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Full Length Research

A predictive Autoregressive Integrated Moving Average (ARIMA) Model for forecasting inflation rates

Adubisi, O. D.[1]*, David, I. J.[1], James F.E.[1], Awa U. E.[2] and Terna A. J.[1]

[1]Department of Mathematics and Statistics, Federal University Wukari, Taraba State, Nigeria.
[2]Departmentof Statistics, University of Port-Harcourt, River State, Nigeria.

*Corresponding author. Email: adubisiobinna@fuwukari.edu.ng, obinnadubisi@yahoo.com

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ABSTRACT: This paper considers the modelling and forecasting of monthly All-items (12 months average change) inflation rates in Nigeria using the Box-Jenkins (ARIMA) model. Time series data used in the study was collected from the Central Bank of Nigeria statistical web database. The data was differenced twice to achieve stationarity in the series as required. Based on the evaluation and diagnostic criteria, the most accurate model is selected. The order of the best ARIMA model was found to be ARIMA (1, 2, 1). The diagnostic analysis of the model residuals showed that they are normally distributed uncorrelated random shocks. The findings in this study showed that the selected ARIMA model captured the dynamics in the series and produced forecasted values which had minimal forecast errors when compared with the actual inflation values in the validation period.

Key words: ARIMA, consumer price index, forecast, inflation rates, Unit-root test.

INTRODUCTION

The major aim of macroeconomic policy in Nigeria is to maintain low and stable inflation rates. This is due to the fact that sustainable economic growth in relation to low and stable inflation is crucial to the development of any country. Inflation as measured by the consumer price index reflects the annual percentage change in the cost of acquiring goods and services over a specified interval. According to (Central bank of Nigeria, 2015), the consumer price index (CPI) approach though it is the least efficient is used to measure inflation on monthly, quarterly and annually basis in Nigeria. Inflation is generally a persistent and appreciable rise in the general level of price over a period of time. Dania (2013) stated that a continuous persistent increase in the general level of price has severally been characterized by an upsetting impact on economic well-being, since it causes the cost of living to rise and the value of investment to fall.

An implication of the above statement therefore is the fact that to keep the cost of living to the barest minimum, price instability must be well managed by monetary policy makers. Hence, in order to achieve and maintain price stability, the evolutionary dynamics and time dependent structure of the inflationary series must be studied using an appropriate stochastic modelling approach. This Box-Jenkins (ARIMA) approach in reference to time series literature have extensively been applied in univariate and multivariate time series analyses in different fields such as tourism, crime, business and sociology. A number of studies using the Box-Jenkins approach have been carried out (Shakira, 2011) with exploring the application of the Box-Jenkins approach to stock prices modelling at different sampling time intervals in order to determine if there is an optimal frame and similarities in autocorrelation patterns of stocks within the same industry. Adubisi et al. (2017a) developed a seasonal ARIMA model with Square-Root variance stabilizing transformation for monitoring Nigeria crude oil export to America. The result of the study showed that the Square-Root transformed series performed better in capturing the dynamics of the system as against the normal variance stabilization using the logarithm transformation. Bakari et al. (2013) used the Box-Jenkins methodology to build models for annual production and utilization of gas in Nigeria from 1970-2004. The models were used to forecast the production and utilization of gas for the up-coming 4 years to help decision makers establish priorities in terms of gas demand management. They also suggested in the paper that an ARIMA intervention time series analysis could be used to forecast the peak value of production and utilization data. Also, Adubisi et al. (2017b) explored the trend and pattern of Nigeria money in circulation system within a specified period. The study revealed a steady rise in Nigeria money in circulation in the three years forecast periods produced by the seasonal ARIMA model.

Hence, it is against this backdrop that we aim to develop an ARIMA model that can predict all items monthly inflation rates in Nigeria with minimal errors.

Literature review

In the last few decades, a number of empirical research studies have been carried-out in the area of inflationary modelling and prediction. Ekpenyong and Udoudo (2016) analysed and forecasted monthly all-items (year-on-year change) inflation rates in Nigeria for the periods 2000 to 2015, using a seasonal ARIMA (0, 1, 0) (0, 1, 1) model. The model was found to be adequately appropriate for predicting the next 12-months inflation rates which agreed closely with the original observed inflationary values.

Osuolale et al. (2017) applied ARIMA models in modelling and forecasting Nigeria's inflation rates for the periods 2006 to 2015. They identified that ARIMA (0, 1, 1) seems suitable for forecasting inflation rates for the next three years which showed a parallel movement from January, 2016 to December, 2018.

Otu et al. (2014) used the Box-Jenkins Seasonal Autoregressive Integrated Moving Average to analyse monthly inflation rates in Nigeria from October 2003 to November 2013. Forecast for the period of November, 2013 to November 2014 was made. ARIMA (1, 1, 1) (0, 0, 1)2 was developed. The forecast results revealed a decreasing pattern of inflation rates in the first quarter of 2014 and turning point at the beginning of the second quarter of 2014, where the rates takes an increasing trend till September. It was found that inflation showed volatility starting from 2006. According to them, the volatility in Nigeria's inflation series can be attributed to several economic factors. Some of these factors are money supply, exchange rate depreciation, petroleum prices increase, and poor agricultural production.

Udegbunam and Onu (2016) modelled Nigeria's urban and rural inflation using monthly consumer price index (CPI) from January 2001 to December 2015. The study results showed that ARIMA (0, 1, 0) and ARIMA (0, 1, 13) were suitable for modelling Urban and Rural inflation rates in Nigeria. November 2006 and July 2008 showed trends in both urban CPI and rural CPI while there was a persistence increase in inflation rate from July 2013 which might be caused by transition in government, economic policies, withdrawals of foreign investors etc. The forecasted inflationary values from 2016 to 2018 with the ARIMA models showed a very high estimated urban and rural inflationary rates of 202.9 and 207 respectively for May, 2018.

Olajide et al. (2012) applied the Box-Jenkins approach to modelling and predicting annual inflation rates in Nigeria for the period of 1961 to 2010. The study showed that ARIMA (1, 1, 1) model captured the dynamics in the yearly series. The developed model was used to forecast the year 2011 inflation rate as 16.27%.

Osarumwense and Waziri (2013) explored the univariate non- linear time series analysis to the inflation data spanning from January,1995 to December, 2011. (GARCH (1,0) + ARMA (1,0)) model was used and 24 months forecast from January, 2012 to December, 2014 was made. From the analysis, the descriptive statistics for the monthly CPI rate and return showed a standard deviation of 29.13 from the series is high with a general mean of 58.550. Skewness of 0.792 implied that the distribution is positively skewed with long right tail and a deviation from Normality. A kurtosis of -0.541 suggest flatness of the distribution.

Etuk (2012) used a multiplicative seasonal autoregressive integrated moving average (ARIMA) model, (1, 1, 0)(0, 1, 1)12 to forecast monthly inflation rate in Nigeria. All items (Year on change) inflation rate from 2003 to 2011 was used in the study. They observed that monthly inflation rate in Nigeria is seasonal and forecast for 2012 was made using the selected model.

David and Raymond (2016) employed a univariate Autoregressive Integrated Moving Average (ARIMA) homoscedastic model in conjunction with Box and Jenkins modelling procedure to model and forecast annual Consumer Price Index (CPI) data in Nigeria from 1950 to 2014. They applied Box-Jenkins modelling methodology to search for an optimal model and found that ARIMA (3, 1, 0) was the best fitting model to describe CPI data series in Nigeria. Based on the model, the future annual CPI in Nigeria for a period of 6 years from 2015 to 2020 was forecasted. The forecasts showed a steady increase in the annual values of CPI in Nigeria. The study predicted that inflation will increase in Nigeria from 2015 since the confidence intervals of the forecast suggest a consistent increase in annual CPI during the forecasted period of 2015 to 2020.

METHODOLOGY

Data source and descriptive analysis

The monthly inflation rate (01/2006 – 12/2017) with 144 observations obtained from the Central Bank of Nigeria web database was used in this study (www.cenbank.org/mnycredit.asp). The R-project statistical software (R core Team, 2017) was used for modelling and forecasting the data series. All graphs and plots were also generated using the R-project statistical software. Before the data modelling procedure, the data series were split into two parts: the historic data used to develop the model (01/2006 – 12/2016) with 132 observations and the validation data used to evaluate the model (01/2017 – 12/2017) with 12 observations. The data for model construction were examined for trends and variability using the time plot, autocorrelation function (ACF) and partial autocorrelation function (PACF) plots as explained in the ARIMA modelling technique section. The ACF and PACF plots provides the graphical representation of the autocorrelation and partial autocorrelation structures of the study series.

ARIMA modelling technique

The method used in this study is the Box-Jenkin approach (Box and Jenkins, 1976) which accommodates the autoregressive integrated moving average *(ARIMA)*model.

Autoregressive moving average (ARMA) model

The autoregressive moving average model provides a parsimonious description of a weakly stationary stochastic process, the autoregressive and the moving average processes. The model is normally referred to as the $ARMA\ (p,q)$ model with (p) autoregressive (AR) terms and (q) moving average (MA) terms. The $ARMA\ (p,q)$ model is mathematically expressed as:

$$y_t = \mu + \varepsilon_t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i\, \varepsilon_{t-i} \text{ ----------------(1)}$$

Where, y_t is the observed series, (μ) is the constant term, (ϕ, θ) are the (AR) and (MA) estimated parameters using maximum likelihood estimation procedure. The error term (ε_t) are assumed to uncorrelated random variables with zero mean and constant variance. Appropriate values of the $ARMA\,(p,q)$ model parameters can be found by plotting the autocorrelation and partial-autocorrelation functions for the estimation of (p,q) estimates. However, it is apparent that for most real time series, the stationarity hypothesis is not appropriate. The analysis of nonstationary time series with ARMA models which requires at least a preliminary transformation of the data to get stationarity leading to the development of the autoregressive integrated moving average $(ARIMA)$ model was addressed by (Box and Jenkins, 1976; Box et al., 1994). Stationarity in the series, according to Box et al. (1994) is normally achieved by removing the trend and seasonal influence through differencing of the series. The first-order difference of the series (y_t) is given by $z_t = \Delta y_t = y_t - y_{t-1}$ or expressed in terms of the Lag operator (L) as $z_t = (1-L)y_t$, so the d^{th} order differencing is expressed as $z_t = \Delta^d y_t = (1-L)^d y_t$. The $z_t = \Delta_s^D y_t = (1-L^s)^D y_t$ represents the seasonal difference of the series in the D^{th} order. Hence, the autoregressive integrated moving average model, $ARIMA\,(p,d,q)$ expressed as:

$$\phi_p(L)(1-L)^d y_t = \theta_q(L)\varepsilon_t \text{--------------------------(2)}$$

If the series is also affected by seasonal variations as a result of seasonality that comes with some monthly series, the $ARIMA\,(p,d,q)$ is extended to include the seasonal component. Thus, we have the seasonal $ARIMA\,(p,d,q)(\,P,D,Q)$, expressed in lag form as:

$$\phi(L)\Phi(L^s)(1-L)^d(1-L^s)^D y_t = \theta(L)\Theta(L^s)\varepsilon_t \text{--------(3)}$$

Where, $(\phi,\theta),(\Phi,\Theta)$ represent the non-seasonal and seasonal parameters for both the autoregressive and moving average orders while (ε_t) is the error term. The approach involves three iterative building process namely model identification, model parameters estimation and residuals diagnostic checking. But before these iterative process, the descriptive statistics of the series is explored in order to ascertain the presence of some basic facts about the series distributional properties. Hence, the first stage known as the model identification stage involves the use of the time series plot, autocorrelation function (ACF) and partial autocorrelation function (PACF) to check for series stationarity, seasonality including the use of methods proposed by Dickey and Fuller (1979) and Kwiatkowski et al. (1990) to also check for the presence of unit roots in the series with the Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The order for both the ordinary and seasonal components of the ARIMA (p, d, q) (P, D, Q) model are identified at this stage. The next stage of the process involves estimation of the parameters after identifying the tentative models. In this stage, the goodness-of fit of the models were evaluated using the Akaike information criterion, Corrected Akaike information criterion proposed by Akaike (1974) and Yang (2005) and Schwarz Bayesian information criterion elaborated by Bumham and Anderson (2002). The model with the lowest AIC or BIC value is normally preferred. The last stage examines the adequacy of the selected model using the model residuals. The diagnostic checking is carried using the Ljung-Box test proposed by Ljung and Box (1978), Shapiro-Wilks normality test proposed by Shapiro and Wilk (1965) and the Lagrange multiplier (LM) test proposed by Engle (1982) to check for the existence of autocorrelation, normality and homoscedasticity behaviors in the model residuals.

Unit root/Stationarity test

The Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were performed to determine if the series contains a unit root (non-stationary). Dickey and Fuller (1979) proposed a test

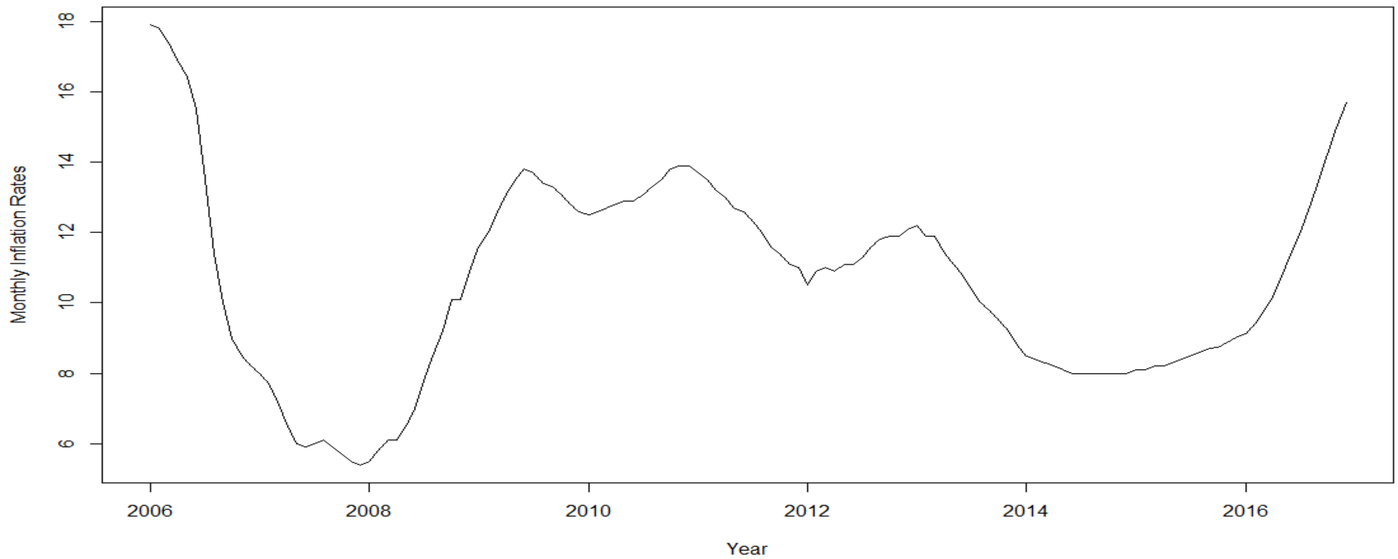

Figure 1. Inflation rate series plot.

based on the assumption that the time series data (y_t) follows a random walk. The ADF test, corresponding to modelling a random walk pattern with drift around a stochastic trend is expressed as:

$$y_t = \alpha + \rho y_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta y_{t-i} + \beta_t + \varepsilon_t \text{---------------(4)}$$

The expression $\rho y_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta y_{t-i}$ is the augmented part, y_{t-1} is the lagged term, Δy_{t-1} shows the lagged change, (t) and (α) represent the deterministic trend and drift components respectively, the (ε_t) is the error term and (p, δ) are coefficients to be estimated. If $(\rho = 1)$ the model is said to be non-stationary which implies the presence of unit root in the series. The unit root test is carried out under the null hypothesis $(\rho = 0)$ i.e. the original series is non-stationary against alternative $(\rho < 0)$ i.e. the original series is stationary. The statistic is computed by $DF_t = \frac{\hat{\rho}}{se(\hat{\rho})}$ and compared to the relevant critical value from the Dickey-Fuller table.

Kwiatkowski et al. (1990) proposed a procedure for testing stationarity in time series data. The procedure has a null hypothesis of stationary time series. The testing point of the KPSS test is given as:

$$Y_t = \alpha_t + \beta_t + \mu_t \text{---------------------------(5)}$$

Instead of the commonly used constant term, a random walk $\alpha_t = \alpha_{t-1} + \varepsilon_t$ is allowed, where (ε_t) is assumed to be normally independent and identically distributed. In all, p-value less than 0.05 from the result of the KPSS test would be enough to reject the null hypothesis at 5% level of significance while for the ADF test, a p-value of greater than 0.05 would lead to acceptance of the null hypothesis which implies the presence of a unit root in the series. Therefore, differencing is applied until the ACF shows an interpretable pattern with only a few significant autocorrelations.

ARIMA model prediction

A view into the future is one of the main objectives of model building. In this study the prediction estimation function for optimal (h) periods ahead is expressed as:

$$\hat{y}_{T+h/_T} = \phi_1 \hat{y}_{T+h-1/_T} - \theta_1 \varepsilon_{T+h/_T} \text{-------------(6)}$$

The forecast error $\hat{\varepsilon}_t(h)$ is the difference between the actual inflationary values and the predicted values from the chosen model. The prediction error $\hat{\varepsilon}_t(h)$ at the lead time (h) is expressed as:

$$\hat{\varepsilon}_t(h) = y_{T+h} - \hat{y}_{T+h/_T} \text{--------------------------(7)}$$

Where y_{T+h} and $\hat{y}_{T+h/_T}$ represent the actual and predicted inflation values at time $(T + h)$ respectively.

RESULTS AND DISCUSSION

Descriptive results

The time series plot for the inflationary series is presented in Figure 1. The series is actually characterized by up and down movements which could be interpreted to signify non-stationarity. The ACF and PACF plots of the inflationary series and the second-order difference are presented in Figure 2a and b. The ACFs in Figure 2a

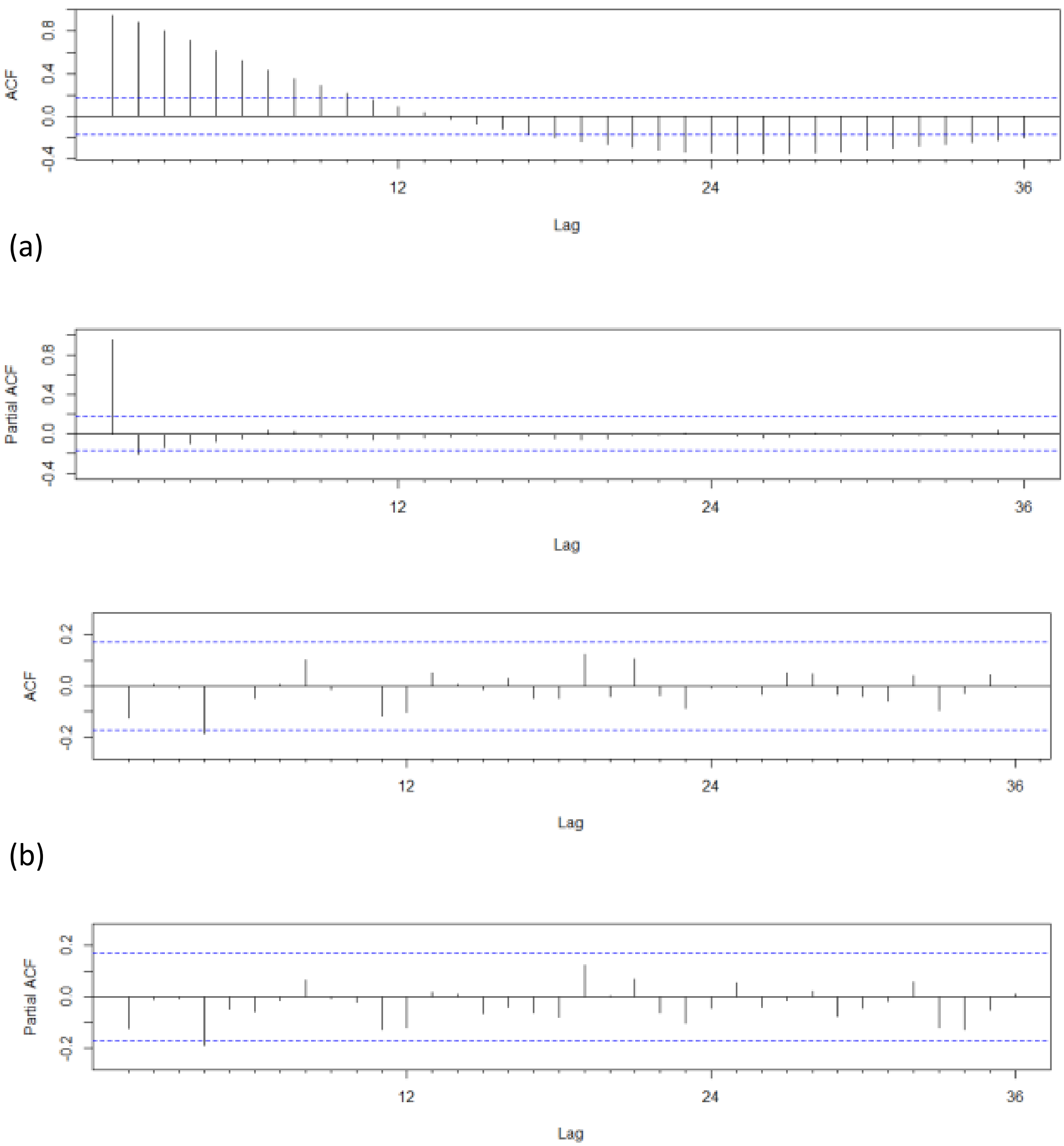

Figure 2. (a) ACF and PACF plots for Sample series and (b) Second-order differencing series.

decayed over time with a persistent autocorrelation structure significant at lags of up to about one year. The inflationary series unit root test result in Table 1 indicates non-stationarity in the series. The first-order differenced series was also found to be non-stationary based on the results of the various preliminary tests carried out as shown in Table 2. Hence, the series was second-order differenced to achieve series stationary before proceeding with series modelling and parameter estimation. The unit root test results in Table 3 after second-order ordinary differencing confirmed the stationarity of the series.

ARIMA Modelling results

The second order differenced series correlogram after the

Table 1. Sample series Unit-root/Stationarity tests.

Test type	Test statistics	Lag Order	P-value
KPSS	0.2628	2	0.01
ADF	-3.0677	5	0.1325

Table 2. First-order differencing series Unit-root/Stationarity tests.

Test type	Test statistics	Lag Order	P-value
KPSS	0.1365	2	0.01
ADF	-4.5793	5	0.067

Table 3. Second-order differencing series Unit root and Stationarity tests.

Test type	Test statistics	Lag Order	P-value
KPSS	0.034208	2	0.1
ADF	-8.0432	5	0.01

Table 4. Comparison of tentative ARIMA (p, 2, q) models (Tentative models**)**.

Models	Selection criteria			
	AIC	AICc	BIC	Log likelihood
ARIMA $(2,2,1)$	4.42	4.74	15.89	1.79
ARIMA $(1,2,1)^{*}$	**2.92**	**3.11**	**11.52**	**1.54**
ARIMA $(1,2,2)$	4.48	4.8	15.95	1.76
ARIMA $(2,2,2)$	6.33	6.82	20.67	1.82

*Represents the best fitted model based on the selection criteria (AIC, AICc and BIC).

Table 5. Parameter for ARIMA (1, 2, 1) model.

Model Fit Statistics				
AIC	**AICc**	**BIC**		
2.92	3.11	11.52		
Coefficients	**Estimates**	**Std. Error**	**t-value**	**p-value** P(>|t|)
AR (1)	0.8677	0.0586	14.8072	0.001
MA (1)	-0.9878	0.0426	-23.1878	0.001

series was proven to be stationary was used to identify the appropriate model for the study series. The various tentative models presented in Table 4 were identified from the ACF and PACF plots of the stationary series. The ARIMA (1, 2, 1) structure in Table 5, with statistically significant parameters was found to be the best model based on the AIC, AICc and BIC selection criteria.

The fitted model was found to be adequate based on the residuals analysis using the Ljung- Box test, Shapiro-Wilk Normality test and the ARCH-LM test as presented in Table 6. Which implied that the fitted model residuals are uncorrelated and normally distributed with zero mean and a constant variance (Gaussian white noise).

Model forecasting results

The ARIMA (1, 2, 1) model was used to forecast the inflation rate values for the year 2017. The forecasted values were compared with the actual inflation values for

Table 6. Model residuals adequacy analysis (Diagnostic Tests).

Test Type	Test Statistics	Degree of freedom	P-value
Ljung-Box	12.396	17	0.7756
Shapiro-Wilk	0.907	-	0.147
ARCH-LM	17.950	12	0.1172

Table 7. The validation/forecasted values.

Periods	Forecast	Actual values	Error	95% Lower CI	95% Upper CI
Jan 2017	16.35	16.44	0.09	15.88	16.82
Feb. 2017	16.93	16.69	-0.24	15.93	17.93
Mar. 2017	17.44	17.32	-0.12	15.85	19.05
Apr. 2017	17.91	17.59	0.39	15.66	20.15
May. 2017	18.32	17.63	0.69	15.40	21.23
June 2017	18.67	17.58	1.09	15.09	22.29
July 2017	19.02	17.47	1.55	14.72	23.31
Aug. 2017	19.32	17.33	1.99	14.33	24.31
Sep. 2017	19.59	17.17	2.42	13.90	25.28
Oct. 2017	19.84	16.97	2.87	13.46	26.22
Nov. 2017	20.05	16.76	3.29	13.00	27.13
Dec. 2017	20.27	16.50	3.77	12.53	28.02

the year 2017, in other to assess the performance ability of our model in forecasting the future values of inflation rates in Nigeria. The forecasted values for twelve months (year 2017) are presented in Table 7.

CONCLUSION

In this study, a univariate time series ARIMA model was developed for forecasting the monthly inflationary series. The study revealed that the inflationary series exhibited a pronounced non-periodic pattern with no visible outliers and structural breaks in the time series data. The ARIMA (1, 2, 1) was found to be the best model based on the AIC, AICc and BIC selection criteria with statistically significant parameters.

Furthermore, the diagnostic checks on the best inflationary series model confirmed that the residuals are uncorrelated and normally distributed with zero mean and a constant variance (White noise). The white noise residuals were clearly portrayed by the randomness of the residuals, non-significant spikes in the ACF residual plots. Finally, the model was used to predict the inflation rate for the year 2017 with the 95% confidence limits. The comparison between the actual inflationary series and the predicted/validation values for the year 2017 showed that the model captured the stochastic nature in the series. The predicted values from the ARIMA model revealed that all items inflation rates in Nigeria will increase gradually, all things being equal.

We suggest further studies on inflationary analysis using intervention analysis with inclusion of various economic factors such as GDP to examine its influence on inflation.

CONFLICT OF INTEREST

All authors have no conflicts of interest to report.

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