African Journal of Economics and Sustainable Development
ISSN: 2689-5080
Volume 6, Issue 3, 2023 (pp. 42-53)
www.abjournals.org

MODELING AND FORECASTING INFLATION IN NIGERIA: A TIME SERIES REGRESSION WITH ARIMA METHOD

Emwinloghosa Kenneth Guobadia[1*], Pamela Owamagbe Omoruyi[2],

Paschal Nnamdi Izuogu[3], Eloho Sophia Omodio[4] and Agu Chidera[5]

[1]Department of Administration, Federal Medical Centre, Asaba, Nigeria

[2]Department of Economics, Faculty of Social Sciences, University of Benin, Nigeria

[3]Department of Banking and Finance, Faculty of Management Sciences, Chukwuemeka Odumegwu Ojukwu University, Nigeria

[4]Department of Economics, Faculty of Education, Delta State University, Abraka, Nigeria

[5]Department of Computer Science, Faculty of Physical Science, University of Lagos, Yaba, Nigeria

Cite this article:

Emwinloghosa K.G., Pamela O.O., Paschal N.I., Eloho S.O., Agu C. (2023), Modeling and Forecasting Inflation in Nigeria: A Time Series Regression with ARIMA Method. African Journal of Economics and Sustainable Development 6(3), 42-53. DOI: 10.52589/AJESD-HFYC2BNW

Manuscript History

Received: 30 May 2023

Accepted: 19 July 2023

Published: 14 Aug 2023

ABSTRACT: *This study uses time series regression with autoregressive integrated moving average (ARIMA) modeling to establish a model for forecasting inflation in Nigeria for the period 1981-2020. Akaike Information Criterion Corrected (AICC) and Bayesian Information Criterion (BIC) were used to select the best model among competing models. Through these methods, regression with ARIMA (0,0,1) error was selected as the most parsimonious model for inflation forecasting in Nigeria. The results of the out-sample-forecast show that a high inflation rate will be experienced by the end of 2023, and between 2024 and 2030, the inflation rate will be alternating but will maintain a lower rate than that of 2023.*

KEYWORDS: Inflation, Forecasting, Time Series Multiple Regression, Regression with ARIMA Error

INTRODUCTION

Consumer prices inflation is an economic indicator that measures the percentage change in the cost to the average consumer for acquiring a basket of goods and services over a fixed or varying time. Inflation is the persistent and continuous rise in the prices of goods and services over time (Lim & Sek, 2015; Ojo, 2000). A stable inflation plays a critical role in the sustainability of economic growth of any nation (Utami et al, 2018), meanwhile high and unstable inflation can lead to a reduction of the purchasing power of a nation's currency (Asekunowo, 2016; Folorunso & Abiola, 2000; Mohamed, 2020) thereby affecting negatively the wellbeing of the people and socio-economic conditions (Isakova, 2007). One of the major objectives of the Central Bank of Nigeria and India is to ensure that price stability is maintained (Udoh & Anietie, 2018), and also to predict future macroeconomic development (Norbert et al., 2016) based on factors that determine such development.

A study by Kuhe and Egemba (2010) found that ARIMA (3,1,0) model is the best model to forecast inflation in Nigeria. Chinonso and Justice (2016) applied the techniques of Box-Jenkins on monthly CPI from January 2001 to December 2015in Nigeria. This study selected ARIMA (0,1,3) model as the best model for forecasting inflation in Nigeria. Adeleke et al. (2020) modelled inflation rate in Nigeria using monthly data from 2003M1 to 2020M10, by applying the Box-Jenkins method, they found SARMA (3,3) (1,2) [12] as the best model for forecasting monthly inflation rate in Nigeria.

Arindam (2021) modelled CPI in India using the Box-Jenkins methods, and his study found the ARIMA (1,1,5) as the best model for predicting CPI in India. In the study by Karthikeyan et al. (2021), by applying Box-Jenkins methodology, ARIMA 91,1,0) was selected as the best model for inflation forecasting in India.

Samrad et al. (2021) in their study by employing the method of Box-Jenkins, found out that ARIMA (1,0,0) is the most appropriate model for forecasting inflation rate in Iran. Another study by Aboobucker and Jahufer (2016) founds ARIMA (1,1,0) (0,0,1) [12] as the most appropriate model for inflation forecasting in Sri Lanka. Mia et al. (2019) modelled the CPI in Bangladesh for the period 1986-2018, and by applying ARIMA modelling, they found ARIMA (2,2,0) as the best model for forecasting Bangladesh inflation.

This study aims at developing a forecast model using time series regression with autoregressive integrated moving average (ARIMA) modeling for inflation in Nigeria. In this study, we used Consumer Prices Inflation as the dependent variable and Exchange Rates, Real Interest Rates, Foreign Direct Investment Inflow, Manufacturing Output, Gross Domestic Product Growth, Broad Money Growth, and Trade Balance as the explanatory variables. The primary objective of this study is to obtain the most appropriate time series regression with autoregressive integrated moving average (ARIMA) errors model that will be used to forecast inflation. The major finding of this study showed that regression with ARIMA (0,0,1) errors is the most appropriate model for inflation forecasting in Nigeria.

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

African Journal of Economics and Sustainable Development
ISSN: 2689-5080
Volume 6, Issue 3, 2023 (pp. 42-53)
www.abjournals.org

MATERIALS AND METHODS

MATERIALS

This study uses data for the period of 40 years (1981-2020) extracted from World Development Indicator (WDI). In this study we used eight (8) economic variables, the dependent used here is inflation (INFR), while the explanatory variables are exchange rate (EXCR) in Naira per US Dollar, real interest rate (RINR) in percent (%), foreign direct investment inflow (FDII) in billion US Dollar, manufacturing output (MOP) in billion US Dollar, GDP growth (GDPG) in percent (%), broad money growth (BMG) in annual percent (%), and trade balance (TB) in billion US Dollar. The variables are presented in Figure 1.

METHODS

In this study, we applied the techniques of time series regression and Box-Jenkins methods (Box et al, 1994) to develop an inflation forecast model for Nigeria. The time series multiple regression model is first developed, after which the residuals are obtained from it, then Breusch-Godfrey test for autocorrelation in the residuals (Breusch, 1978; Godfrey, 1978) and Breusch-Pagan-Godfrey test for heteroscedasticity or constant variance (Breusch & Pagan, 1979) are also carried out. In addition to this, the residuals are tested for normality using the Shapiro-Wilk test of normality and for stationarity using the autocorrelation function (ACF) plot. Next the autoregressive integrated moving average (ARIMA) is modeled to the stationary residuals. The best time series regression with ARIMA errors is selected using the least Akaike Information Criterion (AIC) or Akaike Information Criterion corrected (AICc) or Bayesian Information Criterion (BIC)

Time Series Regression Model

The mathematical time series linear regression model is presented as:

$$INFR = f(EXCR, RINR, FDII, MOP, GDPG, BMG, TB) \quad (1)$$

This equation can be rewritten as

$$INFR_t = \beta_0 + \beta_1 EXCR_t + \beta_2 RINR_t + \beta_3 FDII_t + \beta_4 MOP_t + \beta_5 GDPG_t + \beta_6 BMG_t + \beta_7 TB_t + \varepsilon_t \quad (2)$$

where: $\beta_1, \beta_2, \cdots, \beta_7$ are the parameters to be estimated; β_0 is the intercept; ε_t is the error associated to the model assumed to be white noise; the variables remain as described above. The residuals from the equation 2 is written as

$$\varepsilon_t = INFR_t - \widehat{INFR}_t \quad (3)$$

Where: $INFR_t$ is the inflation at time t; $\widehat{INFR}_t$ is the predicted inflation for time t

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

African Journal of Economics and Sustainable Development
ISSN: 2689-5080
Volume 6, Issue 3, 2023 (pp. 42-53)
www.abjournals.org

Regression with Autoregressive Integrated Moving Average (ARIMA) Errors

If the error term or the residual in equation 2 contains autocorrelation, then ε_t is replaced by an error series $\omega_t$that is assumed to follow an ARIMA or ARMA model. However, if all the variables in the model 2 are stationary, then the ARMA errors will be considered, and in the case we applied differencing, then an ARIMA errors is required (Harris & Sollis, 2003). The time series multiple regression model with error series ω_t are written as

$$INFR_t = \beta_0 + \beta_1 EXCR_t + \beta_2 RINR_t + \beta_3 FDII_t + \beta_4 MOP_t + \beta_5 GDPG_t + \beta_6 BMG_t + \beta_7 TB_t + \omega_t \quad (4)$$

For the time series regression model containing an ARMA (p, q) errors, the ω_t is written as

$$\omega_t = \phi_1 \omega_{t-1} + \cdots + \phi_p \omega_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \quad (5)$$

For the time series regression model containing an ARIMA (p, d, q) errors, the ω_t is written as

$$\omega_t' = \phi_1 \omega_{t-1}' + \cdots + \phi_p \omega_{t-p}' + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \quad (6)$$

Where: $\omega_t \sim iid(0, \sigma_\varepsilon^2)$; $\phi_1, \cdots, \phi_p$ are the parameters of the autoregressive (AR) errors part to be estimated; $\theta_1, \cdots, \theta_q$are the parameters of the moving average (MA) errors part to be estimated

Stationarity Test

The stationarity of the time series can be obtained by visualizing the time plot or the autocorrelation function (ACF) plot, while a formal way of ascertaining if there is actually stationarity is by carrying out an Augmented Dickey-Fuller (ADF) test for unit root. The ADF test does not test stationarity explicitly, but test through the presence/absence of a unit root. Thus, if the series tested for stationarity is not stationary, then there is all evidence for transforming the series, and this can be done using differencing or power transformation. The null hypothesis states that there is unit root in the residuals

Model Selection for Regression with ARIMA Error

Once appropriate models are obtained by either through the observation of the autocorrelation function (ACF) plot, where the ARIMA or ARMA model to be fitted on the series should have the possible smallest parameters, i.e., p and q should be less than or equal to 2 $(p, q \leq 2)$ or by direct computation, then the next is to select among them the best model through some information criteria such as Akaike information criterion corrected (AICc) and Bayesian information criterion (BIC). The decision is that ARIMA/ARMA model with the least AICc and/or BIC is selected as the best model amongst other competing models. The AICc and AIC are obtained as

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

$$AICc = AIC + \frac{2p(p+1)}{n-p-1};\ AIC = -2\ln L + 2p \qquad (7)$$

The Bayesian Information Criterion (BIC) is obtained using

$$BIC = AIC + p(\ln(n) - 2) \qquad (8)$$

Where: AIC is the Akaike information criterion, p is the number of fitted model parameters, n is the sample size.

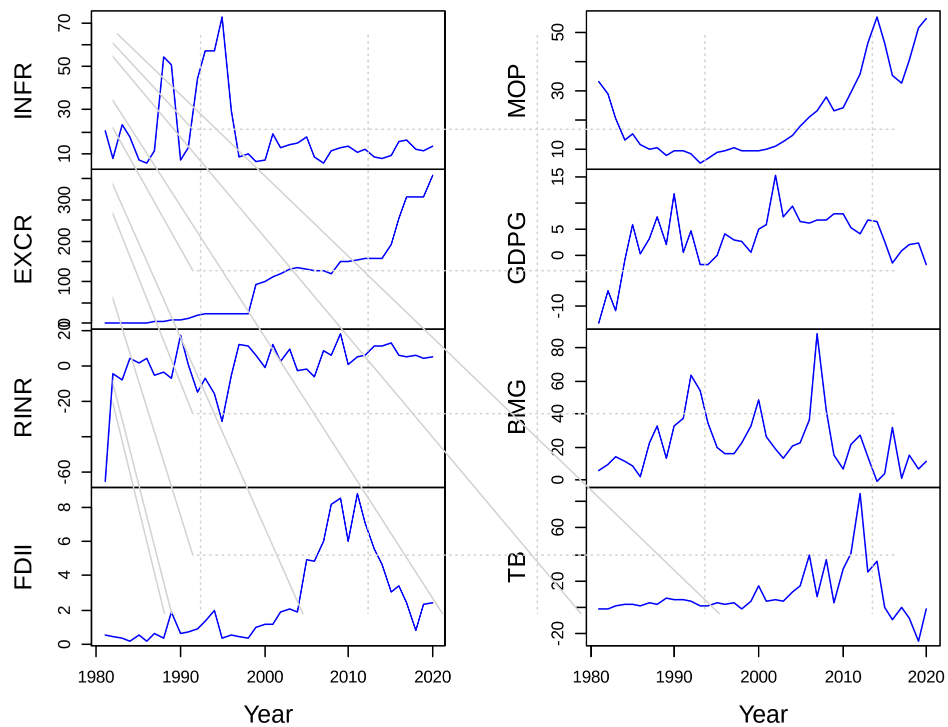

Figure 1. Plot for original data

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

African Journal of Economics and Sustainable Development
ISSN: 2689-5080
Volume 6, Issue 3, 2023 (pp. 42-53)

RESULTS AND DISCUSSION

Table 1 presents the summary statistics for the variables used in this study. INFR has a mean value of 19.00 that lies between 5.4 and 72.8 and a standard deviation of 16.87. EXCR has a mean of 100.76 lying between 0.62 and 358.81 and a standard deviation of 100.73. The mean value of RINR is 0.43% lying between -65.9 and 18.2 and a standard deviation of 14.45%. FDII shows a mean of 2.512 billion US Dollar which lies between 0.19 and 8.84 billion US Dollar and a standard deviation of 14.68 billion US Dollar. Furthermore, MOP shows a mean of 21.59 billion US Dollar and a standard deviation of 14.68 billion US Dollar. The GDPG shows a mean of 3.03% which lies between -13.1 to 15.3% and a standard deviation of 5.45%. BMG has a mean value of 22.99 and it lies between -0.8 and 87.8 and with a standard deviation of 17.98. TB shows a mean value of 9.28 billion US Dollar and it lies between 125.01 and 86.12 billion US Dollar and with a standard deviation of 18.31.

The results further showed that only GDPG is negatively skewed while other variables are positively skewed. Again, the results showed that INFR, RINR, GDPG, BMG, and TB series are leptokurtic, while EXCR, FDII, and MOP series are playkurtic. The value of Jarque-Bera tests show that all the variables were not normally distributed except EXCR.

Table 2 shows the unit root test for the variables using the Augmented Dickey-Fuller test. At the level, only INFR, RINR, GDPG, BMG, and TB were the only stationary series. The first difference showed that all the variables are stationary.

Table 1. Summary statistics for the variables

	INFR	**EXCR**	**RINR**	**FDII**	**MOP**	**GDPG**	**BMG**	**TB**
Mean	19.00	100.76	0.43	2.512	21.59	3.03	22.99	9.28
Median	12.75	106.47	4.3	1.61	15.14	3.7	19.1	3.71
Maximum	72.8	358.81	18.2	8.84	55.33	15.3	87.8	86.12
Minimum	5.4	0.62	-65.9	0.19	5.1	-13.1	-0.8	-25.01
Std. Dev.	16.87	100.73	14.45	2.565	14.68	5.45	17.98	18.31
Skewness	1.8223	0.8887	-2.68	1.169	0.942	-0.8	1.49	2.11
Kurtosis	5.1533	2.9948	12.583	3.156	2.703	4.501	5.81	9.2592
Jarque-Bera	29.867	5.2654	200.94	9.149	6.063	8.022	27.99	94.975
Probability	0.000	0.072	0.000	0.010	0.048	0.018	0.000	0.000
Observations	40	40	40	40	40	40	40	40

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

Table 2. ADF test for the variables

Variable	Level	Variable	First difference
INFR	-2.9580 (0.0479)**	D(INFR)	-5.7511 (0.000)***
EXCR	2.1689 (0.9999)	D(EXCR)	-4.1204 (0.000)***
RINR	-7.3558 (0.0000)***	D(RINR)	-9.9604 (0.000)***
FDII	-1.5432 (0.5015)	D(FDII)	-7.3284 (0.000)***
MOP	0.0821 (0.9600)	D(MOP)	-5.2407 (0.0001)***
GDPG	-3.0203 (0.0419)**	D(GDPG)	-10.0875 (0.000)***
BMG	-3.5203 (0.0126)**	D(BMG)	-6.7027 (0.000)***
TB	-3.4276 (0.0159)**	D(TB)	-10.0889 (0.000)***

Note: p-value in parentheses, *, **, and *** means a rejection of the null hypothesis of the unit root in the variables at the 10%, 5%, and 1% level of significance respectively

Table 3. Time series regression coefficients

Variable	Coefficient	Std. Error	t-Statistic	P-value
Intercept	25.2123	6.8736	3.668	0.0009***
EXCR	0.0207	0.0414	0.499	0.6213
RINR	-0.5907	0.2104	-2.808	0.0084**
FDII	0.4425	1.5155	0.292	0.7722
MOP	-0.4502	0.3066	-1.469	0.1517
GDPG	0.0142	0.6186	0.023	0.9818
BMG	0.0634	0.1509	0.420	0.6773
TB	-0.1005	0.1832	-0.549	0.5870
BG	18.781 (0.0651)			
BPG	8.1452 (0.3200)			

Note: BG stands for Breusch-Godfrey test for serial correlation; BPG stands for Breusch-Pagan-Godfrey test for homoscedasticity; p-value in parentheses

The estimated inflation from the time series regression model is given as

$$\begin{aligned} INFR_t = 25.21 + 0.0207EXCR_t - 0.5907RINR_t + 0.4425FDII_t - 0.4502MOP_t \\ + 0.0142GDPG_t + 0.0634BMG_t - 0.1005TB_t \\ + \varepsilon_t \end{aligned} \tag{9}$$

The ACF plot in Figure 2 shows a rapid drop of lag at 2. This is an indication of stationarity. However, the residuals are stationary at the level stage. Therefore, there will no need of differencing the residuals.

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

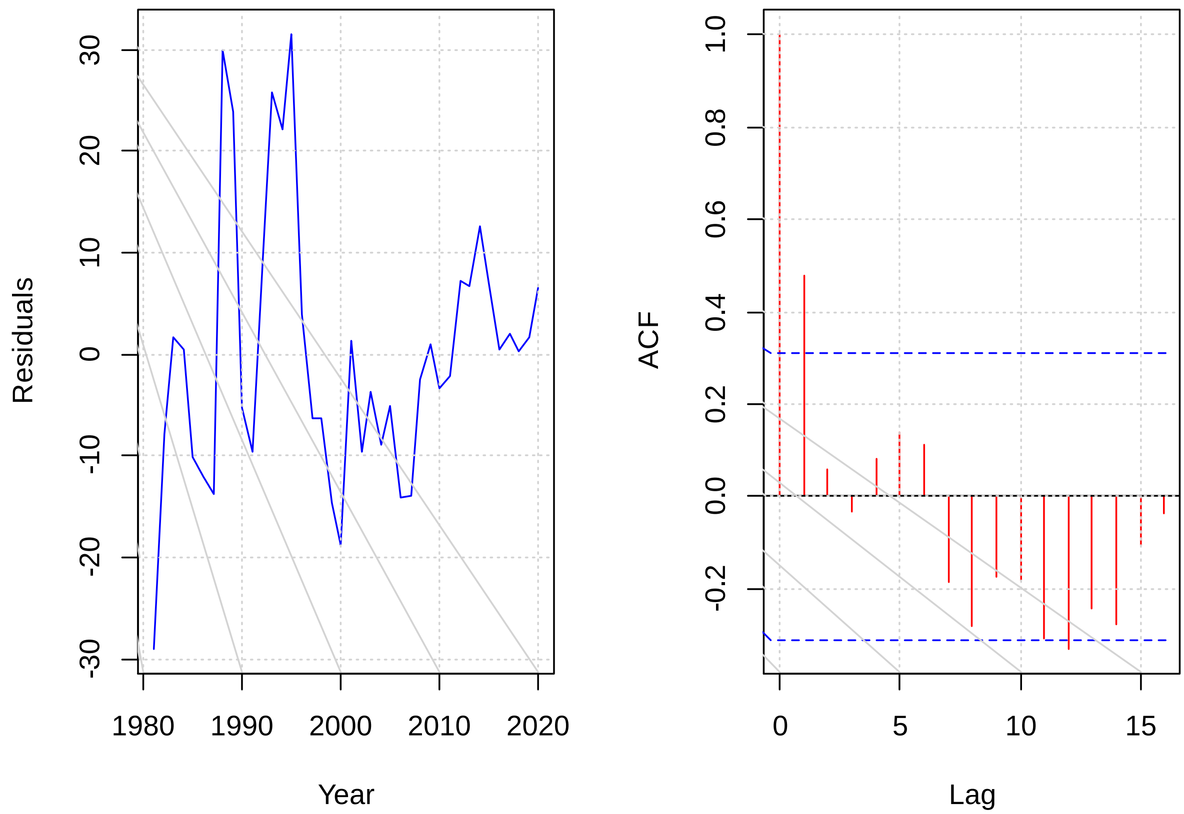

Figure 2. Plot of the residuals and ACF from the time series regression

Table 4. Time series regression with ARIMA model selection

Regression with	AIC	AICc	BIC
ARIMA (0,0,0)	337.14	343.14	352.34
ARIMA (0,0,1)	319.83	327.42	336.72
ARIMA (1,0,0)	326.10	333.68	342.99
ARIMA (1,0,1)	322.67	332.10	341.25
ARIMA (2,0,0)	323.86	333.29	342.44
ARIMA (0,0,2)	322.37	331.79	340.94
ARIMA (1,0,2)	323.95	335.51	344.22
ARIMA (2,0,1)	324.31	335.86	344.57

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

The regression with ARIMA (0,0,1) has the least AIC (319.83), AICc (327.42), and BIC (336.72) among the other competing models in Table 4. Thus, regression with ARIMA (0,0,1) is considered the most parsimonious model for inflation forecasting in Nigeria. Table 5 shows the estimated coefficients of the regression with ARIMA (0,0,1) error. The model is written as:

$$INFR_t = 31.0137 + 0.0272EXCR_t - 0.0746RINR_t - 0.8463FDII_t - 0.5274MOP_t - 0.8302GDPG_t + 0.0527BMG_t - 0.0062TB_t + \varepsilon_t - \varepsilon_{t-1} \quad (10)$$

Table 5. Regression with ARIMA (0,0,1) errors coefficients

Variable	Coefficient	Std. Error
MA 1	1.0000	0.0799
Intercept	31.0137	6.2034
EXCR	0.0272	0.0433
RINR	-0.0746	0.1099
FDII	-0.8463	1.0338
MOP	-0.5274	0.2934
GDPG	-0.8302	0.1888
BMG	0.0527	0.1006
TB	-0.0062	0.0546

Note: MA1 stands for moving average of order 1

Figure 3 presents the diagnostic test for the regression with ARIMA (0,0,1) errors. The plot of the residuals shows a constant variance, while from the ACF plot for the residuals, all the lags falls within the lower and upper bounds, and the histogram shows a normal distribution with mean almost zero. This implies that the regression with ARIMA (0,0,1) errors is an adequate model for inflation forecasting in Nigeria.

Table 6 shows the out-sample forecast for the period of 8 years (2023-2030). This result shows that a high inflation rate will be experienced by the end of 2023, and between 2024 and 2030, the inflation rate will be alternating but will maintain a lower rate than that of 2023.

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

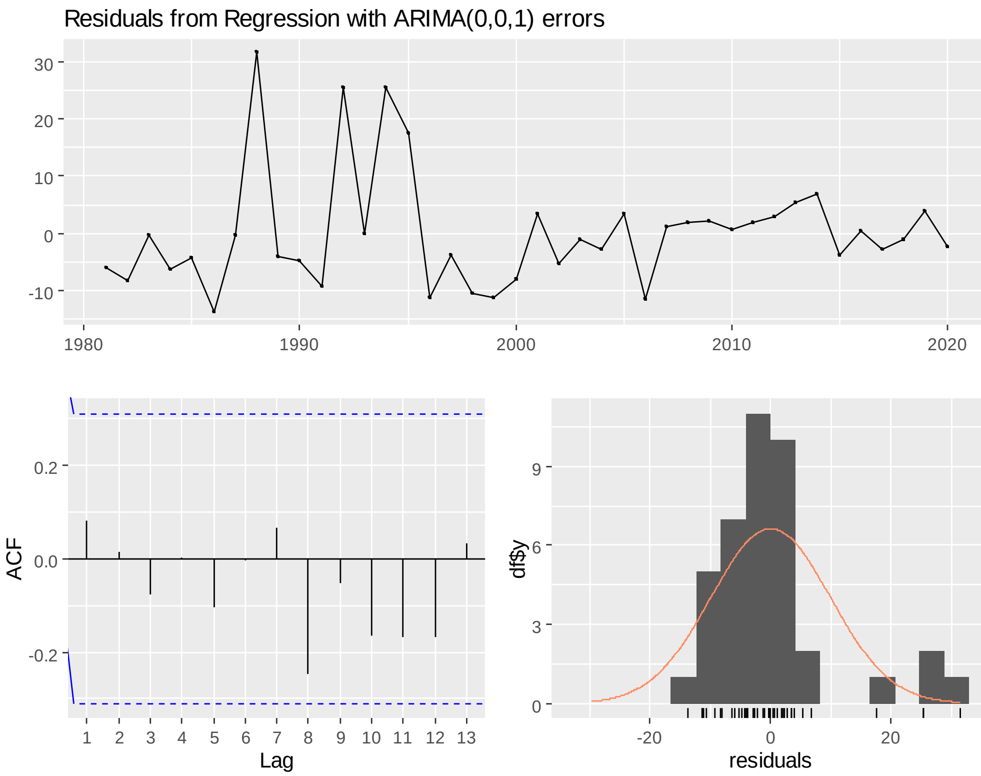

Figure 3. Diagnostic test for the time series regression with ARIMA (0,0,1) errors model

Table 6. Out-of-sample forecast using regression with ARIMA (0,0,1)

Year	Point forecast	95% Lower bound	95% Upper bound
2023	30.30	-0.56	61.16
2024	25.19	-5.67	56.05
2025	17.82	-13.04	48.68
2026	24.52	-6.33	55.39
2027	24.25	-6.61	55.11
2028	21.19	-9.67	52.05
2029	24.91	-5.95	55.77
2030	16.25	-14.61	47.11

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

CONCLUSION

The aim of this paper is to obtain the best time series regression model that will be used to forecast inflation in Nigeria using data for the period 1981-2020. We selected exchange rate, real interest rate, foreign direct investment inflow, manufacturing output, gross domestic product growth, broad money growth, and trade balance as the determinants of inflation. Regression model and residuals were obtained and normality test, homoscedasticity test and stationarity test were carried, and regression with ARIMA error was modelled. The findings show that regression with ARIMA (0,0,1) errors was the best parsimonious model for inflation forecasting in Nigeria. The results of out-of-sample forecast show that Nigeria will be experiencing a high inflation rate from 2023 compared to what it was in 2020, and from 2024 it will reduce.

REFERENCE

Aboobucker, H., & Aboobucker, J. (2018). Modelling and forecasting inflation rates in Sri Lanka. *International Journal of Science and Research (IJSR)*, 7 (9), 415-419. https://doi.org/10.21275/ART20191043

Adelekan, O. G., Abiola, O. H., & Ankeli, U. C. (2020). Modelling and forecasting inflation rate in Nigeria using ARIMA models. *KASU Journal of Mathematical Sciences (KJMS)*, 1 (2), 127-143.

Arindam, B. (2021). Forecasting price levels in India – An ARIMA framework. *Academy of Marketing Studies Journal*, 25 (1)

Asekunowo, V. O. (2016). The cause of persistent inflationin Nigeria. *CBN Journal of Applied Statistics*, 7 (2), 49-75.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian Economic Papers*, 17(31), 334-355. https://doi.org/10.1111/j.1467-8454.1978.tb00635.x

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47 (5), 1287-1294. https://doi.org/10.2307/1911963

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control.* Prentice Hall, Englewood Cliffs, NJ, USA, 3rd edition.

Chinonso, U. E., & Justice, O. I. (2016). Modelling Nigeria's urban and rural inflation using Box-Jenkins model. *Scientific Paper Series on Management, EconomicEngineer in Agriculture and Rural Development*, 16 (4), 61-68.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74 (366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Folorunso, B. A., & Abiola, A. G. (2000). The long-run determinants of inflation in Nigeria, 1970-1998. *Nigerian Journal of Economic and Social Statistics*, 42 (1), 37-53.

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica*, 46(6), 1293-1301. https://doi.org/10.2307/1913829

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW

Harris, R., & Sollis, R. (2003). *Applied time series modelling and forecasting.* Chichester, UK: John Wiley & Sons.

Isakova, A. (2007). Modeling and forecasting inflation in developing countries: The case of Economies in Central Asia. Center of Economic Research and Graduate Education, Discussion Paper, (2007-174).

Karthikeyan, P., Manikandan, M., Mani, N., & Gopalakrishnan, B. (2021). Forecasting inflation rate in India. *Indian Institute of Finance*, XXXV (4), 1209-1220.

Kuhe, D. A., & Egemba, R. C. (2016). Modeling and forecasting CPI inflation in Nigeria: Application of autoregressive integrated moving average homokedastic model. *Journal of Scientific and Engineering Research*, 3 (2), 57-66.

Lim, Y. C., & Sek, S. K. (2015). An examination of the determinants of inflation. *Journal of Economics, Business and Management*, 3(7), 678-682.

Mia, M. S., Rahman Nabeen, A. H. M. M., & Akter, M. M. (2019). Modelling and forecasting the consumer price index in Bangladesh through econometric models. *American Scientific Research Journal for Engineering, Technology, and Sciences*, 59 (1), 118-127.

Mohamed, J. (2020). Time series modeling and forecasting of Somaliland consumer price index: A comparison of ARIMA and regression with ARIMA errors. *American Journal of Theoretical and Applied Statistics*, 9 (4), 143-153. https://doi.org/10.11648/j.ajtas.20200904.18

Norbert, H., Wanjoya, A., & Waititu, A. (2016). Modeling and forecasting consumer price index (case of Rwanda). *American Journal of Theoretical and Applied Statistics,* 5, 101-107.

Ojo, M. O. (2000). The role of the autonomy of the Central Bank of Nigeria in promoting macroeconomic stability. *Central Bank of Nigeria Economic and Financial Review*, 38 (1), 23-44.

Samrad, J.-N., Seyyed, M. T. F. G., Mohsen, S., & Saeed, S. (2021). Annual forecasting of inflation rate in Iran: Autoregressive integrated moving average modeling approach. *Engineering Reports*, 3 (4), e12344. https://doi.org/10.1002/eng2.12344

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, 52 (3-4), 591-611. https://doi.org/10.1093/biomet/52.3-4.591

Udoh, N. S., & Anietie, S. I. (2018). A predictive model for inflation in Nigeria. *CBN Journal of Applied Statistics*, 9 (2), 103-129. https://doi.org/10.33429/Cjas.09218.5/6

Utami, B., Wijayanto, H., & Sumertajaya, I. M. (2018). Time-series data modeling for inflation forecasting based on subcategories of commodity using TSClust approach as pre-processing. *International Journal of Sciences: Basic and Applied Research (IJSBAR),* 39 (1), 21-33.

Article DOI: 10.52589/AJESD-HFYC2BNW
DOI URL: https://doi.org/10.52589/AJESD-HFYC2BNW