

ARIMA forecast of Nigerian inflation rates with Covid-19 pandemic event in focus

Emmanuel Akingbola ODUNTAN

American University of Nigeria, Yola, Adamawa State, Nigeria
emmanuel.oduntan@aun.edu.ng

Olusola Osho AJAYI

American University of Nigeria, Yola, Adamawa State, Nigeria
osho.ajayi@aun.edu.ng

Abstract. *We modelled Nigeria Inflation rate using univariate time series methodology. A data set covering January 2003 to June 2022 was divided into two time periods, vis-à-vis, Pre COVID-19 pandemic event 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 data generation mechanism of Nigeria Inflation rate. The Inflation rate data was found to be non-stationary and was appropriately differenced to attain stationarity. ARIMA models were fitted for the two scenarios using Box Jenkins methodology. Appropriate diagnostic analysis was conducted and the estimated models were used for forecasting. While the estimated model for Pre COVID-19 event series yielded forecast rates that suggest an onward rise in Nigeria Inflation rate, the Combined period model yielded forecast rates that suggest a downward movement of the Inflation rate.*

Keywords: inflation rate, ARIMA, Covid-19 pandemic, Box-Jenkins methodology, forecasting.

JEL Classification: C22, C51, C52, C53.

1. Introduction

The roots of the rapidly developing inflationary regime in Nigeria is traceable to neglect of the real production sector as well as the preoccupation of the country with the distribution of oil revenue. The oil sector furnishes the Nigerian domestic economy essentially with financial infusions for fueling inflation and no real productive gains (Okongwu, 1986). It has been established in literature that rising inflation and higher interest rates have deleterious effect on investment. The problems of excess liquidity, money growth and inflation persist due to inconsistent fiscal activities of the government. There is, therefore, need for the Nigerian government to ensure sustainable fiscal policy management, low inflation rate, minimal exchange rate premium, and avoidable systemic banking crisis for economic development and social wellbeing of the people to be achieved (Iyoha and Itsed, 2002). The Nigeria Consumer Price Index (CPI) a measure of Inflation rate shows the movement in the cost-of-living. The CPI stood at 2638.1 in 1996, while the inflation rate was 29.3%. By 2000, the CPI stood at 3,509, although the inflation rate had declined to 6.9% [Central Bank of Nigeria (CBN), 2000]. High inflation have implications for standards living of Nigerians.

Given the excessive fiscal deficits and falling productivity in the Nigerian manufacturing sector, the rate of inflation has had the history of sharp movement from 5.4% in 1986 to 57.0% in 1994. Ten years after the inflation rate came down to 10.40% in January 2004, moved up to 14.00% in January 2009, down to 8.0% in January 2015, it moved up to 11.37% in January 2019 and further up to 15.6% in January 2022 (CBN).

Time series analysis of the Nigeria inflation rate have been studied in the past by various researchers on the basis of the Box-Jenkins methodology. While Popoola, et.al., (2017), used Box-Jenkins methodology to model an ARIMA (0,1,1) to forecast the Nigeria inflation rate, Etuk, (2012), fitted ARIMA (1,1,0) and (0,1,1) for Time series analysis of Nigerian Monthly Inflation Rates and obtained forecasts on the basis of the estimated models. Their forecasts were shown to agree closely with the actual observations. Also, Olajide, et.al., (2012), modeled the inflation rate in Nigeria using Box-Jenkins approach. Their study reveals that the most adequate model for the inflation rate is ARIMA (1,1,1). The model developed was used to forecast inflation rates for the year 2011. Omekara, et.al., (2013), considered the application of Periodogram and Fourier Series Analysis to model all-items monthly inflation rates in Nigeria from 2003 to 2011. They found that inflation cycle within the period was fifty-one (51) months, which coincides with the two administrations within the period. Further, Fourier series model was fitted to the data and this model is further used to make forecast of inflation rates for thirteen months. Their forecasts compare favourably with the actual values.

Univariate time series analysis of inflation rates of other African countries based on Box-Jenkins methodology is also prevalent in literature. Ngailo, et.al., (2014), examined time series modelling with a special application to modelling Tanzania inflation data spanning from January 1997 to December 2010. GARCH (1,1) model was found to be the best model

for forecasting. Based on the selected model, twelve-month inflation rates of Tanzania are forecasted in-sample period (that is from January 2010 to December 2010). From the results, it is observed that the forecasted series are close to the actual data series. Abdulrahman, et.al., (2018), Forecasted Sudan Inflation Rates using ARIMA Model obtained the Box-Jenkins methodology. They found that there is a convergence between predictive values and actual values during the period (1970-2016), their result indicated that inflation rate in Sudan would increase in the coming years (2017-2026). Jere and Siyanga, (2016), used the Holt's exponential smoothing and Auto-Regressive Integrated Moving Average (ARIMA) models to forecast inflation rate of Zambia. Their results found ARIMA (12, 1, 0) an adequate for forecasting inflation rate of Zambia. The study also showed that the choice of the Holt's exponential smoothing is as good as an ARIMA model.

Beyond Africa, Delima and Lumintac, (2019), using Box-Jenkins methodology, found ARIMA (1,0,0) and ARIMA (7,0,0) the best-fitted model for the Philippine inflation rate. Fibriyani and Chamidah, (2021), carried out Indonesia inflation prediction through two approaches: the parametric regression model approach based on the Autoregressive Integrated Moving Average (ARIMA) model and the nonparametric regression approach based on the local polynomial estimator. Genc, et.al., (2007), analyzed a set of countries which adopted inflation targeting (IT) as a policy tool. They modeled the pre-IT period with ARIMA and GARCH methods and found that even though the actual inflation levels are lower than the forecasted ones, there is no statistical evidence to suggest that the adoption of IT causes a structural break in the inflation levels of the countries which adopt it.

COVID-19 pandemic has induced chaos and turbulence in financial markets (Gunay, 2020). The pandemic came with its attendant disruption to the economic, social, and cultural activities of the continents of the world.

Many studies in the literature have considered the event of COVID-19 and its effect on some socio-economic variables. Examples are, Aslam, et al., (2021), Gunay (2020), Xu, and Lien, (2022), Hofmann, et.al., (2020), Zhixi Wei Yu Luo Zili Huang Kun Guo (2020), Hoshikawa and Yoshimi, (2021), Beckmann and Czudaj, (2022), and Fang and Zhang, (2021). Some of these studies on the foreign exchange rates of some countries of the world reported negative impact of COVID-19 event on the foreign exchange rates of the currencies considered. We would through this study consider the effect of COVID-19 on data generation mechanism of Nigeria inflation rate.

In this study, we used a secondary data of the Nigeria inflation rate obtained from the Central Bank of Nigeria (CBN). The data set covers the period January 2003 to October 2022. Taking into account the COVID-19 pandemic event, we modeled a time series ARIMA processes of the monthly inflation rate over the following periods of time: January 2003 to June 2019 representing the pre-COVID-19 pandemic period and January 2003 to June 2022 representing the combination of the pre COVID-19 pandemic and COVID-19 pandemic periods. This is with a view to evaluate the impact of COVID-19

shock on the generation mechanism of the Nigeria inflation rate. The rest of the paper is organized into 3 sections. Section 2 contains the Materials and Methods of the study. The findings and discussion from our study are presented in Section 3, while Section 4 contains our conclusion.

2. Materials and methods

2.1. Theoretical framework

A stationary time series Y_t that follows an ARMA(1, 1) process it can be written as:

$$Y_t = \theta + \alpha_1 Y_{t-1} + \beta_0 \mu_t + \beta_1 \mu_{t-1}$$

Where θ is a constant term; α_1, β_0 and β_1 are coefficients; μ_t and μ_{t-1} are uncorrelated random error terms with zero mean and constant variance σ^2 at time t and $t-1$. Here, there is one autoregressive and one moving average term. In general, in an ARMA(p, q) process, there will be p autoregressive and q moving average terms. Where Y_t is integrated of order d and we have to difference Y_t d times to make it stationary and subsequently apply ARMA(p, q), then the series Y_t is ARIMA(p, d, q) process. The Box-Jenkins methodology shall be employed for identification, estimation, diagnostic checking and forecasting of the ARIMA process.

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) for model identification.

Firstly, we analyzed the times series data of the Nigeria inflation rate series in order to investigate the underlying relationships and trend 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 inflation rate for the period January 2003 to October 2022. The series consist of monthly central inflation rate for the period under review. Our data was obtained from the Central Bank of Nigeria website.

Using the Box-Jenkins Model Selection methodology on Nigeria inflation rate secondary data set for the period under review with due consideration of the COVID-19 pandemic event as highlighted above, we adopt a three-stage procedure for our ARIMA modeling. These are: (i) Check the inflation rate data set for stationarity, and transform the data set to induce stationarity, (ii) From the autocorrelation properties of the transformed data set

choose a few ARIMA specifications for estimation and testing in order to arrive at a preferred specification with white noise residuals, and finally, (iii) calculate forecasts over a relevant time horizon from the preferred specification. The Box-Jenkins Model Selection methodology is described below:

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.

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.

Diagnostic Checks: We evaluated 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 invertibility of MA parameters).

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 for the two scenarios under consideration are presented in figures 1 and 2.

Figure 1. Time plot for the Pre COVID-19 Period Series

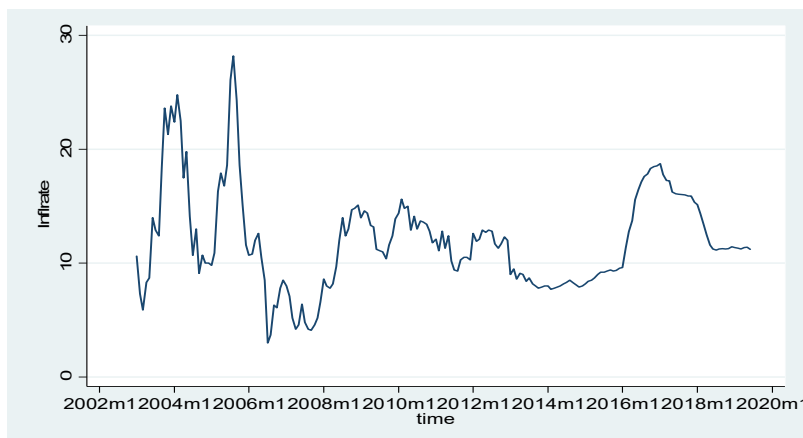
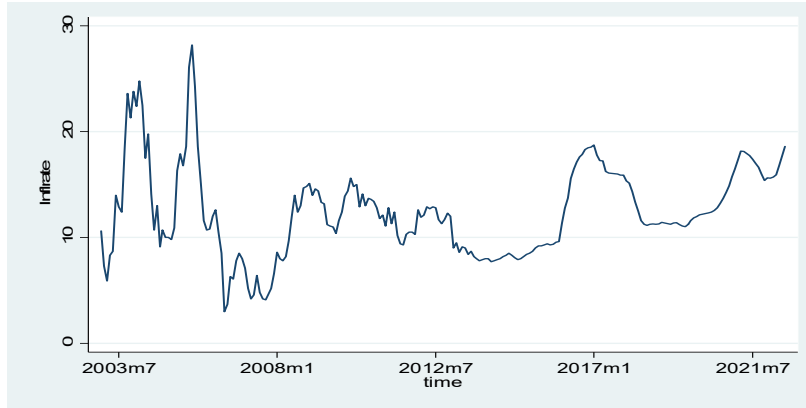


Figure 2. Time plot for the Combined Period Series

It is apparent from figures 1 and 2 that the series are nonstationary. The Dickey Fuller and Phillip Perron test we conducted further confirmed this position.

3.2. Stationarity condition and model identification

3.2.1. Pre COVID-19 period series

For the Pre COVID-19 period series, we achieved stationarity at the 1st difference. This position is also supported by the Dickey Fuller and Phillip Perron results we obtained for this series. Figure 3 highlights the time plot of the 1st difference of the Pre COVID-19 data, while figures 4 and 5 highlights the autocorrelation (AC) graph and partial autocorrelation (PAC) graphs of the series respectively.

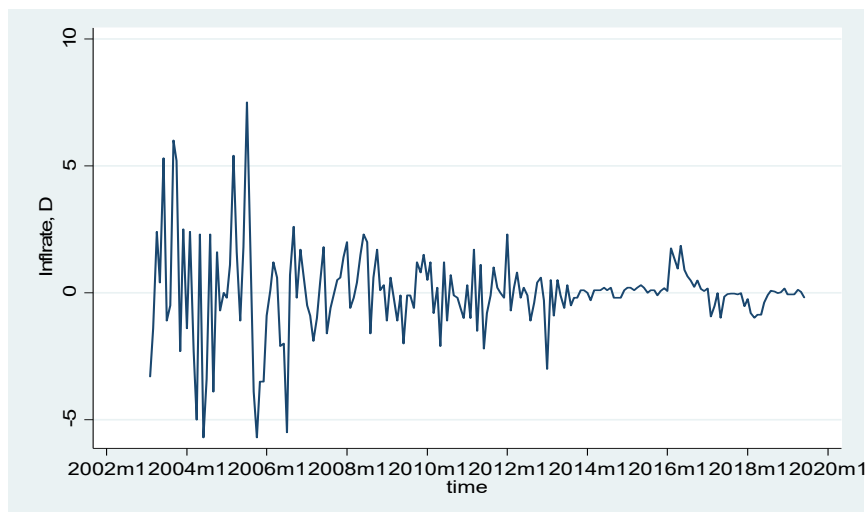
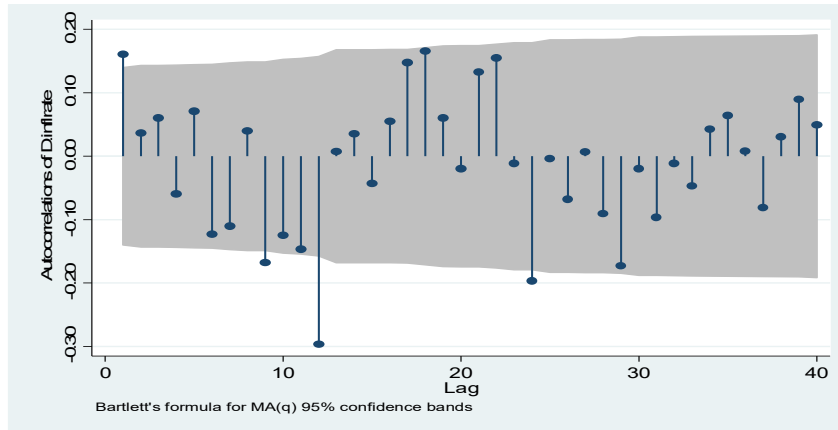
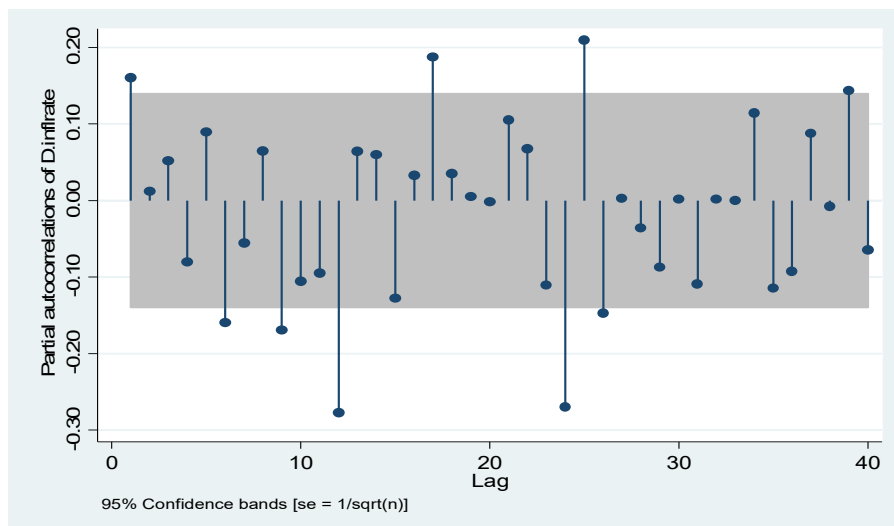
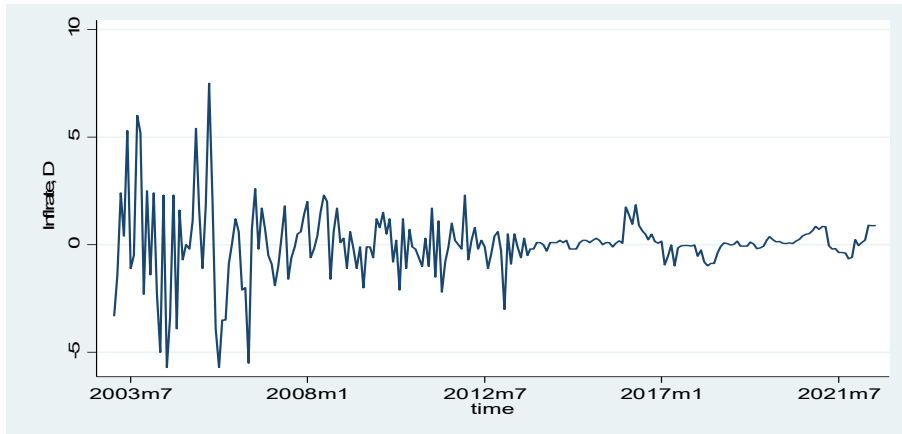
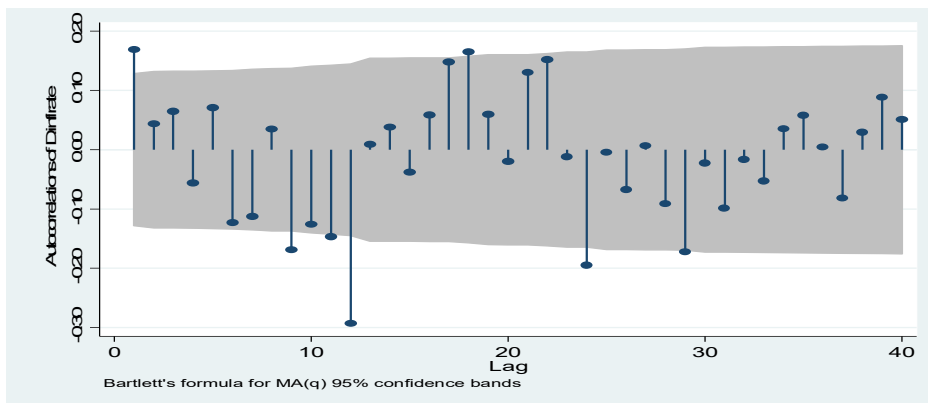
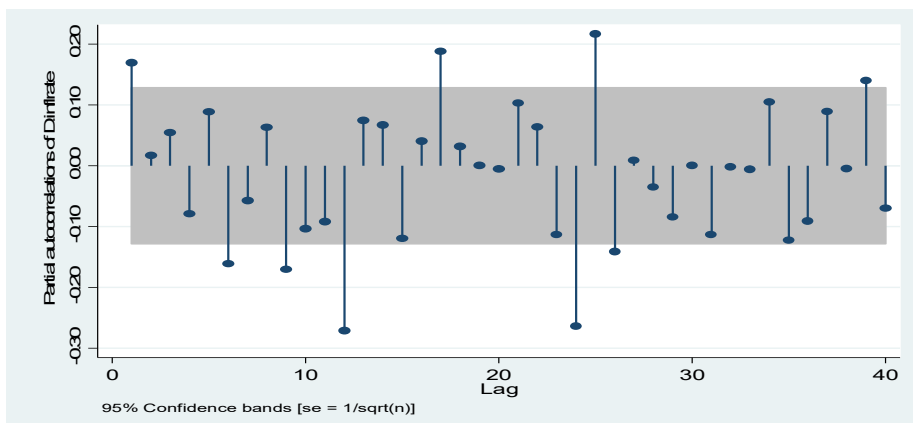
Figure 3. The Time Plot of the 1st Difference of Pre COVID-19 Period Series

Figure 4. The AC graph of the 1st Difference of Pre COVID-19 Period Series**Figure 5.** The PAC graph of the 1st Difference of Pre COVID-19 Period Series

An evaluation of the time plots in figure 3 confirmed the stationarity of the 1st differenced series. Similarly, our evaluation of the AC and PAC graphs in figures 4 and 5 suggests the consideration of ARIMA(1,1,1) and ARIMA(6,1,1) for model selection criteria.

3.2.2 Combined period series

For this series, as is the case with Pre COVID-19 series, we achieved stationarity at 1st difference. Figure 6 highlighting the time plot of the 1st difference of the Combined Period data as well as Dickey Fuller and Phillip Perron tests confirmed this position, Figures 7 and 8 highlights the autocorrelation (AC) graph and partial autocorrelation (PAC) graphs of the series respectively.

Figure 6. *The Time Plot of the 1st Difference of the Combined Period Series***Figure 7.** *The AC graph of the 1st Difference of the Combined Period Series***Figure 8.** *The PAC graph of the 1st Difference of the Combined Period Series*

As we obtained in the case of Pre COVID-19 series, a review of the AC and PAC graphs of the 1st differenced Combined period series suggests the consideration of ARIMA(1,1,1) and ARIMA(6,1,1) for model selection process.

3.3. ARIMA estimation and model selection

The suggested ARIMA models for each of the two series were estimated and the estimation results obtained were subjected to model selection criterion to enable us elect the best model for each series. The summary of our model selection procedure is presented in tables 1 and 2. In tables 1 and 2, 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 1. Model Selection Summary for Pre COVID-19 Period Series

Criteria	Model A ARIMA(1,1,1)	Model B ARIMA(6,1,1)	Best Model
C, AR, MA	2/2	5/7	A
SIGMA SQ	1.6683	1.5890	B
Log Likelihood	-380.504	-372.4454	B
AIC	767.008	760.5907	B
BIC	776.858	787.1564	B
OVERALL BEST			MODEL B ARIMA (6,1,1)

Table 2. Model Selection Summary for Combined Period Series

Criteria	Model A ARIMA(1,1,1)	Model B ARIMA(6,1,1)	Best Model
C, AR, MA	½	6/7	B
SIGMA SQ	1.5470	1.4688	B
Log Likelihood	-432.3036	-423.4141	B
AIC	870.6072	862.8281	B
BIC	880.9802	890.4364	A
OVERALL BEST			MODEL B ARIMA (6,1,1)

In summary, the selected model for both the Pre-COVID-19 pandemic period series as well as the Combined period series is ARIMA(6,1,1). The estimated ARIMA models for the selected model are presented in table 3 and 4.

ARIMA regression

D.inflrate	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
ARMA						
ar						
L1.	1.093538	.0529592	20.65	0.000	.9897402	1.197336
L2.	-.1633889	.0760654	-2.15	0.032	-.3124744	-.0143035
L3.	.0752264	.0732823	1.03	0.305	-.0684043	.2188572
L4.	-.1583224	.0710461	-2.23	0.026	-.2975703	-.0190745
L5.	.1980996	.072772	2.72	0.006	.0554691	.34073
L6.	-.1661107	.050832	-3.27	0.001	-.2657396	-.0664817
ma						
L1.	-1.000004	123.0675	-0.01	0.994	-242.2079	240.2079
/sigma	1.589019	97.79633	0.02	0.494	0	193.2663

ARIMA regression

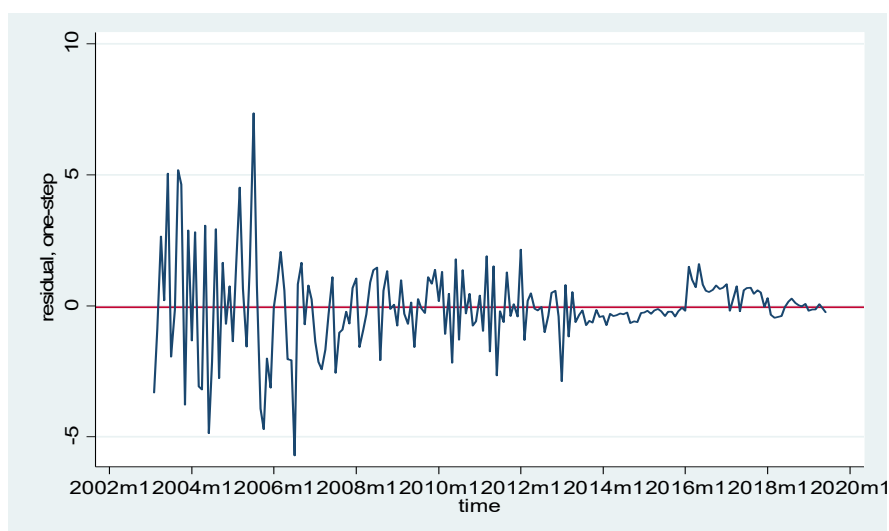
	OPG					
D.inflrate	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ARMA						
ar						
L1.	1.109205	.0463551	23.93	0.000	1.018351	1.200059
L2.	-.1677501	.0649504	-2.58	0.010	-.2950505	-.0404496
L3.	.0725871	.0624944	1.16	0.245	-.0498996	.1950739
L4.	-.1602444	.0609459	-2.63	0.009	-.2796963	-.0407926
L5.	.196478	.0623342	3.15	0.002	.0743052	.3186508
L6.	-.1606077	.0438108	-3.67	0.000	-.2464752	-.0747401
ma						
L1.	-1.009662	.0597448	-16.90	0.000	-1.12676	-.8925643
/sigma	1.468827	.07343	20.00	0.000	1.324907	1.612747

3.4. Diagnostics

3.4.1. Pre COVID-19 period series

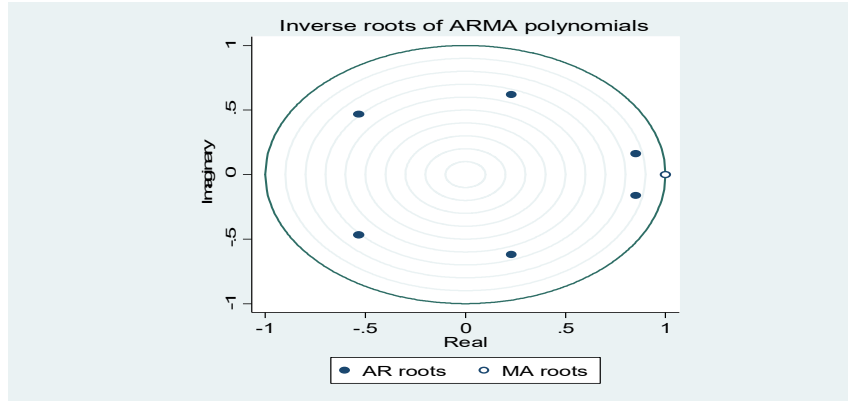
The mean of the residuals was found to be -0.0629 (Table 5). As can be seen in the residuals plot shown in Figure 9, all values wriggle around the mean. Hence going by virtual examination of the residual plot, the residuals are white noise.

Figure 9. *Residual Plot for the Pre COVID-19 Period Series*



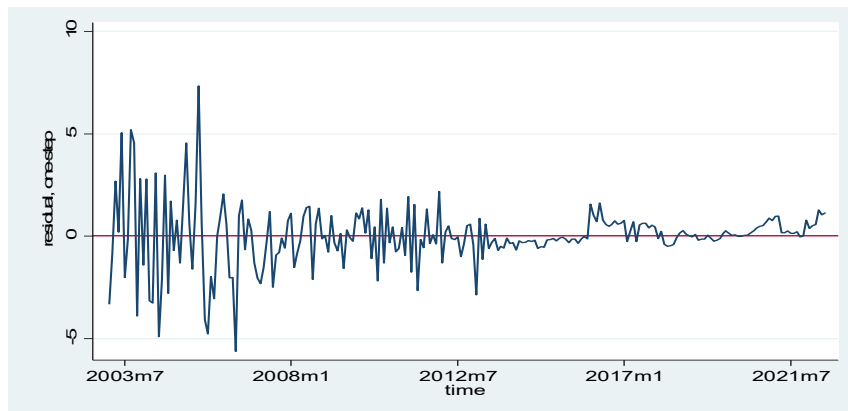
We further evaluated the residuals with Portmanteau test. The null hypothesis for the portmanteau test is that the residuals are white noise. We reject the null hypothesis if the p-value < 0.05 . Our p-value of 0.0112 is less than 0.05 so we reject the null hypothesis. Therefore, while the residual plot depicts the residuals as white noise, the portmanteau test failed to confirm them as white noise.

We evaluated the estimated ARIMA process for covariance stationarity with the requirement that all AR roots should lie within the unit circle. Stability condition was satisfied as shown in figure 10 as all AR roots are inside the unit circle. Also we checked whether or not the estimated ARIMA process is invertible with the requirement that all MA roots should lie inside the unit circle. Figure 10 confirms that the MA parameters all lie on the unit circle. Hence from our diagnostic check process, the estimated model for the Pre-COVID period series turned out good that may be useful for forecasting.

Figure 10. Unit Root Circle for the Pre COVID-19 Period Series

3.4.2. Combined period series

The mean of the residuals was found to be 0.1898 (Table 5). As can be seen in the residuals plot shown in Figure 11, all values wriggle around the mean line; a confirmation that the residuals are white noise.

Figure 11. Residual Plot for the Combined 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 . Our p -value of 0.0015 is less than 0.05 so we reject the null hypothesis. Hence by graphical analysis, the Combined period series residuals are white noise.

Further, we analyzed the estimated ARIMA process for covariance stationarity with the requirement that all AR roots should lie within the unit circle. Stability condition was satisfied as shown in Figure 12 as all AR roots are inside the unit circle. Also we checked whether or not the estimated ARIMA process is invertible with the requirement that all MA roots should lie inside the unit circle. Figure 12 confirms that the MA parameter lie on the unit circle. As a result, the invertibility condition is not precisely fulfilled for the Combined

period series. Hence, from our diagnostic check process, the estimated model for the Combined period series may also be considered for forecasting.

Figure 12. Unit Root Circle for the Combined Period Series

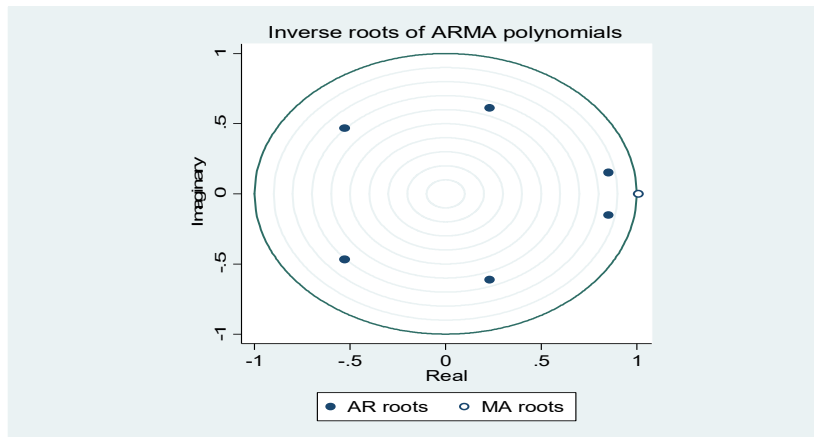


Table 5. Summary of the Diagnostic Analysis

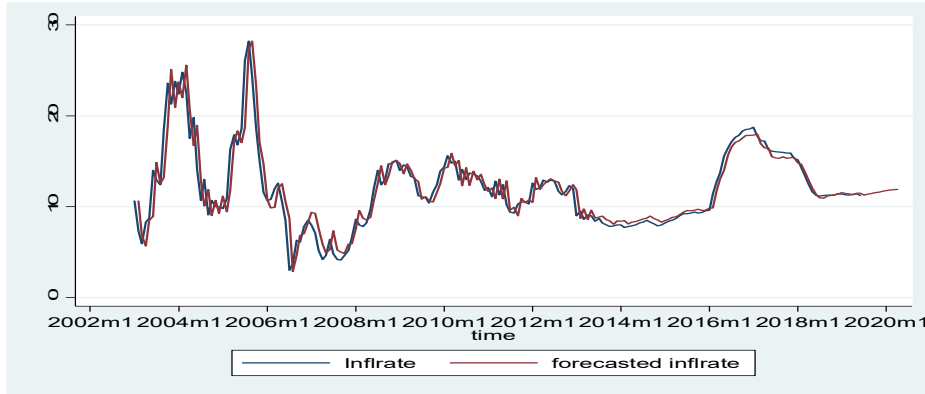
	Pre COVID Period Model ARIMA(6,1,1)	Combined Period Model ARIMA(6,1,1)
Observations	197	233
Mean of the Residuals	-0.0629	0.1898
Standard Deviation of Residuals	1.6218	1.5065
Minimum Residual	-5.7104	-5.6170
Maximum Residual	7.3571	7.3365
Portmanteau (Q) Stat	63.1916	71.8870
Portmanteau Test P-Value	0.0112	0.0015
Stability Condition of AR Parameters	SATIFIED	SATISFIED
Invertibility Condition of MA Parameters	The MA root is on the unit roots circle	The MA root is on the unit roots circle

In summary, graphical analysis and covariance stationarity test of the residuals, we confirmed that the estimated ARIMA processes for the two scenarios we investigated (Pre COVID-19 period and Combined period) are stable and therefore fit for forecasting.

3.5. Forecasting

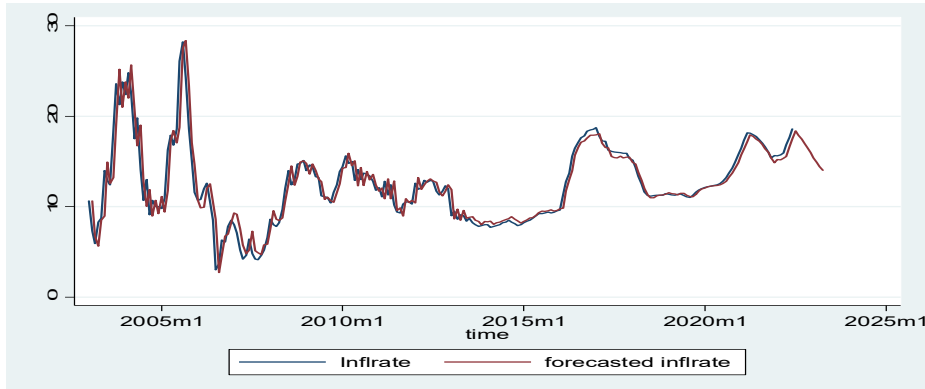
3.5.1. Pre COVID-19 series

With the estimated ARIMA (6,1,1) process for the Pre COVID-19 period series, we did a 10-month forecast of the Nigeria inflation rate. This is presented graphically in figure 13. From Figure 13, it is apparent that the fitted model appropriately represents the data generation mechanism of the Nigeria inflation rate. The forecast suggests an onward slight depreciation of the Naira beyond June 2019.

Figure 13. Forecast Plot of the Nigeria inflation rates for Pre Covid-19 Period Series

3.5.3. Combined period series

Using the estimated ARIMA (6,1,1) process for the Combined period series, we also did a 10-month forecast of the monthly average Nigeria inflation rates. This is presented graphically in figure 14. From figure 14, we can also see that the fitted model appropriately depicts the data generation mechanism of the Nigeria inflation rates. The forecast suggests an onward appreciation of the Naira beyond June 2022.

Figure 14. Forecast Plot of the Nigeria inflation rates for Combined Period Series

Tables 6 and 7 present the forecast inflation rates and the actuals rates for Pre-COVID-19 and Combined models.

Table 6. Forecast and Actual Values of Nigeria Inflation Rates for Pre COVID-19 Period Model

Month	Actual values	Forecast values
2019-M7	11.08	11.28
2019-M8	11.02	11.36
2019-M9	11.24	11.44
2019-M10	11.61	11.55
2019-M11	11.85	11.60
2019-M12	11.98	11.68

Month	Actual values	Forecast values
2020-M1	12.13	11.76
2020-M2	12.20	11.82
2020-M2	12.26	11.88
2020-M2	12.34	11.92

From table 6, it can be observed that for July, August and September 2019, the forecast inflation rates are slightly bigger than the actuals. A noticeable turning point was observed in October 2019 when the forecast rates began a downward trend when compared with the actuals. This appears to suggest that without the event of COVID-19 pandemic, Nigeria inflation rate would have maintained a downward trend through 2020.

Table 7. Forecast and Actual Values of Nigeria Inflation Rates for the Combined Period Model

Month	Actual values	Forecast values
2022-M7	19.64	18.36
2022-M8	20.52	17.90
2022-M9	20.77	17.49
2022-M10	21.09	16.98
2022-M11	21.47	16.53
2022-M12	21.34	15.96
2023-M1	21.82	15.38
2023-M2	21.91	14.88
2023-M3	22.04	14.42
2023-M4	22.22	14.03

The forecast values shown in table 7 suggests that Nigeria inflation rates would start a downward movement from July 2022. This observation appears to suggest a dwindling effect of COVID-19 on Nigeria Inflation rate. This trend is expected to continue through to April 2023. However, the forecast rates are markedly different from the actuals from July 2022. This may be largely attributable to the global economic shock that was occasioned by the ongoing Russian/Ukraine war.

4. Conclusions

The aim of this study is to build a univariate time series model of the Nigeria inflation rate with a data covering the period January 2003 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 Nigeria inflation rate, we classified the study period into two (2) distinct sub-periods: The Pre COVID-19 period (January 2003 to June 2019), and the Combined period (January 2003 to June 2022). The Nigeria inflation rate series was found to be non-stationary over the two periods. We fitted ARIMA (6,1,1) for both the Pre COVID-19 and Combined periods data. The three models were found to be well behave 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. Furthermore, while the estimated model for the COVID-19 period data yielded forecast values that suggests slight onward fall of the Nigeria inflation rate, the estimated models for the Combined periods produced forecast values that suggests onward fall of the

Nigeria Inflation. By and large, our forecast result suggests that the Nigeria inflation rate is on a downward trend. The Nigeria government should do everything possible to facilitate and encourage this outcome. We recommend that the Nigerian Government should as a matter of urgency modulate the fiscal and monetary policies that are currently in reign in the country in order to make this forecast a reality for the benefit of the Nigerian citizens.

References

- Allemar, J.P. and Lumintac, M.T.Q., 2019. Application of Time Series Analysis for Philippines' Inflation Prediction, *International Journal of Recent Technology and Engineering (IJRTE)* ISSN: 2277-3878, Volume 8, Issue 1, May 2019.
- Abderhim, E.Y., Abuzar, Y.A.A. and Badreldin, M.A.A., 2018. Forecasting of Sudan Inflation Rates using ARIMA Model. *International Journal of Economics and Financial*, Issues 8(3), pp. 17-22.
- Etuk, E.H., 2012. Predicting Inflation Rates of Nigeria Using a Seasonal Box-Jenkins Model, *Journal of Statistical and Econometric Methods*, Vol. 1, No. 3, pp. 27-37.
- Fibriyani, V. and Chamidah, N., 2021. Prediction of Inflation Rate in Indonesia Using Local Polynomial Estimator for Time Series Data, *Journal of Physics: Conference Series, Volume 1776*, Konferensi Nasional Penelitian Matematika dan Pembelajarannya (KNPMP) V, 5th August 2020.
- Genc, I.H., Lee, M., Rodríguez, C.O. and Lutz, Z., 2007. Time Series Analysis of Inflation Targeting in Selected Countries, *Journal of Economic Policy Reform*, Volume 10, Issue 1.
- Iyoha, M.A. and Itsed, C.O., 2002. Nigerian Economy Structure, Growth and Development, *Mindex Publishing*.
- Jere, S. and Siyanga, M., 2016. Forecasting Inflation Rate of Zambia Using Holt's Exponential Smoothing, *Open Journal of Statistics*, Vol. 6, No. 2, April 2016.
- Ngailo, E., Luvanda, E. and Massawe, E.S., 2014. Time Series Modelling with Application to Tanzania Inflation Data, *Journal of Data Analysis and Information Processing*, Vol. 2, No. 2, Article ID:46380,11 pages <DOI:10.4236/jdaip.2014.22007>
- Okongwu, C.S.P., 1986. The Nigerian Economy: Anatomy of a Traumatized Economy with some Proposal for Stabilization, *Issues in Nigerian Development*, Fourth Dimension Publishing Co. LTD. 1986.
- Olajide, J.T., Ayansola, O.A., Odusina, M.T. and Oyenuga I.F., 2012. Forecasting the Inflation Rate in Nigeria: Box Jenkins Approach, *Journal of Mathematics (IOSR-JM)*, ISSN: 2278-5728. Volume 3, Issue 5 (Sep-Oct. 2012), pp. 15-19.
- Omekara, C.O., Ekpenyong, E.J. and Ekerete, M.P., 2013. Modeling the Nigerian Inflation Rates using Periodogram and Fourier Series Analysis, *CBN Journal of Applied Statistics*, ISSN: 2476-8472, Volume 04, Issue 2, pp. 51-68.
- Popoola, O.P., Ayanrinde, A.W., Rafiu, A.A. and Odusina, M.T., 2017. Time Series Analysis to Model and Forecast Inflation Rate in Nigeria, *Annals. Computer Science Series*. Jul. 2017, Vol. 15, Issue 1, pp. 174-178.
- Samet, G., 2020. Covid-19 Pandemic Versus Global Financial Crisis: Evidence from Currency Market, *Working Paper*.