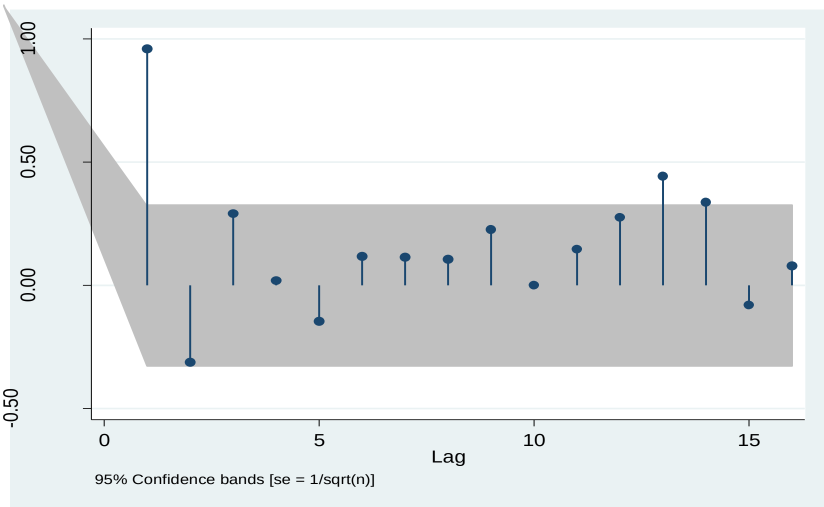

Figure 8: PACF Plot of Level Data Covid-19 Period Series

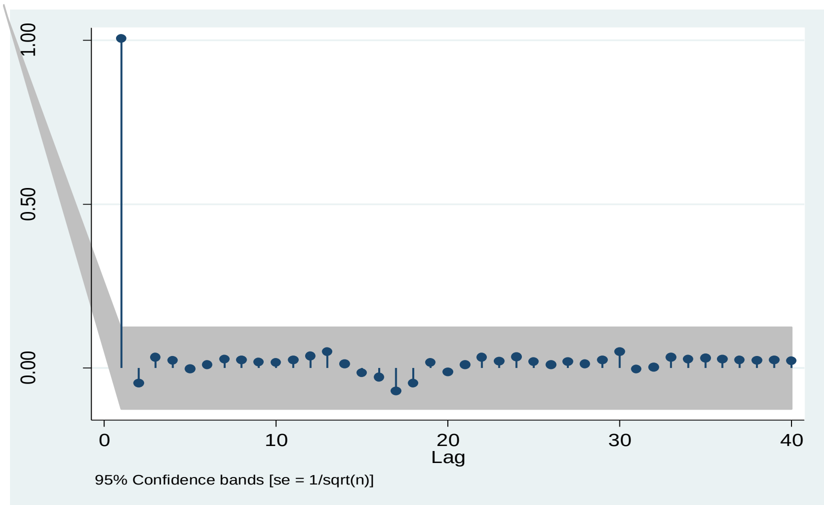

Figure 9: PAC Plot of Level for Combined Period Series

As can be seen from the time plot, ACF and PAC plots shown in Figures 1 to 9, the three series are nonstationary. This position is also confirmed by results obtained from Dickey Fuller and Phillip Perron test we conducted on the level data as presented in Table 1.

Table 1: Result of Dickey Fuller and Phillip Perron Stationarity Test on Level Data

SERIES	**P-values**		**Remarks**
	Dickey Fuller Test	**Phillip Perron Test**	
Pre COVID-19 Period	0.9628	0.9638	Non Stationary
COVID-19 Period	0.6554	0.6595	Non Stationary
Combined Period	0.9936	0.9934	Non Stationary

As can be observed in Table 1, the p-values of the three series under both Dickey Fuller and Phillip Perron tests are greater than 0.05, this suggests that the level data of the series are non-stationary at 5% level of significance and are to be differenced appropriately.

3.3 Stationarity Condition and Model Identification

Pre COVID-19 Period Series: For the Pre COVID-19 period series, we achieved stationarity at the 2nd difference. Figure 10 highlights the time plot of the 2nd difference of the Pre COVID-19 data, while Figures 11 and 12 highlights the autocorrelation (AC) and partial autocorrelation (PAC) graphs of the series respectively.

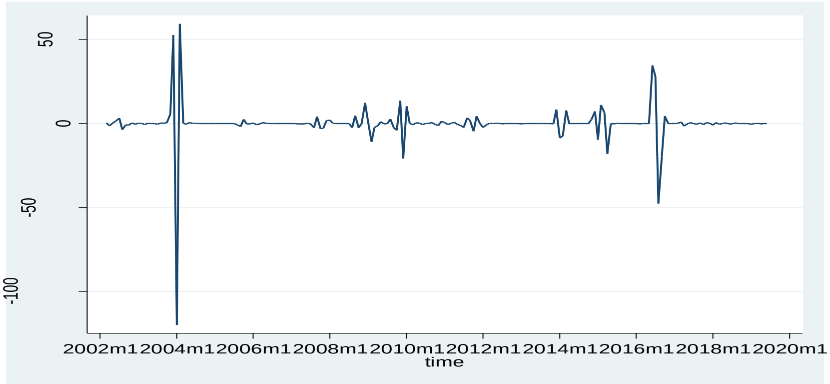

Figure 10: The Time Plot of the 2nd Difference of Pre COVID-19 Period Series

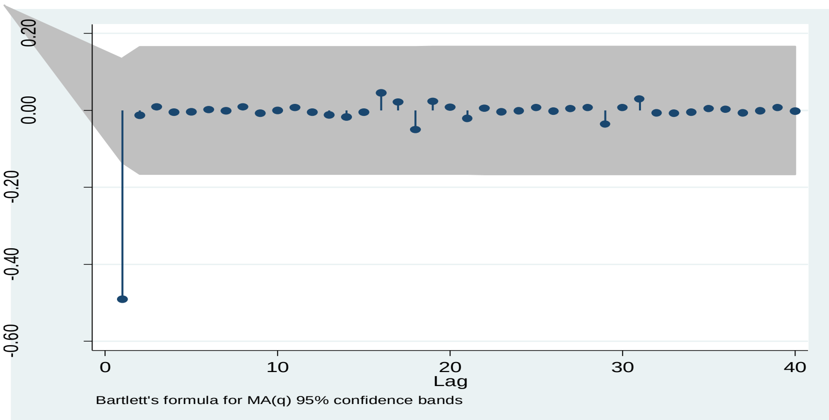

Figure 11: The AC graph of the 2nd Difference of Pre COVID-19 Period Series

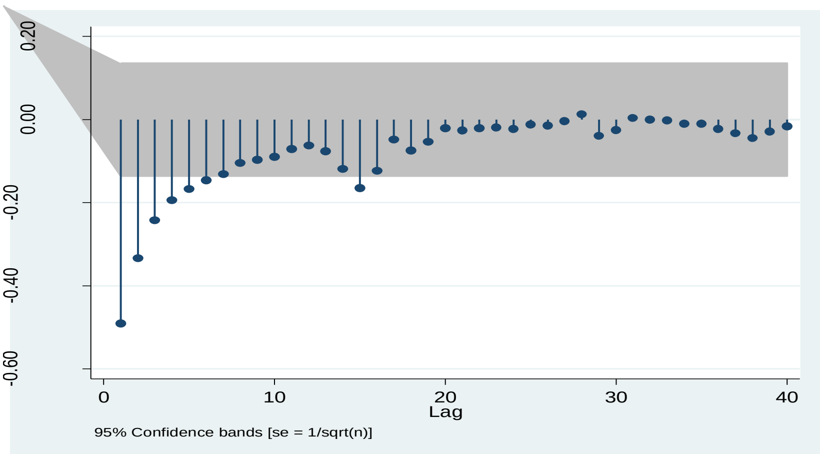

Figure 12: The PAC graph of the 2nd Difference of Pre COVID-19 Period Series

An evaluation of the time plot in Figure 10 suggests stationarity of the 2nd differenced series. Similarly, our evaluation of the AC and PAC graphs in Figures 11 and 12 suggests the consideration of

ARIMA(1,2,1), ARIMA(2,2,1) and ARIMA(3,2,1) for model selection criteria.

COVID-19 Period Series: We achieved stationarity for the COVID-19 period series at the 3rd difference. This position is also supported by Dickey Fuller and Phillip Perron tests result we obtained. Figure 13 highlights the time plot of the 3rd difference of the COVID-19 data indicating that the series is stationary at 3rd difference, while Figures 14 and 15 highlights the autocorrelation (AC) graph and partial autocorrelation (PAC) graphs of the series respectively.

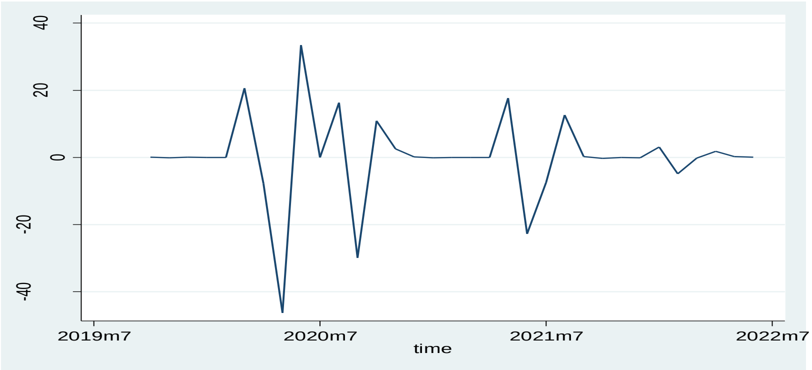

Figure 13: The Time Plot of the 3rd Difference of COVID-19 Period Series

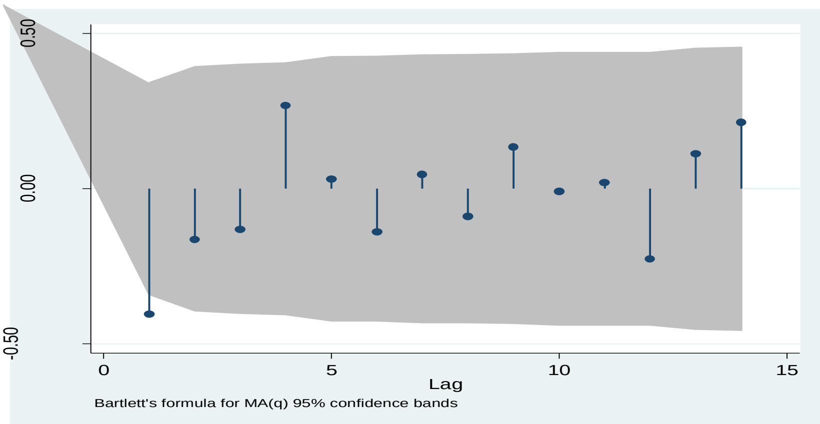

Figure 14: The AC graph of the 3rd Difference of COVID-19 Period Series

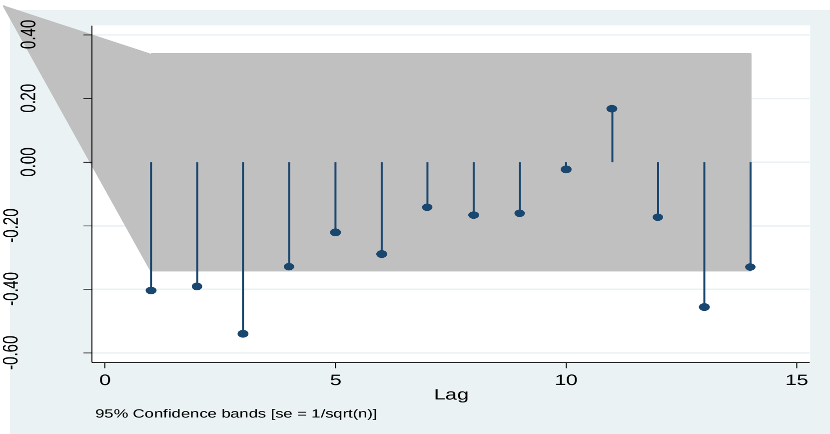

Figure 15: The PAC graph of the 3rd Difference of COVID-19 Period Series

Evaluation of the AC and PAC graphs in figures 14 and 15, as is the case with the Pre COVID-19 series, suggests that we should subject ARIMA(1,3,1), ARIMA(2,3,1) and ARIMA(3,3,1) to model selection criteria.

Combined Period Series: For this series, as is the case with Pre COVID-19 series, we achieved stationarity at 2nd difference. Figure 16 highlighting the time plot of the 2nd difference of the Combined Period data as well as Dickey Fuller and Phillip Perron tests confirmed this position, Figures 17 and 18 highlights the autocorrelation (AC) graph and partial autocorrelation (PAC) graphs of the series respectively.

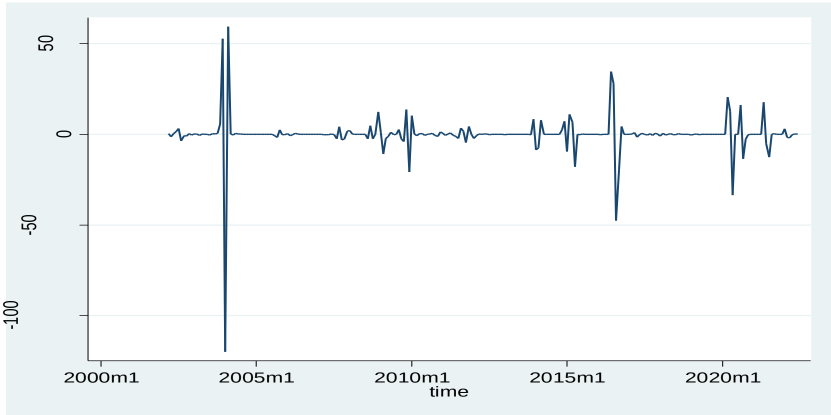

Figure 16: The Time Plot of the 2nd Difference of the Combined Period Series

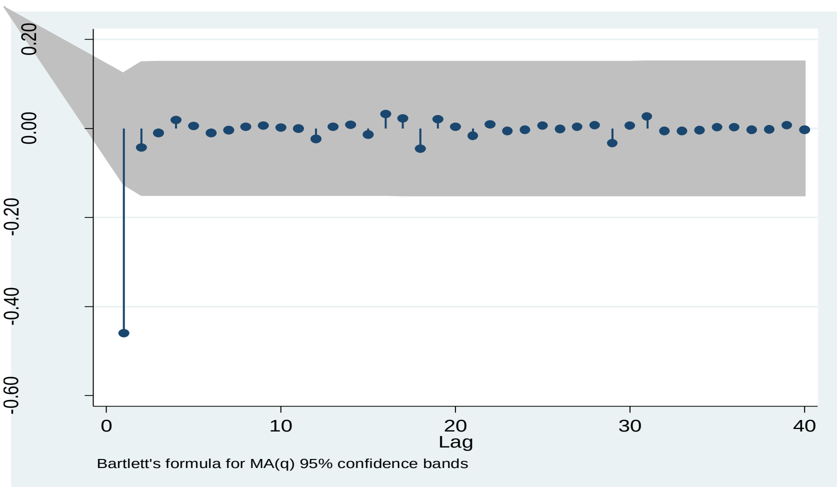

Figure 17: The AC graph of the 2nd Difference of the Combined Period Series

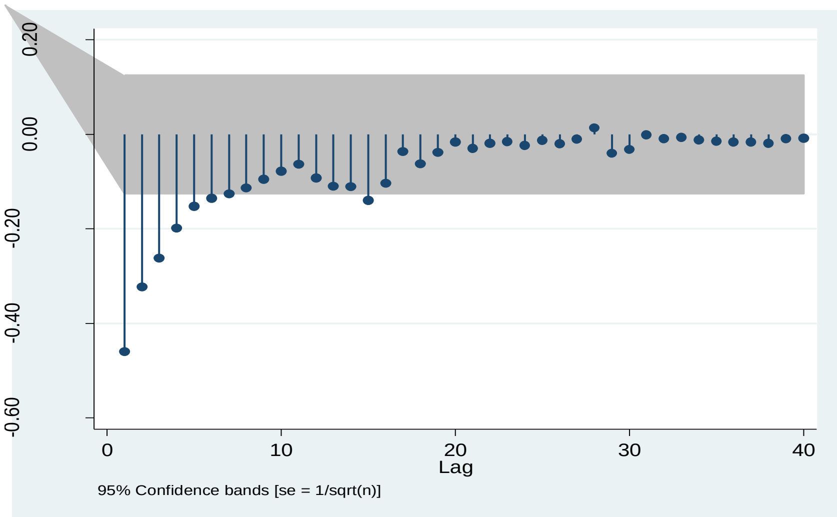

Figure 18: The PAC graph of the 2nd Difference of the Combined Period Series

Like we did in the case of Pre COVID-19 series, a review of the AC and PAC graphs of the 2nd differenced Combined period series suggests the adoption of ARIMA(1,2,1), ARIMA(2,2,1) and ARIMA(3,2,1) for model selection process.

3.4 ARIMA Estimation and Model Selection

As highlighted above, the suggested ARIMA models for each of the three series were estimated and the estimation results obtained were subjected to appropriate model selection criterion to enable us elect the best model for each series. The summary of our model selection procedure is presented in Tables 2 to 3. In Tables 2 to 4, the first criterion relates to analysis of the significance of the coefficients of AR, AM, and constant components of the competing models. For each model subjected to selection analysis, the number of significant coefficients is reflected as a fraction of the total number of terms in the model. Sigma SQ, the estimate of the error variance is obtained from the regression estimation result, the smaller the value of Sigma SQ the better the model for selection. For Log Likelihood value, also obtained from the regression estimation results, the bigger the better the model for selection. Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were also obtained from the regression estimation results for the competing models. For AIC and BIC, the smaller the better the model for selection.

Table 2: Model Selection Summary for the Pre COVID-19 Period Series (January 2002 – June 2019)

CRITERIA	MODEL A ARIMA(1,2,1)	MODEL B ARIMA(2,2,1)	MODEL C ARIMA(3,2,1)	BEST MODEL
Significance of coefficients (C, AR, MA)	1/2	1/3	1/4	A
SIGMA SQ	8.18218	8.1215	8.1833	B
Log Likelihood	-734.4578	-734.4499	-734.4496	C
AIC	1474.916	1476.90	1478.889	A
BIC	1484.928	1490.25	1495.587	A
OVERALL BEST MODEL				**MODEL A ARIMA (1,2,1)**

Note: AIC stands for Akaike Information Criteria and BIC is Bayesian Information Criteria

Table 3: Model Selection Summary for COVID-19 Period Series (July 2019 – June 2022)

CRITERIA	MODEL A ARIMA(1,3,1)	MODEL B ARIMA(2,3,1)	MODEL C ARIMA(3,3,1)	BEST MODEL
Significance of coefficients (C, AR, MA)	1/2	2/3	2/4	B
SIGMA SQ	8.9182	8.2264	7.5586	C
Log Likelihood	-120.9049	-118.6696	-116.3846	C
AIC	245.8098	243.3393	242.7691	C
BIC	248.8028	247.8288	250.2517	B
OVERALL BEST MODEL				**MODEL C ARIMA (3,3,1)**

Note: AIC stands for Akaike Information Criteria and BIC is Bayesian Information Criteria

Table 4: Model Selection Summary for the Combined Period Series (January 2002 – June 2022)

CRITERIA	MODEL A ARIMA(1,2,1)	MODEL B ARIMA(2,2,1)	MODEL C ARIMA(3,2,1)	BEST MODEL
Significance of coefficients (C, AR, MA)	2/2	2/3	2/4	A
SIGMA SQ	8.0969	7.9886	8.0926	B
Log Likelihood	-858.36	-858.2	-858.22	C
AIC	1722.72	1724.52	1726.44	A
BIC	1733.21	1738.51	1743.93	A
OVERALL BEST MODEL				**MODEL A ARIMA (1,2,1)**

Note: AIC stands for Akaike Information Criteria and BIC is Bayesian Information Criteria

Based on Tables 2 to 4, the selected model for the Pre-COVID-19 pandemic period series is ARIMA(1,2,1), that for the COVID-19 period series is ARIMA(3,3,1), while the selected model for the Combined period series is ARIMA(1,2,1). The estimated ARIMA models of the selected model for the three scenarios are presented in Tables 5 – 7.

Table 5: Estimated ARIMA (1,2,1) Model for the Pre COVID-19 Period Series

```
ARIMA regression

Sample:  2002m3 - 2019m6                        Number of obs     =       208
                                                Wald chi2(2)      =   2249.80
Log likelihood = -734.4578                      Prob > chi2       =    0.0000

------------------------------------------------------------------------------
             |                 OPG
  D2.avgrate |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .0095409   .0271075     0.35   0.725    -.0435887    .0626706
             |
          ma |
         L1. |  -.9928819   .0354687   -27.99   0.000    -1.062399   -.9233644
-------------+----------------------------------------------------------------
      /sigma |   8.182177   .0885943    92.36   0.000     8.008536    8.355819
------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.
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Table 6: Estimated ARIMA (3,3,1) Model for the COVID-19 Period Series

ARIMA regression

Sample: 2019m10 - 2022m6 — Number of obs = 33; Wald chi2(4) = 21.28; Prob > chi2 = 0.0003

Log likelihood = -116.3846

D3.avgrate	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf. Interval]	
ARMA						
ar						
L1.	-.3206878	.1744327	-1.84	0.066	-.6625696	.0211939
L2.	-.4259628	.136939	-3.11	0.002	-.6943583	-.1575672
L3.	-.3478217	.3412149	-1.02	0.308	-1.016591	.3209472
ma						
L1.	-.9999892	2513.975	-0.00	1.000	-4928.301	4926.301
/sigma	7.558586	9500.862	0.00	0.500	0	18628.91

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

Table 7: Estimated ARIMA (1,2,1) Model for the Combined Period Series

ARIMA regression

Sample: 2002m3 - 2022m6 — Number of obs = 244; Wald chi2(2) = 4294.82; Prob > chi2 = 0.0000

Log likelihood = -858.357

D2.avgrate	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf. Interval]	
ARMA						
ar						
L1.	.0505097	.0247611	2.04	0.041	.0019789	.0990405
ma						
L1.	-.9877882	.0234863	-42.06	0.000	-1.033821	-.9417559
/sigma	8.096918	.0833058	97.20	0.000	7.933642	8.260195

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

For the Pre-COVID-19 period series, as shown in Table 5, ARIMA (1,2,1) without drift was estimated. While the coefficient of the 1st lag of the AR component is 0.0095409 with a p-value of 0.725 suggesting insignificant at 5% level, that of the 1st lag of the MA component is -0.9928819 with a p-value of 0. 000. For COVID-19 period series, as shown in Table 6, only the coefficient of the 2nd lag of the AR component is significant at 5% level. All other coefficients are insignificant. Finally, for the Combined period series, as shown in Table 7, the 1st lags of the AR and MA component are both significant at 5% level.

3.5 Diagnostic Analysis

The summary of the diagnostic analysis we conducted on the residuals of the three models (Pre-COVID-19 period model, COVID-19 period model and the Combined period model) as obtained from Stata output, is presented in Table 8. Table 8 contains the mean, standard deviation, minimum and maximum statistics of the residuals. The table also presents the portmanteau test Q statistics, portmanteau test p −values, stability conditions of AR parameters as well as invertibility conditions of MA parameters. Diagnostics are presented for the three selected models in the succeeding sections. For goodness of fit of the selected ARIMA models, the models were analyzed for stability. First, we checked if the residuals of the models are white noise using the portmanteau test. Secondly, we checked if the ARMA process is covariance stationary in which case, the AR roots lie inside the unit circle. Finally, we checked if the estimated ARMA process is invertible in which case, the MA roots lie inside the unit circle.

Table 8: Summary of Diagnostic Analysis

	Pre COVID Period Model	**COVID Period Model**	**COMBINED Period Model**
Observations	208	33	244
Mean	0.3282	-0.7740	0.3975
Standard Deviation	8.2814	8.2061	8.1694
Minimum	-64.3956	-27.3535	-66.8284
Maximum	61.6555	20.6164	60.0354
Portmanteau (Q) Stat	6.5618	10.1089	6.9614
Portmanteau Test p-Value	1.0000	0.7542	1.0000
Stability Condition of AR Parameters	SATISFIED	SATISFIED	SATISFIED
Invertibility Condition of MA Parameters	SATISFIED	SATISFIED	SATISFIED

3.6.1 Pre COVID-19 Period Diagnostics

The mean of the residuals was found to be 0.3281756 (Table 8). As can be seen in the residuals plot shown in Figure 19 all values wriggle around the mean line with the exceptions of values around the years 2004 and 2017.

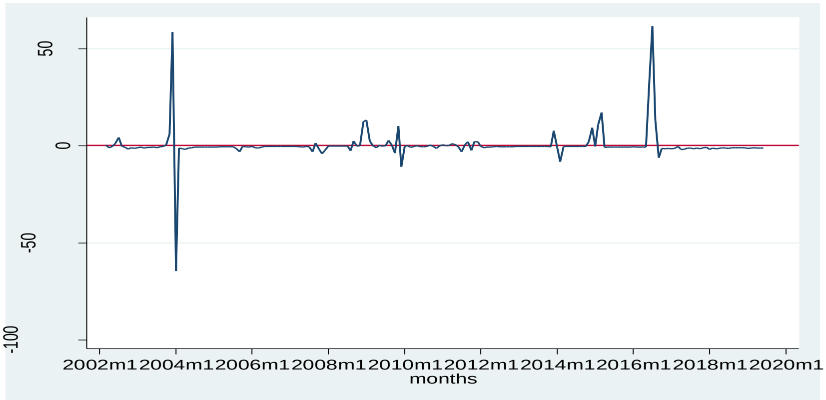

Figure 19: Residual Plot for the Pre COVID-19 Period Series

We further evaluated the residuals with Portmanteau test. The null hypothesis for Portmanteau test is that the residuals are white noise. We reject the null hypothesis if the p −value < 0.05. From table 8, portmanteau test p-values of 1.0000 is greater than 0.05 so we cannot reject the null hypothesis. We therefore conclude that the residuals are white noise. Hence by graphical analysis as well as portmanteau test, the Pre COVID-19 period series residuals are white noise. Figure 20 presents the Unit Roots Circle plot for Pre COVID-19 series

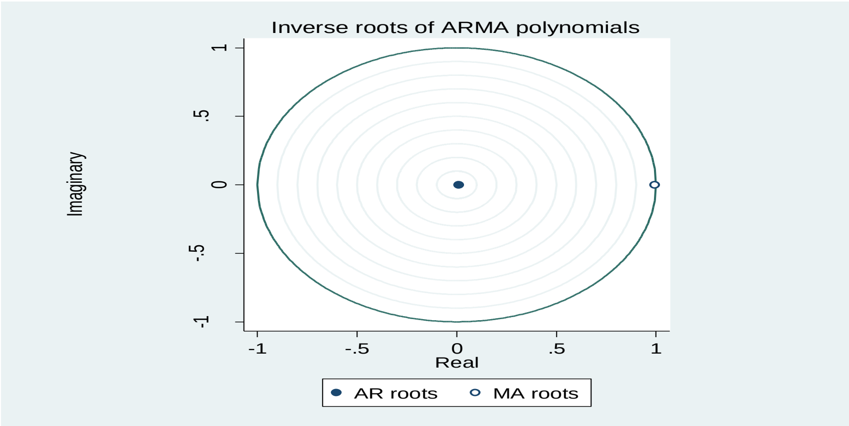

Figure 20: Unit Root Circle for the Pre COVID-19 Period Series

With Figure 20, we evaluated the estimated ARMA process for covariance stationarity with the requirement that all AR roots should lie within the unit circle. The stability condition was satisfied as all AR roots lie inside the unit circle. Also we checked whether or not the estimated ARMA process is invertible with the requirement that all MA roots should lie inside the unit circle. Figure 20 confirms that all MA parameters satisfy inevitability condition. Hence from our diagnostic checks, the estimated process for the Pre COVID period series is stable and is fit for forecasting.

3.5.2 COVID-19 Period Diagnostics

The mean of the residuals was found to be -0.7739516 (See Table 8). As can be seen in the residuals plot shown in Figure 21, all values wriggle around the mean line, although with an exception around the first quarter of the years 2020.

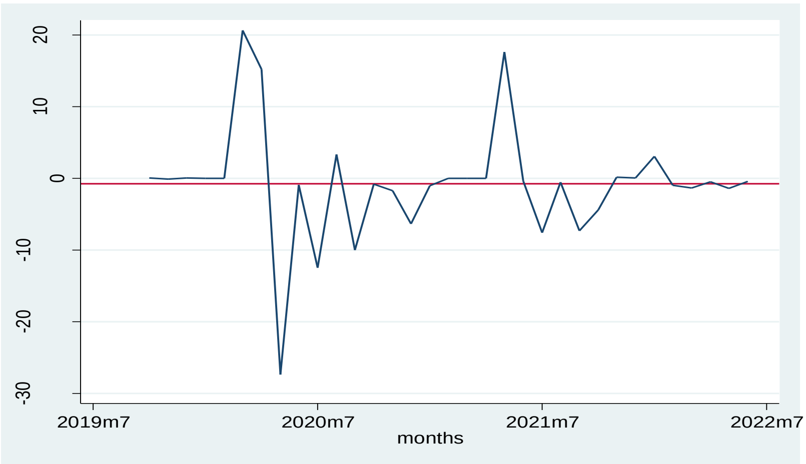

Figure 21: Residual Plot for the COVID-19 Period Series

We further evaluated the residuals with Portmanteau test. The null hypothesis for the portmanteau test is that the residuals are white noise. We reject the null hypothesis if the p −value < 0.05. Portmanteau test p-value of 0.7542 is greater than 0.05 so we cannot reject the null hypothesis. We therefore conclude that the residuals are white noise. Hence by graphical analysis as well as portmanteau test, the COVID-19 period series residuals are white noise.

Further, we analyzed the estimated ARMA process for covariance stationarity with the requirement that all AR roots should lie within the unit circle. The stability condition was satisfied as shown in figure 22 as all AR roots are inside the unit circle. Also, we checked whether or not the estimated ARMA process is invertible with the requirement that all MA roots should lie inside the unit circle. Figure 22, the unit root circle for the COVID-19 period series, confirms that the MA parameter satisfy inevitability condition. Hence, the process for COVID period series turned out is also stable and good for forecasting.

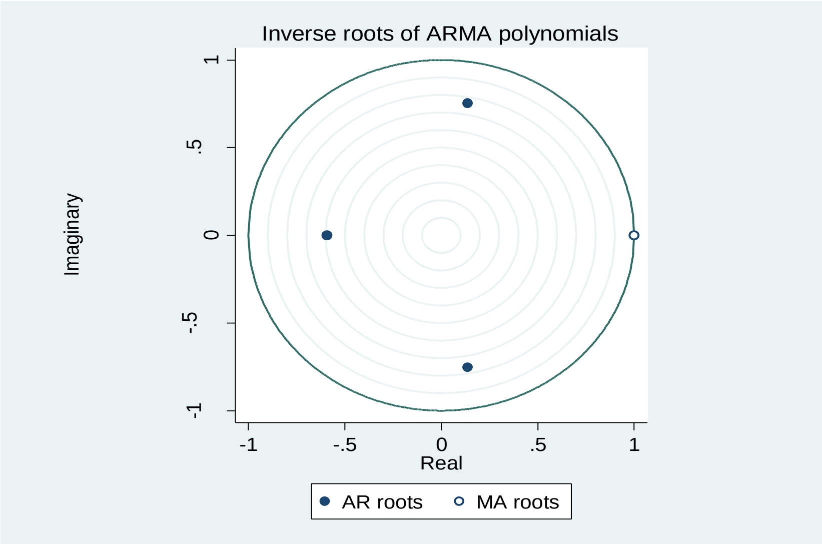

Figure 22: Unit Root Circle for the COVID-19 Period Series

3.5.3 COMBINED Period Diagnostics

The mean of the residuals was found to be 0.3975 (See Table 8). As can be seen in the residuals plot shown in Figure 23, all values wriggle around the mean line with the exceptions of values around the years 2004 and 2017.

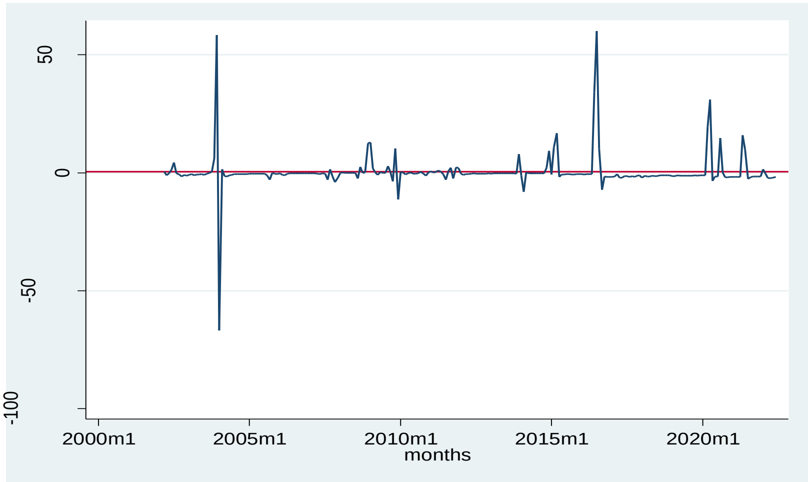

Figure 23: Residual Plot for the Combined Period Series

We further evaluated the residuals with Portmanteau test (Table 8). The null hypothesis for the portmanteau test is that the residuals are white noise. We reject the null hypothesis if the p −value < 0.05. Portmanteau test p −value of 1.0000 is greater than 0.05 so we cannot reject the null hypothesis. We therefore conclude that the residuals are white noise. Hence by graphical analysis as well as portmanteau test, the COMBINED period series residuals are also white noise.

Further, we analyzed the estimated ARMA process for covariance stationarity with the requirement that all AR roots should lie within the unit circle. The stability condition was satisfied as shown in figure 24, all AR roots are inside the unit circle. Also we checked whether or not the estimated ARMA process is invertible with the requirement that all MA roots should lie inside the unit circle. Figure 24 confirms that the MA parameter satisfy inevitability condition. Therefore, process for the COMBINED period series also turned out to be stable and fit for forecasting.

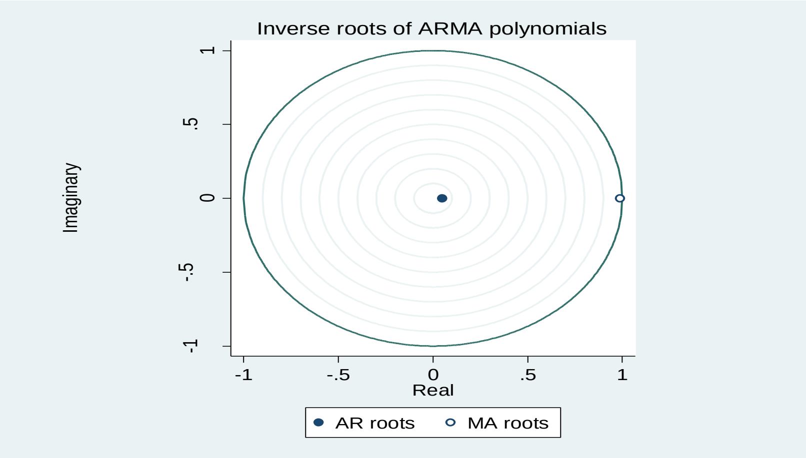

Figure 24: Unit Root Circle for the Combined Period Series

In summary, diagnostic analysis we conducted on the residuals of the selected models; graphical residual analysis, portmanteau test, covariance stationarity test and invertibility tests, all confirmed that the estimated ARIMA processes for the three scenarios we studied, (Pre COVID-19 period series, COVID-19 period series and COMBINED period series), stable. Hence, they are fit and proper for forecasting.

3.6 Forecasting

3.6.1 Pre COVID-19 Series

With the estimated ARIMA (1,2,1) process for the Pre COVID-19 period series, we did a 10-month forecast of the Naira/ US Dollar monthly average exchange rates. This is presented graphically in Figure 25. From Figure 25, it is apparent that the fitted model appropriately represents the data generation mechanism of the Naira/US Dollar Exchange Rate. The forecast suggests an onward depreciation of the Naira beyond June 2019.

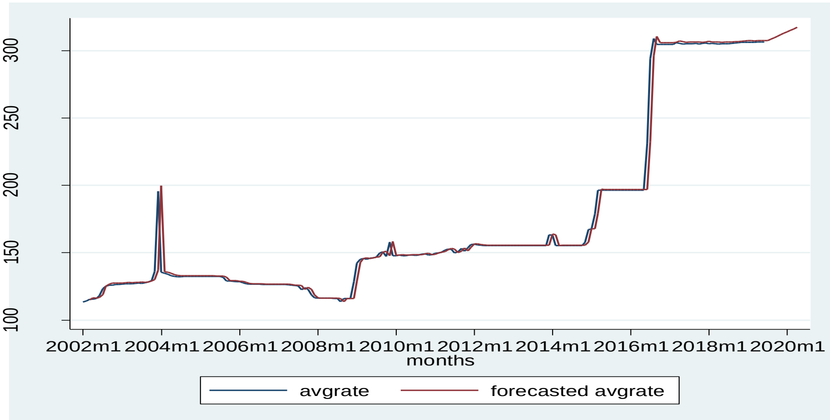

Figure 25: Forecast Plot for Pre Covid-19 Period Series

3.6.2 COVID-19 Period Series

On the basis of the estimated ARIMA (3,3,1) process for the COVID-19 period series, we also did a 10-month forecast of the Naira/ US Dollar monthly average exchange rates. This is presented graphically in Figure 26. Although the sample size of this scenario is small, Figure 26, suggest that the fitted model appears to follow the data generation mechanism of the Naira/US Dollar Exchange Rate. This model, having cuts off the Pre COVID-19 history of the Naira/US Dollar Exchange Rates, produced a forecast that suggests slight appreciation of the Naira against US Dollar post June 2022.

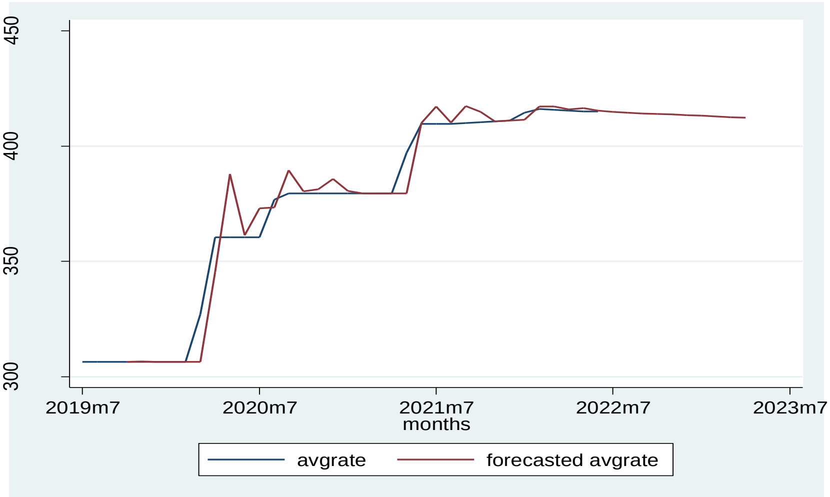

Figure 26: Forecast Plot for Covid-19 Period Series

3.6.3 Combined Period Series

Using the estimated ARIMA (1,2,1) process for the COMBINED period series, we finally did a 10-month forecast of the Naira/ US Dollar monthly average exchange rates. This is presented graphically in Figure 27. From Figure 27, the fitted model appropriately depicts the data generation mechanism of the Naira/US Dollar Exchange Rate. The forecast suggests an onward depreciation of the Naira beyond June 2019.

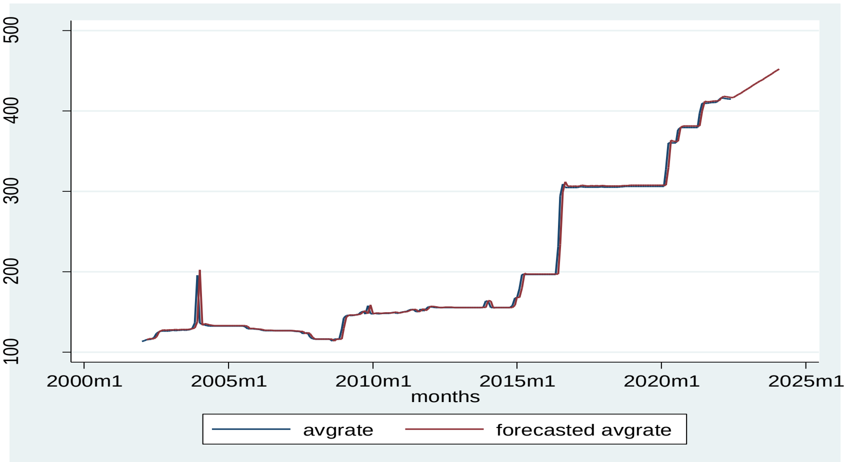

Figure 27: Forecast Plot for Combined Period Series

Tables 9 presents out-of-sample forecast of the models estimated for the pre COVID-19 period series, COVID-19 period series and Combined period series. The table provides a comparison of the forecast values of Naira/US Dollar exchange rates with the actual values. Also, the mean absolute error measurements were computed for the three scenarios under consideration.

Table 9: Four-Month's Out-of-Sample Forecast of Naira/US Dollar Exchange Rates

Pre COVID-19 Period Series				**COVID-19 Period Series**				**Combined Period Series**			
Month	**Actual Values**	**Forecast Values**	**Error**	**Month**	**Actual Values**	**Forecast Values**	**Error**	**Month**	**Actual Values**	**Forecast Values**	**Error**
2019-M7	306.44	307.53	-1.10	2022-M7	415.11	414.83	0.28	2022-M7	415.11	416.77	-1.66
2019-M8	306.43	308.63	-2.20	2022-M8	419.97	414.53	5.44	2022-M8	419.97	418.63	1.34
2019-M9	306.42	309.72	-3.31	2022-M9	428.75	414.21	14.54	2022-M9	428.75	420.48	8.27
2019-M10	306.46	310.82	-4.36	2022-M10	436.12	413.98	22.14	2022-M10	436.12	422.34	13.78
		MAFE	1.10			MAFE	4.24			MAFE	2.51

Note: MAFE stands for Mean Absolute Error

4. Conclusions

We set out to build a univariate time series model of the Naira/USDollar exchange rate with a data covering the period January 2002 to June 2022. This period covers the event of the recent COVID-19 pandemic. In order to evaluate the impact of COVID-19 pandemic on the data generation mechanism of the Naira/USDollar exchange rate, we classified the study period into three (3) distinct sub-periods: The Pre COVID-19 period (January 2002 to June 2019), The COVID-19 period (July 2019 to June 2022) and the Combined period (January 2002 to June 2022). The Naira/USDollar exchange rate series was found to be non-stationary over the three periods. While we fitted ARIMA (1,2,1) for both the Pre COVID-19 and Combined periods data, we fitted ARIMA (3,3,1) for the COVID-19 period data. The order of integration of the COVID-19 data appears to be as a result of the smallness of the sample size as well the impact of the pandemic on the data generation mechanism during that period.

The three models were found to be well behaved and stable. The long span of the Pre COVID-19 and the Combined periods series appears to have contributed to the faster attainment of stationarity in their individual models than for the COVID-19 period data with a shorter span. Furthermore, while the estimated model for the COVID-19 period data yielded forecast values that suggests an appreciation of the Naira against the USDollar, the estimated models for the Pre-COVID-19 and Combined periods, respectively, produced forecast values that suggests continual depreciation of the Naira against the USDollar. Generally, our forecast results showed that the Naira appears to be on an upward trend against the USDollar. This trend has to be arrested by the Nigerian government with a view to ensuring the stability of the Naira and preventing economic instability in the country that may bring hardship to millions of Nigerians. We therefore, recommend that the Nigerian government should as a matter of urgency revise the fiscal and monetary policies that are currently in reign in the country which are responsible for the depreciation of the Naira.

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