FORECASTING NIGERIA'S INFLATION USING SARIMA MODELING

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ABSTRACT

Inflation series exhibit trend or seasonality that makes it difficult to analyze the inflationary pressures for monetary policy decision making. It is imperative to note that few empirical studies have tilted towards addressing the seasonality issues to track the sources responsible for these fluctuations. It is against this background that the study aims at developing a model of inflation with higher data points and taking into cognizance its periodic seasonal component and use the estimated model to make forecast. The study used monthly data sourced from the Central Bank of Nigeria (CBN) Statistical Bulletin. Data was analysed using seasonal ARIMA model (SARIMA) which is an extension of autoregressive (AR) and moving average (MA) process in the popular Box-Jenkins methodology. With 300 data points, the study developed SARIMA (1,0,0) x (1,1,0)12 from among the competing models based on its AIC and BIC values. The estimated model is found to be adequate in making forecast using a sample data for 2019. The study thus recommends that monetary authorities should consider the seasonal component in designing monetary policies targeted at inflation to stabilize the economy.

Keywords: Autoregressive, Forecast, Inflation, Modeling, Seasonality
JEL Classification Codes: C22, C51, E00, E31, E37,

1. INTRODUCTION

Inflation is one of the macroeconomic variables whose influence is pervasive and blooms into the whole economy. Analysis of price movement and its management is crucial for the smooth running of different sectors of the economy. Hence, it is on this note that central bank derives one of its function of achieving macroeconomic stability by manipulating monetary variables and ultimately the prices. Adebisi (2020) observed that inflationary developments in Nigeria created fundamental challenges to the task of monetary management via monetary policy applications. Different strategies in the past have failed to arrive at the objective of price stability due to various reasons such as ineffectiveness of the transmission mechanism to bring about changes in the ultimate target- that is when the operating and average targets are altered. In Nigeria, central bank of Nigeria (CBN) and the National Bureau of Statistics (NBS), provides adequate data on the state of inflation in the country. Notably, the authorities provide monthly consumer price indices and inflation rates given in three forms: - headline, core and food. The inflation rate is designed to measure the rate of increase of a price index. It is a percentage rate of change in price level over time.

The upsurge of inflation in Nigeria has its origin in the early 1970s in the aftermath of the country's civil war (Asekunowo, 2016; Awogbemi & Taiwo, 2012; Bamidele & Joseph, 2014; Bayo, 2005; Imobighe, 2012; Iwuaggwu, 2012; and Nafziger 1972). This sudden surge and the murky performance of the economy during the period prompted the monetary authorities' decision to refocus the country's monetary policy regime from from exchange rate targeting to the direct monetary targeting framework in response to the inflationary pressure resulting from increased public expenditure as a result of the reconstruction works after the civil war (CBN, 2014). Since then, the inflationary pressure kept on mounting on the economy. A 40-year review by the CBN shows the average annual rate of headline inflation (inflation rate estimates based on the price 20 of all essential commodities including food and energy) was a double-digit rate of 20. 47 percent (CBN, 2008; CBN, 2010; CBN, 2011 and CBN, 2013 cited in Asekunowo, 2016). Recent statistics shows that inflation in Nigeria rose to 12.26 per cent in the first quarter of 2020 from 11.98 per cent in December 2019, reflecting, largely, the continued impact of border protection and hike in VAT tax rate (CBN, 2020). The all-items composite Consumer Price Index (CPI), at the end of March 2020 stood at 315.2 (November 2009=100), indicating 2.5 per cent and 12.3 per cent increase above the levels in December 2019 and the corresponding period of 2019, respectively. The development was attributed, largely, to food supply shortages caused by the persisting security challenges in producing regions, the effect of increase in VAT rate from 5.0 per cent to 7.5 per cent, the negative supply shocks, arising from the COVID-19 pandemic, and increased food demand in preparation for the Easter festivity. The report further sows that Inflationary pressures continued, as headline inflation rose to 12.26 per cent in March 2020, 0.06 per cent point higher than the rate recorded in February 2020. The development was driven, largely, by increase in food prices. It should be noted, however, that the inflation was not significantly affected in March, as the effects of major state lockdowns, due to COVID-19 pandemic, effectively manifested in April 2020.

Forecasting inflation is a vital fundamental task (Duncan & Martinez-Garcia, 2018; Madhou, Sewak, Moosa & Ramiah, 2019; Marcelo, Gabriel, Vasconcelos, & Eduardo, 2019; Tumala et al, 2019; Zardi, 2017). Its importance stems from the fact that the time lags between monetary policy and its effects on the economy, particularly on inflation, makes it necessary for monetary authority to base its monetary policy decisions not on past inflation outcomes but on inflation forecasts (Zardi, 2017). The detection and assessment of its unusual changes in seasonal patterns and outliers is important for short-term forecasting in order to disentangle short-lived shocks from cyclical fluctuations and medium to long-term trends. Seasonal fluctuations per se have no impact on annual inflation rates, but changes in the seasonal factor do. A considerable part of the increased seasonality is due to methodological changes, although some of it also appears to reflect a more general development (Lis & Mario-Porqueddu, 2018).

Implementing effective inflation targeting strategy requires the knowledge of all the factors that are responsible for the inflationary process. The consumer price index includes sub-components; such as trend or seasonality that makes it difficult to analyze the inflationary pressures for the monetary policy decision making. It is imperative that empirical studies tilted towards "addressing the seasonality issues for the CPI to track the sources responsible for seasonal fluctuations" (Partachi & Motelica, 2016:1). This coupled with the proliferation of different results on Nigeria and the need to have a model that differs in terms of the number of data points motivates the research. It is against this background that the study is aimed at developing model of inflation with higher data points and taking into cognizance its periodic seasonal component and use the estimated model to make forecast.

The paper is structured into five (5) sections. Following this section, Section Two comprises of the literature review, Section Three contains the methodology, and Section Four captures the results and discussions while Section Five covers the conclusion and recommendations.

2. Literature review

This section briefly discussed the concept of inflation and its theoretical foundation. However, the large chunk of it contained empirical studies on inflation autoregressive modelling and forecast with particular reference to Seasonal Autoregressive Integrated Moving Average (SARIMA) method.

Conceptual Issues

There is a consensus on the definition of inflation as a sustained rise in the general prices of goods and services with a resultant fall in purchasing power (Mustapha & Kubalu, 2016). Inflation rate is designed to measure the rate of increase of a price index. It is a percentage rate of change in price level over time. The different measures of inflation according to Gathingi, (2014) are the Consumer Price Index (CPI) that measures the changes in prices of essential household basket from a consumer perspective; Employment Cost Index (EPI) that tracks changes in the labor market cost hence measuring inflation of wages, and employer-paid benefits; Gross Domestic Product Deflator (GDP-Deflator) that measures the change in level of prices of all new domestically produced, final goods and services in an economy;

and the International Price Program (IPP) that tracks price changes in the foreign trade sector. From among the five measures, CPI the most widely used.

Theoretical Literature

There are different views on inflation in relation to the economists' views across divides in their analysis of the root causes of inflation and in the way and manner the inflationary spiral should be managed and controlled. The views can be summarized as the demand and supply side causes of inflation. The demand-pull theories views inflation as situations where aggregate demand for goods and services exceed aggregate supply, thereby leading to a general rise in price levels (Onuchuku & Adoghor, 2000; Otto & Ukpere, 2016) The theory may be explained using the old or new quantity theory of money or the Keynesian theory. The quantity theory of money attempts to explain the link between money and general price levels. The quantity theory (also referred as monetarists view) emphasize the influence of money supply as prime determinants of inflation while the Keynesians emphasize non-monetary factors such as government expenditure, spending pattern and credits.

The classical economist of the 17th Century connected the quantity theory of money to the general rise in prices. The crude quantity theory of money (of classical economy) state that the quantity of money at any given point in time is proportional to rise in prices. The monetarist school of thought led by Milton Friedman (1942) posits that inflation is always and everywhere a monetary phenomenon and that it is everywhere since increases in the quantity of money.

Cost-push defines inflation arising from the supply side. It is often caused by the rising cost of

production. This occurs when production costs increase and impact on the prices of the final products. The cost push inflation can also be called the "market power inflation" because the increase in the prices of goods and services originates from the supply side of the economy. These increases may arise from increased wage rates or a fall in productivity which also increases cost of labour output. It may also arise out of other factors of production or cost of inputs such as power supply, transport or raw materials.

Empirical literature

The use of autoregressive methods in modelling inflation and evaluating the forecast efficiency of the estimated model is well documented in the literature (Adebisi, 2020; Mustapha & Kubalu, 2016; Otu, Osuji, Jude, Ifeyinwa & Andrew, 2014; among others). On Nigeria, recent studies on inflation dynamic modelling includes Tumala et al. (2019) using Model Averaging Methods of Modelling Frameworks to Central Banks; Duncan and Martinez-Garcia (2018) in a multi-country study via a broad-range set of inflation models and pseudo out-of-sample forecasts; Mustapha and Kubalu (2016) applying ARIMA Box-Jenkins methodology; Yemitan and Shitu (2015) using Kalman filter methodology of state-space mod. Others on the same framework are Shittu and Yemitan (2014), Doguwa and Alade (2013), Olajide, Ayansola, Odusina, and Oyenuga (2012), Shittu, Yaya and Yemitan

(2012), Mordi et. al (2012), Essien (2002), Ojo (2000), Gil-Alana, Shittu and Yaya (2011), Olu-busoye and Oyaromade (2008) and Adebiyi et. al (2010).
Of particular note are the following studies that used Seasonal Autoregressive Integrated Moving Average (SARIMA) method. To begin with, Adelekan, Abiola, & Constance (2020) used a monthly inflation series from 2003m1 to 2020m10 to develop the variants of autoregressive models (169 ARMA, 169 ARIMA, 1521 SARMA, and 1521 SARIMA) of Nigeria's inflation. Out of the 3380 models examined, SARMA (3, 3) x $(1, 2)_{12}$ was adjudged by the study to be the best model for forecasting the monthly inflation rate in Nigeria.

Similarly, Imande, Ikughur and Ibrahim (2018) used Nigeria's inflation series from January 2001 to December 2015. SARIMA(1,1,2) (2,0,1)12 model was identified as the most fitted model. The result of the monthly forecast indicated that Nigeria will experience high (double digit) inflation rates which will be at its peak in the months of August and September
and its lowest rate occurs in January of the year.
Likewise, Naden and Etuk (2017) fitted SARIMA (0, 1, 0) x (1, 1, 1)12 on Nigerian Food Consumer Price Indices (NFCPI) data extracted from January 2003 to November 2014. Using
SARIMA model and a Multiplicative Seasonal Autoregressive Integrated Moving Average (SARIMA) (0, 1, 0) x (1, 1, 1)12 was fitted to the time series variable. The study found the estimated model of NFCPI adequate in explaining and predicting Nigeria's inflation.
Equally, Ekpenyong and Udoudo (2016) used monthly all-items Inflation rates from 2000 to 2015 to determine the fitted model for Nigeria. Their findings revealed that the Inflation rates of Nigeria are seasonal and follow a seasonal ARIMA Model, (0, 1, 0) (0, 1, 1)12. The model is shown to be adequate and the forecast obtained from it are shown to agree closely with the original observations.
Correspondingly, Otu, Osuji, Jude, Ifeyinwa and Andrew (2014) used Nigeria's monthly inflation rates for the period November 2003 to October 2013 with a total of 120 data points. The study developed ARIMA (1, 1, 1) (0, 0, 1)12 model and used it to forecast Nigeria's monthly inflation for the upcoming year 2014.

An observation from the empirical studies on Nigeria revealed that all those on SARIMA framework used monthly data. The only variance here is the use of different data points as reported in Table 1.

Table 1: Data Points Analysis

Study	*Period*	*Data points*	*SARIMA Model Fitted*
Adelekan, Abiola, & Constance (2020)	2003:1-2020:10	204	(3, 3) x (1, 2)12
Imande, Ikughur and Ibrahim (2018)	2001:1-2015:12	180	(1,1,2) x (2,0,1)12
Naden and Etuk (2017)	2003:1-2014:11	143	(0, 1, 0) x (1, 1, 1)12
Ekpenyong and Udoudo (2016)	2000:1-2015:12	180	(0, 1, 0) x (0, 1, 1)12
Otu, Osuji, Jude, Ifeyinwa and Andrew (2014)	2003:11-2013:10	120	(1, 1, 1) x (0, 0, 1)12

Source: Author (2021)

It's so startling to have two studies (Ekpenyong & Udoudo, 2016 and Imande, Ikughur & Ibrahim, 2018) and on the same methodology and data points having different SARIMA specification. This coupled with the proliferation of different results and the need to have a model that differs in terms of the number of data points motivates the research.

3. Methodology

Data type and source

The study used Nigeria's monthly inflation series from 1995:1 to 2019:12 sourced from the 2019 CBN Statistical Bulletin. The choice of monthly data is informed by the fact that "a lengthy time series data is required for univariate time series forecasting. It is usually recommended that at least 50 observations be available" (Meyler, Kenny & Quinn, 1998). With 300 data points, it is likely that the potential model will be passable for making forecast. The series will be analysed using Stata version 14 and method of data analysis is presented in the following subsections.

Model

The study intends to use seasonal ARIMA model (SARIMA). It is an extension of autoregressive (AR) and moving average MA process in the popular Box-Jenkins methodology. SARIMA otherwise known as multiplicative seasonal ARIMA model is applied when time series exhibit a periodic seasonal component. It is denoted by ARIMA (p,d,q)(P,D,Q)s,

Generically, the Autoregressive Moving Average (ARMA) model can be written with (p)Autoregressive (AR) terms and (q) Moving Average (MA) terms as:

$$\mathrm{y_t} = \varepsilon_t + \left(a_1 Y_{t=1} + a_2 Y_{t=2} + \cdots + a_p Y_{t=p}\right) + \left(b_o \varepsilon_{t=1} + \cdots + b_q \varepsilon_{t=q}\right)\gamma \mathrm{y_{t-1}} \ldots. \quad (1)$$

This can be rewritten as $\emptyset(Z)\mathrm{Y_t} = \theta(Z)\varepsilon_t$

Where $\emptyset(Z) = 1 + a_1 Z + \cdots + a_p Z^p$ and $\theta(Z)1 + b_1 Z + \cdots + a_q Z^q$ are the characteristic polynomials of the AR part and of the MA part of an ARMA (p, q) process $(\mathrm{Y_t})$. z is the back-shift (lag) operator.

ARIMA is an extension of ARMA models to include differencing. A process $\mathrm{y_t}$ is said to be an ARIMA (p, d, q) if $(1 - z)^d \mathrm{Y_t}$ is a causal ARMA (p,q). The corresponding ARIMA equation is:

$$\emptyset(Z)(1 - z)^d \mathrm{X_t} = \theta_q(Z)\varepsilon_t \qquad \ldots\ldots..(2)$$

The SARIMA process for a non- stationary time series possibly containing seasonality is that with seasonal periodic component that repeats itself after every *s* observation. Box, Jenkins, Reinsel and Ljung (2016) defined the general multiplicative SARIMA model as:

$$\emptyset_p \Phi_P(Z^s)(1 - z)^d (1 - Z^s)^D \mathrm{Y_t} = \theta_q(Z)\Theta_Q(Z^s)\varepsilon_t \quad \ldots\ldots\ldots\ldots(3)$$

Where: $\emptyset_p(\mathrm{Z}), \Phi_P(Z^s), \theta_q(Z), and\ \Theta_Q(Z^s)$ are characteristic polynomials of orders p, P, q and Q respectively.d and D are the orders of non-seasonal and seasonaldifferencing respectively.

Estimation Techniques

To achieve the objective of the study, follows the B-J steps of identification, estimation, diagnostic checking and forecasting.

i. Identification

SARIMA model is appropriate for stationary time series therefore, the data under consideration must satisfy the condition of stationarity. The Augmented Dickey and Fuller (ADF) and the Phillips and Perron (PP) tests will be performed to accomplish this. The ADF and PP tests are conducted from the ordinary least squares estimation of the following equations, respectively:

$$\Delta Y_t = \propto + \beta T + \gamma y_{t-1} + \sum_{i=1}^{n} \propto_i \Delta y_{t-i} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$$

$$\Delta Y_t = \propto + \beta T + \gamma y_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(5)$$

where Y is the variable of interest (in this case the CPI), α_0 is the intercept, T is a linear time trend, Δ is the first difference operator, and ε_t is the error term with zero mean and constant variance. The hypothesis ($\mathrm{Ho}: \gamma = 0$) that Y is a nonstationary is rejected if the test fails to reject the alternative hypothesis ($H_1: \gamma < 0$). Since the *t*-statistic does not have the standard *t* distribution for both tests, MacKinnon (1991) finite sample critical values are used to determine the statistical significances. The unit root test will be followed up with the autocorrelation function (ACF) partial autocorrelation function and the (PACF) plots of the series in order to determine values for p, q and P, D, Q.

ii. Estimation

The parameters are estimated by the maximum likelihood estimation method. For the estimated models, we select the one with the minimum values of Akaike Information Criterion (AIC)
Bayesian Information Criterion (BIC).

iii. Diagnostics

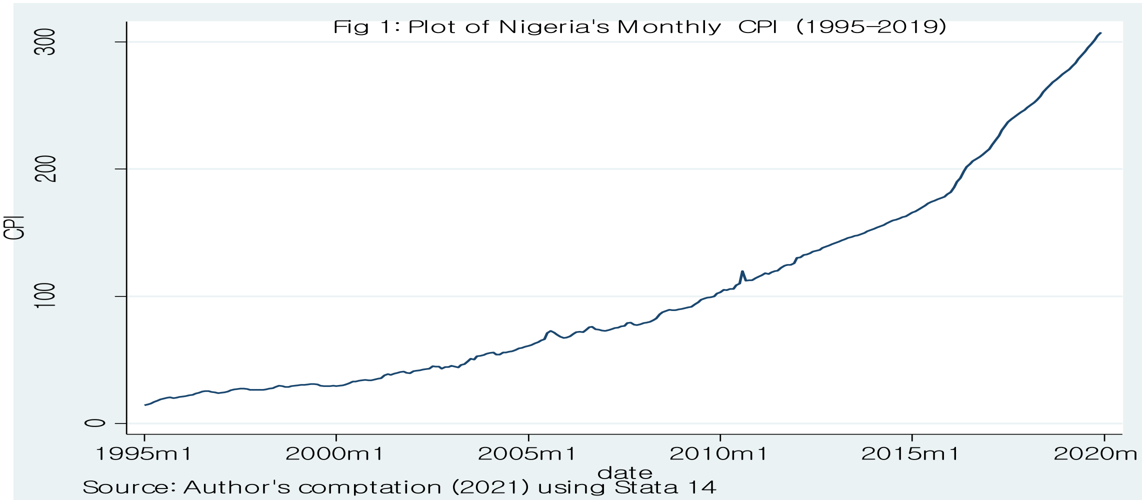
After estimating the parameters of the chosen model based on the information criteria, the last step is model diagnostics. This step is aimed at certifying the adequacy of the chosen model. The commonly used test is the examination of the ACF and PACF plots of the residuals to satisfy the assumption of SARIMA model that the the residuals of the model should be white noise. The ACF of the white noise residuals is approximately zero. Other tests such as the Ljung – Box Q statistic and ARCH - LM test compliments the residual diagnostics.

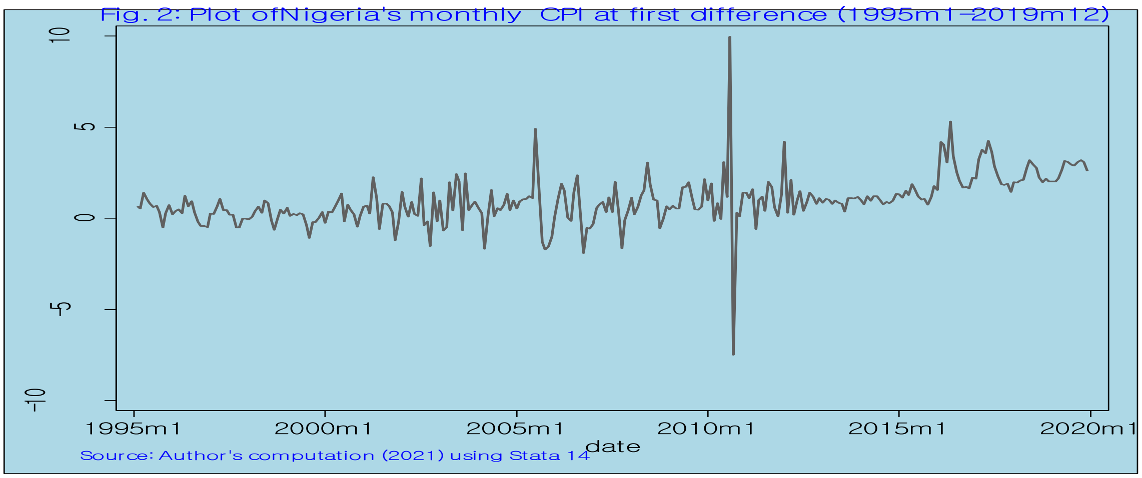
iv. Forecasting

In this stage we test the forecasting ability of the chosen model. In the case, the study will use in-sample forecast.

4. Results and Discussion of Findings

The data used for the study is depicted graphically for visual exploration. Figure 1 and 2 shows the plot of the original and differenced CPI series respectively





Both plots denote the pattern of nonstationary series. A series is said to be nonstationary, if it has a non-constant mean, variance and autocovariance over time. If a nonstationary series has to be differenced d times to become stationary, then it is said to be integrated of order d: i.e. I(d). However, visual observation of the plots will not be enough to establish definite evidence of the presence of a unit root or otherwise. Thus, standard ADF and PP unit root tests will be conducted on the series. Table 2 reports the results of the tests at level and first difference.

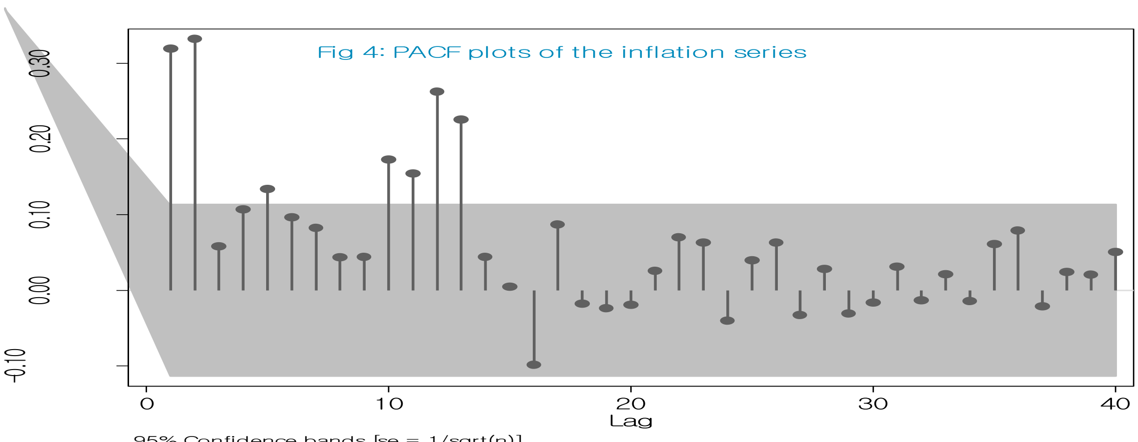
Table 2: Unit root test result

Variable	ADF	PP
CPI (at level)	11.161	10.588
CPI (at first diff.)	12.327***	13.212***

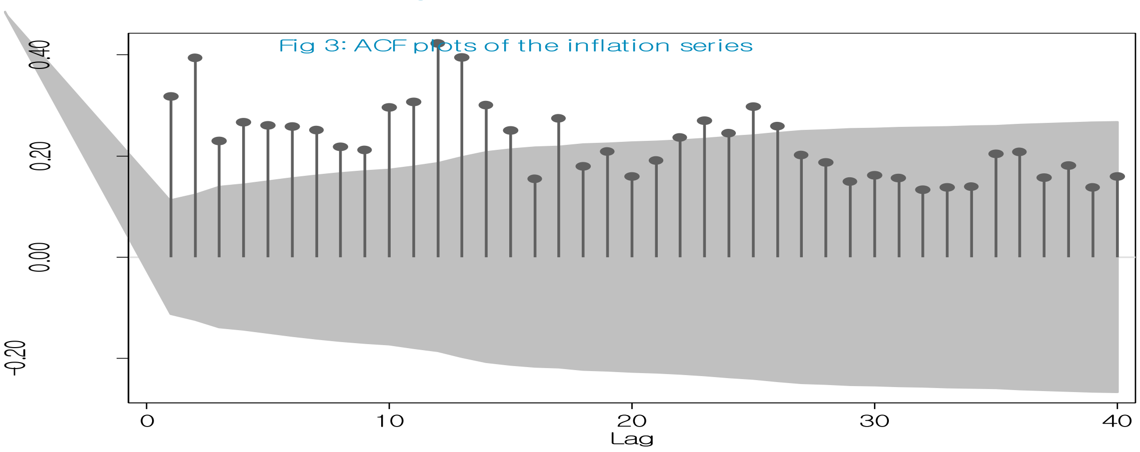
*Source: Computed using Stata14. *** indicates significance at 1 percent, 5 percent and 10 percent level.*

The results on Table 2 indicates that the null hypothesis of unit root in CPI series at level series cannot be rejected based on the ADF and PP statistics and their respective probability values. Running the two tests on the differenced data, we can now conclude that it is stationary at a 1% significance level. The result shows that CPI series are I(1). The plot of the differenced series is depicted as Fig. 2 .

The next step is to determine the order of the AR and MA for seasonal and non - seasonal components using the sample ACF and PACF plots of the series.



Source: Author (2021) using Stata 14



Source: Author (2021) using Stata 14

A visual observation of the ACF shows that a reasonably number of lags beyond the Bartlett 95% confidence region. On the other hand, the PAC plot shows a first significant lag and subsequently noticeable significant lags appear to be seasonal (multiple of 12 or roughly 12) indicating a very strong seasonal AR term (seasonal AR term of a unit order). Thus, we started from the rudimentary model in order to identify and select the parsimonious one. Three SARIMA models were estimated. This is done to "slim the likelihood of missing out on a good fitting model observing the correlograms alone" (Adongoa, Lewis, Essieku, Boamah, & Chikelu, 2018:5). The fitting model is SARIMA (1,0,0) x (1,1,0) 12 after comparing the Akaike (1974) Information Criterion (AIC) and the Schwarz (1978) Bayesian Information Criterion (SBIC) for each of the estimated models. Table 3 contains the summary of the models along with their AICs, BICs and Ljung-Box (LB) statistics.

Table 3: Summary of models estimation

Model	*AIC*	*BIC*	*LB Stat.*	*Prob.*
SARIMA (0,0,0) x (0,1,0)12	-847.9005	-840.5745	7015.9997	0.000
SARIMA(1,0,0) x (1,1,0)12	-1475.106	-1460.454	7015.9997	0.000
SARIMA (0,0,1) x (1,1,0)12	-1103.351	-1088.699	6408.6522	0.000

Source: Author (2021)

Following the estimation, the standard diagnostic check in the B-J methodology is the examination of the residuals. Fig. 4 and 5 depicts the ACF and PACF plots of the residuals.

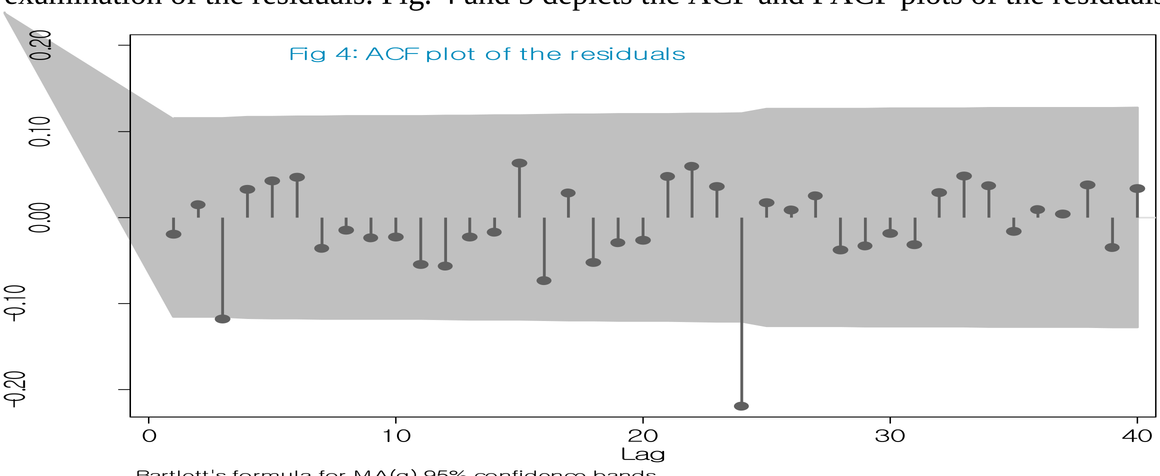
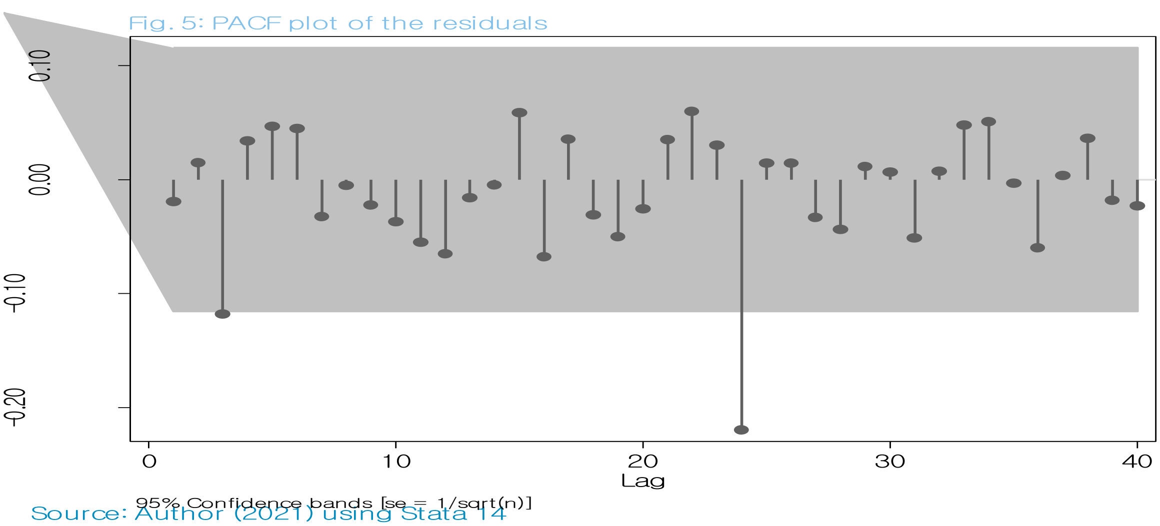


Fig 4: ACF plot of the residuals

Source: Author's computation (2021) using Stata 14

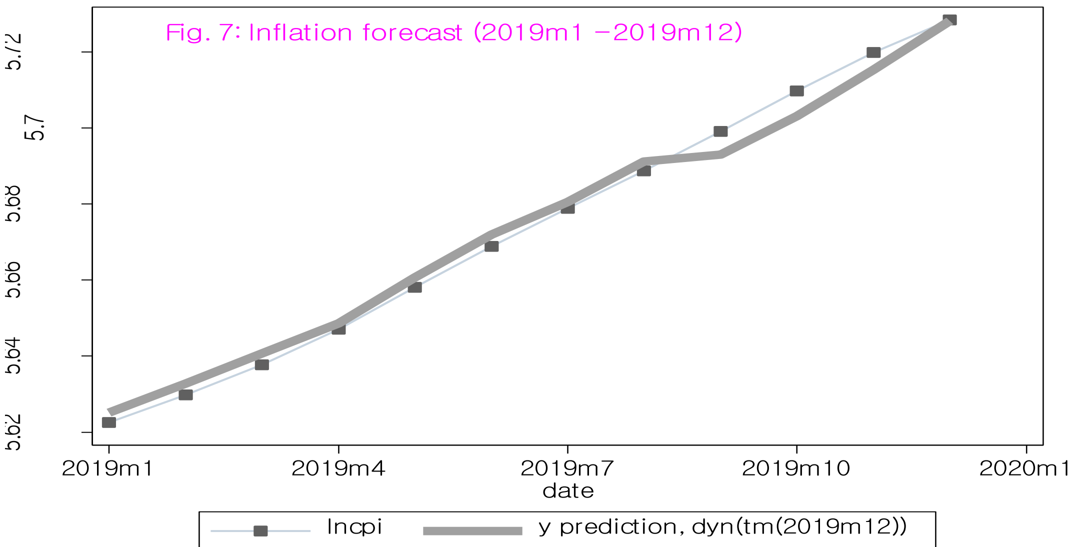
Fig. 5: PACF plot of the residuals



Source: Author (2021) using Stata 14

Close examination of the ACF and PACF plots of the residuals shows that they have zero mean, constant variance and also uncorrelated (white noise process). Thus, signifying the fitness of the model. This is in addition to the probability values of *0.000* for the Ljung-Box statistic as depicted in Table 3.

Having determined and ascertained the SARIMA (1,0,0) x (1,1,0)12 model for Nigeria, we now turn to its use in predicting the country's inflation series. Fig. 7 and Table 3 compares the actual and predicted CPI series for the in-sample period 2019:1 to 2019:12 using the estimated model.



Source: Author (2021) using Stata 14

Fig 7 reports the logged (transformed) actual vs fitted CPI. As we can observe, the estimated model closely predicts the series up to September. Even then, the difference is 1.80 and 1.99 in September and October respectively. The difference at that point fades away through December. Table 4 further portrays the CPI in absolute terms.

Table 4: CPI vs CPI predicted in absolute terms

Date	*CPI (Actual)*	*CPI (Predict)*	*Difference*
2019M1	276.601	277.3045	0.7035
2019M2	278.62	279.459	0.839
2019M3	280.812	281.6669	0.8549
2019M4	283.463	283.9103	0.4473
2019M5	286.613	287.3547	0.7417
2019M6	289.693	290.6031	0.9101
2019M7	292.623	293.1281	0.5051
2019M8	295.507	296.2587	0.7517
2019M9	298.59	296.7841	-1.8059
2019M10	301.78	299.791	-1.989
2019M11	304.869	303.4997	-1.3693
2019M12	307.473	307.427	-0.046

Source: Author's computation (2021) using Stata 14

Table 4 is simply an exponential of the logged values of inflation. Based on the sampled data the model has adequately predicted the CPI series for the period in question.

5. Conclusion and Recommendations

The study has developed the model of Nigeria's inflation with higher data points and taking into cognizance its periodic seasonal component. From among the competing models, SARIMA (1,0,0) x (1,1,0)12 was adjudged the best in explaining the country's inflation series from January 1995 to December 2019 based on its AIC and BIC values. Nevertheless, the trend of mixed findings on Nigeria's data on the topic surges. The estimated model is found to be adequate in making forecast using a sample data for 2019. The study thus recommends that authorities should consider the seasonal component in designing monetary policies targeted at inflation to stabilize the economy.

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