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Application of SARIMA to Modelling and Forecasting Money Circulation in Nigeria

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Authors' contributions

This work was carried out in collaboration between all authors. Author ODA designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors CEA and CCE managed the analyses of the study. Author TTM managed the literature searches. All authors read and approved the final manuscript.

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Abstract

This paper discusses the trend and pattern of money circulation in Nigeria. Its relevance lies in the fact that it could assist in monitoring the level of money circulation in the economy. Data on monthly records of money in circulation obtained from the central bank of Nigeria web database from January, 2000 to December, 2016 was analysed using the Box-Jenkins (ARIMA) methodology. The series was logarithmic transformed to normalise the series and stabilize the variance and thereafter differenced to achieve series stationarity. The Seasonal ARIMA (2, 1, 0) (0, 1, 1)$_{12}$ model was found to be appropriate in describing the patterns observed in the series. The model having passed the basic ARIMA diagnostic test was used to forecast for the next three years. This model is recommended for use until further analysis proves otherwise.

Keywords: SARIMA; money in circulation; forecast; unit-root test; transformation.

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1 Introduction

Money in circulation is the total amount of coins and naira banknotes issued, subtracting the amount that had been removed from the country's economy by the central bank [1]. The major determinant of money in circulation is the money demanded by both the public and banking systems in Nigeria. It is wise to note that the share of money circulation in money supply and the ratio in nominal Gross Domestic Product (GPD) reveals its relative importance in any country's economy [2,3]. The Nigeria central bank defines money supply in two ways: Narrow money includes currency in circulation plus current account deposited with commercial banks while broad money is defined as narrow money plus savings and time deposits with banks including foreign denominated deposits and basically measures the total volume of money supply in the economy. The basic problem is when money supply exceeds the level the economy can efficiently absorb, leading to variation in money circulation; it could dislodge the stability of the price system, leading to inflation or higher prices of goods and the inability of banks to make loans available for investment within Nigeria [4]. Hence, the purpose of this study is to use the well-established ARIMA methodology to look at the pattern and growth of money circulation in Nigeria. Furthermore, the study revelation will greatly assist the central bank of Nigeria in making appropriate financial policies in the nearest future. An umpteen of studies have been carried out by researchers using autoregressive integrated moving average modelling procedure. Albert et al. [5], modelled the monthly currency in circulation in Ghana using Seasonal Autoregressive Integrated Moving Average (SARIMA) model, O. Adubisi and C. Okorie [6] used ARIMA procedure in modelling the growth pattern of reserve currency in Nigeria. Dheerasinghe R. [7] modelled the currency in circulation in Sri-Lanka using the times series decomposition method, Iwueze et al. [8], modelled the Nigeria external money reserves with Autoregressive Integrated Moving average model. Obinna Adubisi and E. T. Jolayemi [9] estimated the impact of the global financial crisis on the Nigeria crude oil export with ARIMA-Intervention Analysis. Also, Albertho et al. [10] modelled the daily banknotes in circulation, the context of liquidity management of European Central bank using the ARIMA methodology.

2 Methodology

2.1 Box-Jenkins methodology

The multiplicative ARIMA $(p,d,q)(P,D,Q)$ model which contain both the non-seasonal and the seasonal parameters is expressed as

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D x_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \tag{1}$$

The observed series is Y_t, (B) represent the Backshift operator, t is the time, $(1-\mathrm{B})^{\mathrm{d}}$ is the regular differencing which is applied to remove the stochastic trend in the series, $(1-\mathrm{B}^{\mathrm{S}})^{\mathrm{D}}$ is the seasonal differencing applied to remove the series seasonal effects and ε_t is the white noise error i.e. $\varepsilon_t \sim WN(0,\sigma_\varepsilon^2)$. The non-seasonal and seasonal autoregressive parameters $(\phi_{\mathrm{p}}, \Phi_{\mathrm{P}})$ with the roots within the unit circle

$$\phi_{\mathrm{p}}(\mathrm{B}) = 1-\phi_1\mathrm{B}-\phi_2\mathrm{B}^2-\ldots-\phi_{\mathrm{p}}\mathrm{B}^{\mathrm{p}} \tag{2}$$

$$\Phi_{\mathrm{P}}(\mathrm{B}^{\mathrm{S}}) = 1-\Phi_1\mathrm{B}^{\mathrm{S}}-\Phi_2\mathrm{B}^{2\mathrm{S}}-\ldots-\Phi_{\mathrm{P}}\mathrm{B}^{\mathrm{PS}} \tag{3}$$

The non-seasonal and seasonal moving-average parameters $(\theta_{\mathrm{q}}, \Theta_{\mathrm{Q}})$ with the roots within the unit circle

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q \tag{4}$$

$$\Theta_Q(B^S) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \ldots - \Theta_Q B^{QS} \tag{5}$$

The Box-Jenkins procedure involve three modelling stages: The model identification stage uses the ACF and PACF plots to check for stationarity and seasonality in the observed time series data. The model parameter estimation stage involves estimation of the parameters after identifying the tentative models. In this study the criteria used in selecting the best fitted model are the Akaike information criterion (AIC), Corrected Akaike information criterion (AIC_C), and Schwarz Bayesian information criterion (BIC). The diagnostic stage checks the selected model to make sure it satisfies the basic Box-Jenkins modelling procedure assumptions using the Ljung-Box serial correlation test, Shapiro-Wilk normality test and the Lagrange Multiplier (LM) conditional heteroscedasticity test. For more details on Autoregressive moving average modelling procedure and the information criteria see Box and Jenkins [11], Box et al. [12], Pankratz [13], Akaike [14], Yang [15].

2.2 Unit root test

The Augmented Dickey-Fuller (ADF) test is based on the assumption that the time series data Y_t follows a random walk. The Augmented Dickey-Fuller (ADF) test, corresponding to modelling a random walk pattern with drift around a stochastic trend

$$\Delta y_t = \alpha + \delta t + \rho y_{t-1} + \sum_{i=1}^{k} \phi_i \nabla y_{t-i} + \varepsilon_t \tag{6}$$

The expression $\rho y_{t-1} + \sum_{i=1}^{k} \phi_i \nabla y_{t-i}$ is the augmented part, y_{t-1} is the lagged term, ∇y_{t-i} shows the lagged change, t and α represent the deterministic trend and drift components respectively, the ε_t is the error term and ρ, ϕ are coefficients to be estimated. The time series data has a unit root if the estimated $(\rho = 0)$. Hence, given a p-value greater than 5% level of significance the null hypothesis (Unit-root) will not be rejected. The Kwiatkowski-Phillip-Schmidt-Shin (KPSS) test proceed by testing for the presence of a random walk α_t in the regression equation

$$Y_t = \alpha_t + d_t + \varepsilon_t \tag{7}$$

The deterministic component is denoted by d_t and ε_t is a stationary $I(0)$ error process. The test has a null hypothesis of a stationary series in the level or trend. Hence, a p-value less than the level of significance would lead to the null hypothesis being rejected. For more details see Dickey and Fuller [16] and Kwiatkowski, et al. [17].

3 Results and Discussion

3.1 Descriptive statistics

The data on Nigeria monthly money in circulation obtained from the Central Bank of Nigeria [18] web database over the periods of January, 2000 to December, 2016 was used in this study. The descriptive statistics in Table 1 shows the data is not normally distributed with a constant variance based on the coefficient of variation (CV), skewness and kurtosis values.

Table 1. Descriptive statistics

Mean	Min	Max	CV (%)	Median	Skewness	Kurtosis
901179.20	193939.3	1857932	53.53	866306.3	0.23	-1.40

The money in circulation series plot shown in Fig. 1(a) depicts an increasing trend with non-constant variability including high peaks at specific periods in each year, suggesting the series require some sort of transformation to stabilize the variance. The logarithmic transformation was applied in other to stabilise the variance and normalise the series for further examination. Fig. 1(b) depicts the logarithmic transformed series with the variance looking stable across the periods used in the study.

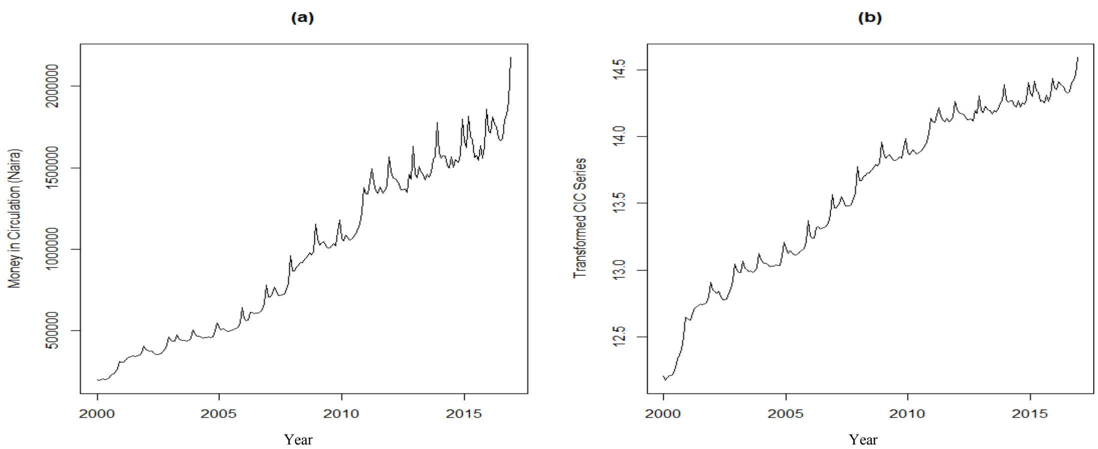


Fig. 1. Money in circulation series Plot (a) and Log transformed series plot (b).

A critical observation of the log transformed series correlogram plots in Fig. 2(a), shows high significant positive spikes which does not die out to zero in the autocorrelation function (ACF) plot and a significant spike at lag 1 in the partial-autocorrelation function (PACF), indicating that the series is not stationary.

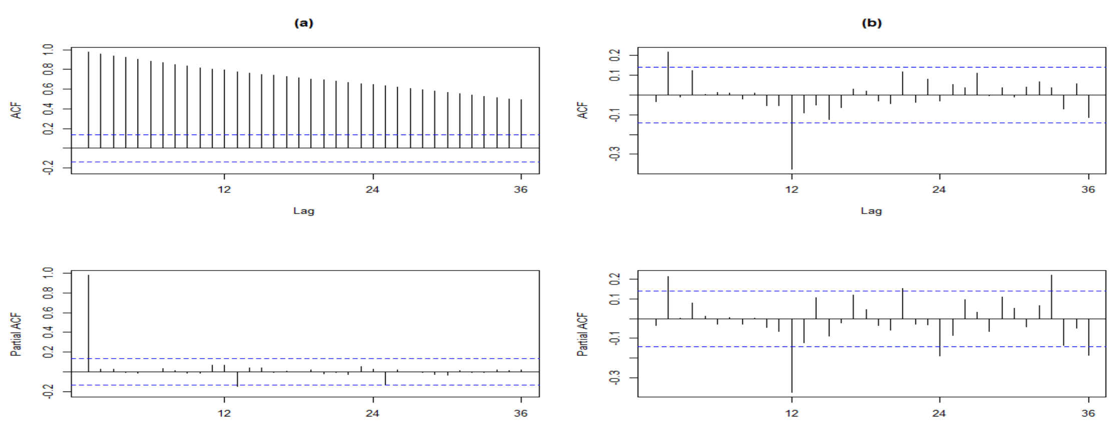


Fig. 2. The transformed series correlogram Plots (a) and the first order non-seasonal & seasonal differenced series corrologram plots (b)

The seasonally adjusted series in Fig. 3(a), depicts no stability in the series while the series in Fig. 3(b), fluctuates about the zero line confirming series stationarity after first-order non-seasonal and seasonal differencing.

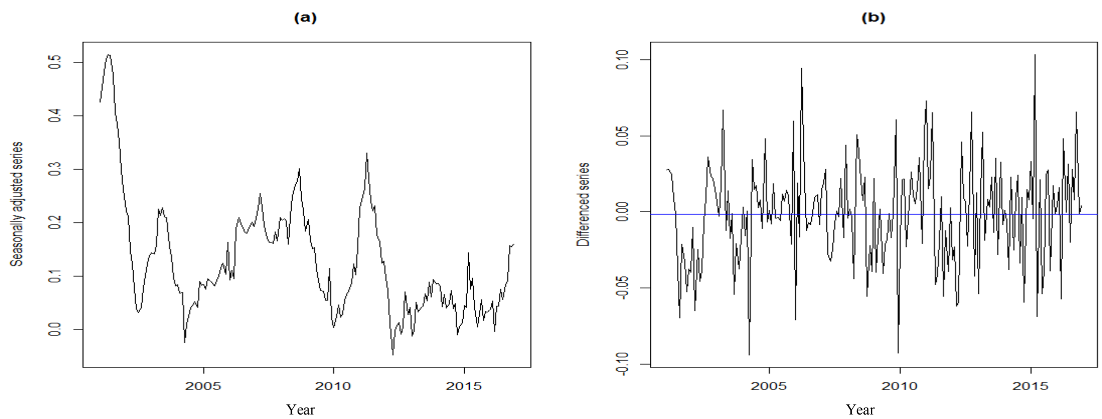


Fig. 3. Seasonally adjusted series plot (a) and the first-order non-seasonal & seasonal differenced series plot (b)

The unit-root tests shown in Table 2(a), confirms the existence of a unit root in the transformed series. The series was first-order non-seasonally and seasonally differenced to achieve series stationarity. The results in Table 2(b) confirmed that the differenced series is stationary.

Table 2. Unit-root and Stationary tests

(a) Transformed (MIC) series				(b) N&S differenced (MIC) series			
Test type	**Test statistics**	**Lag order**	**P-value**	**Test type**	**Test statistics**	**Lag order**	**P-value**
ADF	-3.5739	5	0.037	ADF	-4.8800	5	0.01
KPSS	0.7664	3	0.01	KPSS	0.0550	3	0.1

***N&S** means first-order non-seasonal and seasonal differenced money in circulation (MIC) series*

3.2 Model identification and estimation

The behaviours of the autocorrelation (ACF) and partial autocorrelation (PACF) were used to identify some tentative models which were further subjected to model selection procedure in other to determine the best parsimonious model for the series. We noticed that the ACF plot displayed significant spikes of 0.241 at lag 2 and -0.352 at lag 12 while the PACF plot likewise had significant spikes of lag 2 (0.238), lag 12 (-0.340) and lag 24 (-0.185). Table 3, presents the summaries of possible tentative models observed from the correlogram plots in Fig. 2(b).

The seasonal ARIMA structures 2 and 3 seem to be the completing models with significant parameter estimates and minimum model standard deviation estimates. Based on the selection criteria, the Seasonal ARIMA structure 2 seem to provide the appropriate fit that best describe the log transformed series with minimum AIC, AICc and BIC compared to other seasonal ARIMA structures considered in Table 3. The estimated coefficients of the seasonal ARIMA structure 2 using the maximum likelihood estimation method are significantly different from zero based on the t-values. The chosen Seasonal ARIMA (2, 1, 0) (0, 1, 1)$_{12}$ model using the Backshift operator (B) is expressed as:

$$(1-B)(1-\mathrm{B}^{12})(1-\phi_1 B-\phi_2 B^2)x_t = (1+\Theta_{12}\mathrm{B}^{12})\varepsilon_t \tag{8}$$

The seasonal ARIMA model in equation (8), is rewritten as

$$\nabla^1 \nabla_{12} x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \varepsilon_t + \Theta_{12} \varepsilon_{t-12} \tag{9}$$

The estimated parameters ϕ_1, ϕ_2 and Θ_{12} are presented in Table 3, ε_t is the white noise and x_t is the log transformed data series.

Table 3. Tentative seasonal ARIMA models

S/N	SARIMA structure	Parameter estimates (Standard error)	t-value	Selection criteria	STD of model
1	ARIMA (2, 1, 2) $(1, 1, 0)_{12}$	AR(1) = 0.0726 (0.2295) AR(2) = 0.4942 (0.1912) MA(1) = -0.1716 (0.2524) MA(2) = -0.2598 (0.2021) SAR(1) = 0.4263 (0.0676)	0.316 2.585* -0.680 -1.285 6.306*	Log-likelihood = 403.42£ AIC = -794.85 AICc = -794.39 BIC = -775.33	0.0291
2	ARIMA (2, 1, 0) $(0, 1, 1)_{12}$	AR(1) = 0.1066 (0.0503) AR(2) = 0.2346 (0.0701) SMA(1) = -0.7551 (0.0637)	2.119* 3.347* -11.854*	Log-likelihood = 417.42 AIC = -826.83^ AICc = -826.62+ BIC = -813.82@	0.0265
3	ARIMA (2, 1, 1) $(0, 1, 1)_{12}$	AR(1) = 0.4109 (0.2288) MA(1) = 0.2859 (0.0696) MA(2) = -0.5572 (0.2391) SMA(1) = -0.7689 (0.0629)	1.796 4.108* -2.330* 12.224*	Log-likelihood = 418.22 AIC = -826.43 AICc = -826.11 BIC = -810.17	0.0263$
4	ARIMA (1, 1, 2) $(0, 1, 1)_{12}$	AR(1) = -0.2319 (0.3879) MA(1) = 0.1153 (0.3871) MA(2) = 0.196 (0.080) SMA(1) = -0.7582 (0.0638)	0.598 0.298 2.450* 11.884*	Log-likelihood = 416.75 AIC = -823.51 AICc = -823.18 BIC = -807.25	0.0266

** denote parameters significant at 5% level of significance.*
^, +, @ and £ denotes the minimum AIC, AICc, BIC and log-likelihood values respectively.
$ denote the minimum model standard deviation estimate (STD means Standard deviation).

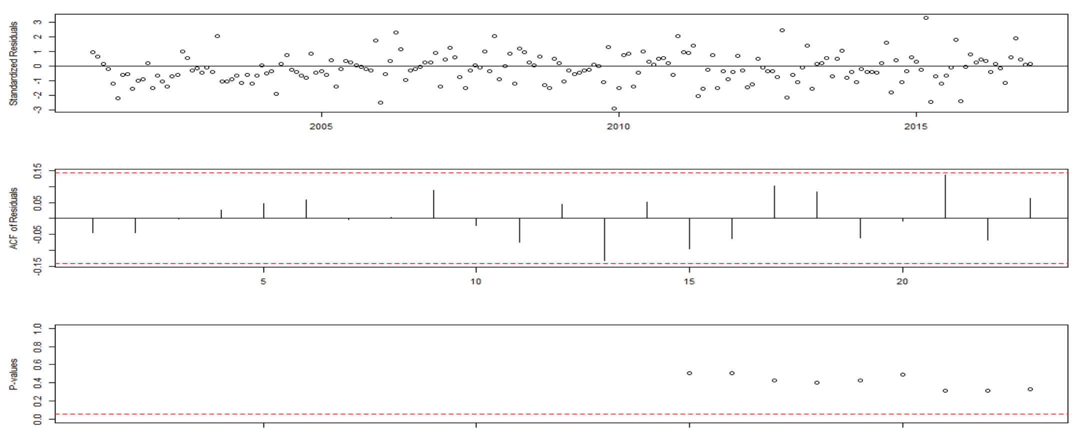


Fig. 4. Residuals diagnostic plots

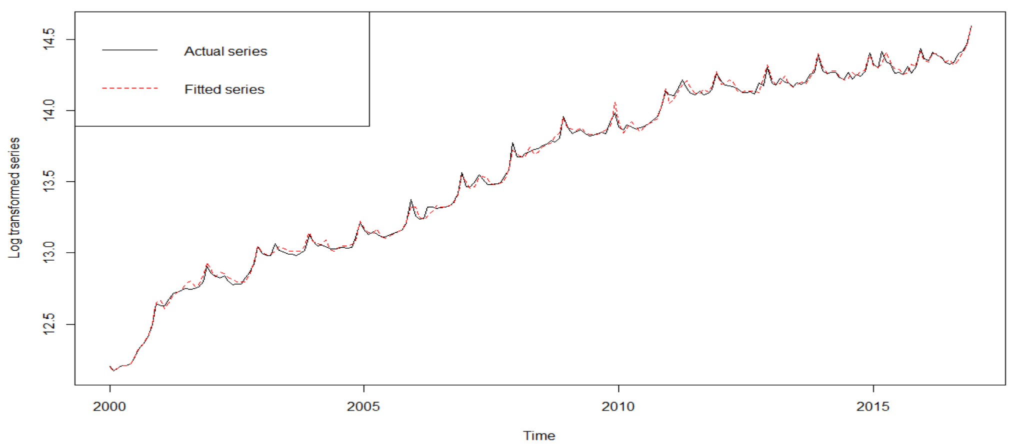
3.3 Model diagnostic tests

In this section, the seasonal ARIMA structure 2 residuals are subjected to the Box-Ljung test [19] for residuals serial correlation, Shapiro-Wilk Normality test [20] for residuals Normality and ARCH-Lagrange Multiplier test [21] for residuals homoscedasticity to confirm its adequacy. The p-values for all the tests shown in Table 4 are statistically insignificant at 5% level of significance which proves that the residuals of the fitted seasonal ARIMA model are Normality distributed, homoscedastic and do not suffer from autocorrelation effects. Fig. 4 depicts the model residuals diagnostic plots which were used to assess whether the selected seasonal ARIMA model appropriately captures the dependence structure of the series.

In the first panel, the standardized residuals do not exhibit any obvious pattern as observed and their empirical ACF in the second panel shows no individually significant autocorrelation at lags > 1. Finally, the p-values for the Ljung-Box statistic in the third panel all clearly exceed 5% for all orders, indicating that there is no significant departure from white noise. The fitness of the selected Seasonal ARIMA structure as shown in Fig. 5 reveals that the actual and fitted series of the log-transformed series strongly agree.

Table 4. Model adequacy tests

Type	Test statistic	Degree of freedom	p-value
Box-Ljung test	$\chi^2 = 17.937$	16	0.3276
ARCH-LM test	$\chi^2 = 20.533$	12	0.06
Shapiro-Wilk test	w = 0.98852	-	0.1003



Year

Fig. 5. Seasonal ARIMA Model fitness plot

3.4 Forecasting

In modelling researchers are motivated by the desire to produce forecasts with minimum error as much as possible. In this section, we assess the forecasting performance of the seasonal ARIMA model. The Box-Jenkins approach can handle effectively many time series datasets. Besides, previous researchers have demonstrated that the Box-Jenkins approach outperformed the Stepwise auto regression and Holt-Winters exponential approaches in terms of forecasting performances, Newbold and Granger [22]. We assumed that the condition(s) under which the seasonal ARIMA model was constructed would persist in the periods for which the forecasts are made. The computation of the forecast values was carried out with forecast estimate function:

$$\hat{x}_{T+h/T} = \phi_1 \hat{x}_{T+h-1/T} + \phi_2 \hat{x}_{T+h-2/T} + \Theta_{12} \hat{\varepsilon}_{T+h-12/T} \tag{10}$$

The forecast error $\hat{\varepsilon}_t(h)$ at lead time (h) is given by

$$\hat{\varepsilon}_t = x_{T+h} - \hat{x}_{T+h/T} \tag{11}$$

Where x_{T+h} is the actual value at $T+h$.

The fitted model monthly forecasts and their 95% confidence interval for 3 years after conversion to the actual currency (Naira) are presented in Table 5.

Table 5. Forecasted values with fitted model

Year	Month	Forecast	95% confidence intervals	
			Lower	Upper
2017	Jan	₦2,010,975	₦1,909,248	₦2,118,100
2017	Feb	₦1,9810,15	₦1,847,807	₦2,123,827
2017	Mar	₦2,080,419	₦1,898,814	₦2,279,394
2017	Apr	₦2,046,231	₦1,837,874	₦2,278,209
2017	May	₦2,009,105	₦1,776,756	₦2,271,839
2017	Jun	₦1,947,681	₦1,699,611	₦2,231,958
2017	Jul	₦1,964,032	₦1,692,606	₦2,278,983
2017	Aug	₦1,955,429	₦1,666,090	₦2,295,015
2017	Sep	₦2,022,713	₦1,705,024	₦2,399,594
2017	Oct	₦2,040,387	₦1,702,724	₦2,445,035
2017	Nov	₦2,113,255	₦1,746,772	₦2,556,654
2017	Dec	₦2,403,004	₦1,968,318	₦2,933,715
2018	Jan	₦2,213,930	₦1,790,598	₦2,737,348
2018	Feb	₦2,179,051	₦1,742,184	₦2,725,439
2018	Mar	₦2,287,706	₦1,807,382	₦2,895,678
2018	Apr	₦2,249,728	₦1,757,671	₦2,879,566
2018	May	₦2,208,800	₦1,706,986	₦2,858,164
2018	Jun	₦2,141,206	₦1,637,629	₦2,799,636
2018	Jul	₦2,159,160	₦1,634,831	₦2,851,655
2018	Aug	₦2,149,681	₦1,611,958	₦2,866,780
2018	Sep	₦2,223,649	₦1,651,839	₦2,993,399
2018	Oct	₦2,243,079	₦1,651,195	₦3,047,158
2018	Nov	₦2,323,186	₦1,695,113	₦3,184,004
2018	Dec	₦2,641,718	₦1,911,044	₦3,651,797
2019	Jan	₦2,433,862	₦1,740,634	₦3,403,143
2019	Feb	₦2,395,518	₦1,694,944	₦3,385,628
2019	Mar	₦2,514,966	₦1,759,711	₦3,594,373
2019	Apr	₦2,473,216	₦1,712,132	₦3,572,621
2019	May	₦2,428,222	₦1,663,343	₦3,544,863
2019	Jun	₦2,353,914	₦1,596,046	₦3,471,648
2019	Jul	₦2,373,651	₦1,593,431	₦3,535,941
2019	Aug	₦2,363,230	₦1,571,058	₦3,554,873
2019	Sep	₦2,444,546	₦1,609,703	₦3,712,366
2019	Oct	₦2,465,906	₦1,608,737	₦3,779,832
2019	Nov	₦2,553,971	₦1,651,080	₦3,950,647
2019	Dec	₦2,904,146	₦1,860,768	₦4,532,572

A critical look at the forecasts table above, we can deduce that the money in circulation increased gradually all through the period from the year 2017 –2019.

4 Conclusion

The paper examined the appropriate model that fits the monthly record of Nigeria Money in circulation for the periods January 2000 to December 2016 obtained from the Central Bank of Nigeria web database. It was discovered that the seasonal ARIMA (2, 1, 0) $(0, 1, 1)_{12}$ model is the most suitable model for the series with the smallest information criteria. The purpose of this study is to look at the pattern and growth of money in circulation in Nigeria. The study result reveals that the money in circulation are rising steadily given the years considered. A critical look at the forecast values also shows the same trend and stead rise in the growth of the Nigeria money in circulation. Having modelled and forecasted the money circulation in the Nigeria economy, we recommend the need to increase central bank independence in order to reduce the effect of fiscal pressure on monetary policy and also create better strategies in managing money supplies in the economy.

Furthermore, we also recommend that the issues of policy transparency and accountability should be addressed. These will provide an implicit commitment mechanism on the part of the central bank.

Competing Interests

Authors have declared that no competing interests exist.

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