

# Modeling and Forecasting Inflation in Nigeria using Autoregressive Integrated Moving Average Technique

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## Abstract

*This paper applies the Autoregressive Integrated Moving Average (ARIMA) methodology of Box-Jenkins (1976) to model and forecast inflation rate in Nigeria, using monthly time series dataset for the period from 2009:1 to 2018:12. The dataset has been subjected to test for unit root using the Augmented Dickey- Fuller (1981), as well as the Zivot and Andrews unit root test which accounts for structural break. The data has been established to be integrated of order 1, that is  $I(1)$  in both tests, with the break date identified in 2017:01, which necessitates the use of sub sample from 2009:1 to 2016:01 and the entire sample to make comparison and determine the best model that fits the data. The study finds that the ARIMA (2, 1, 13) model using the sub sample data; which considers the structural break date is the parsimonious model as it has passed all the diagnostic tests and thus utilized to predict the future values of the rate of inflation for the period from 2018:7 to 2018:12. The forecast values are not much different from the actual values of the inflation. The study thus recommends the use of ARIMA modeling in forecasting inflation rate in Nigeria, so as to aid policy makers in designing policy measures to cushion the effects of inflation on the living conditions of Nigerians.*

**Keywords:** Structural Breaks, Inflation, ARIMA models

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## Introduction

Inflation which is commonly referred to as the persistent increase in the overall level of prices of goods and services has some effects on the economy (Nathaniel & Emmanuel, 2018). On the positive side, it tends to increase the revenue of investors as the profit level tends to increase, lenders equally tend to benefit. There is also the likely benefit of increased investments. On the negative aspect of it, inflation reduces the incomes of savers and the people with fixed income (such as salary owners) suffer. It also causes instability in the balance of payments position of the country (Kelukume & Salami, 2014). Therefore, there is the need to have price stability which can be attained through the use of monetary policy to achieve a stable and sustainable economic growth. A very difficult macroeconomic concern facing economies and central banks is the effective and efficient monitoring as well the ability to forecast with precision future values of inflation. Nigeria as in most developing countries there exist wide gaps between formulation of policy, its

implementation and its target goals. The lag between policy objectives and achievements is because of policy inconsistencies that result from the problem of monetary authorities to accurately predict future trends in the general price level.

Inflation is a vital indicator used to evaluate the performance of monetary policy instruments and thus serves as key indicator showing the trends in the movement of other important macroeconomic variables. The understanding of performance and trends of other macroeconomic indicators helps in determining future inflations and therefore serves as a nominal measure for determining value of goods and services (Moser, Rumler & Scharler, 2004). Therefore, a better and clear knowledge of inflation predicting methods is necessary for the ability of monetary policy in monitoring and evaluating the movement of macroeconomic variables as well as in ensuring stable and continuous growth of the economy.

A number of studies have been conducted in Nigeria, that tried to model and forecast future values of inflation (Kelukume & Salami, 2014; Feridun & Adebisi, 2005; Ikoku & Okany, 2017) among others. However, to the best knowledge of the author none of the previous studies have tested for the existence of structural breaks in the inflation variable while predicting its future value, even though they have sample size greater than 50 and that failure to test for structural breaks when modeling and forecasting a time series variable with more than 50 observations could lead to misleading results (Meyler, Kenny & Quinn, 1998). The objective of this paper is to model and predict future values of inflation in Nigeria taking into cognizance the existence of structural breaks in the data. In addition, this study differs from the previous studies, as it uses most recent data in modeling and forecasting of inflation rate in Nigeria coupled with conflicting findings from previous studies, it also compares the performance of models without and with structural breaks to determine an optimal model.

This paper is structured as follows; following this introduction, section two is the review of theoretical and empirical literature, section three deals with the methodology of the ARIMA model for estimation and forecast, section four presents the results and discusses the findings and section five concludes and gives recommendations.

### **Theoretical and Empirical Literature**

The main objective of monetary policy in a developing country like Nigeria as in most developed and developing countries is the achievement of stable prices and adequate expansion of production that could serve as a stimulus of economic

growth and development (Kelukume & Salami, 2014). Generally, there are diverse views among economists as to the main factors that drive inflation and ways of its management. While, the monetarists such as Friedman (1956, 1960 and 1971) contend that inflation results when money supply is greater than the quantity of output produced in the economy, the structuralist economists contends that inflation could result in the long run in a developing country from such factors as conflicts which could affect the relative elasticity of food supply, lack of enough foreign exchange, protective measures such as the use of quota and other import restrictive measures and other structural defects in an economy (Thirwell, 1974; Aghevei & Khan 1977).

Given the divergent views, on the main factors that cause inflation, it is becoming hard to predict accurately future values inflation in developed economies as well as in emerging and developing countries. Callen and Dongkoo (1999) analyze and predict inflation in India with the use of quarterly dataset from 1982Q2 to 1998Q2 using Johansen (1988) cointegration approach period from 1997Q2 to 1998Q2 were predicted moderately well. In a study of 14 emerging market economies inflation forecasts Duncan and Martinez- Garcia (2018) apply the random walk model developed by Atkeson and Ohanian (2001) and Bayesian Vector Autoregressive model on a quarterly data from 1980Q1 to 2016Q4, finding indicates that the random walk model produce better result than the Bayesian vector autoregressive model.

Wanjoya and Waitiitu (2016) used data from the monthly values of Consumer Price Index (CPI) obtained from the database of Central Bank of Rwanda measured in Rwandan currency covering the period from 1995:2 to 2015:12 comprising a total of 251 observations. The data from 1995:2 to 2013:12 were used to fit in the parsimonious model, while observations from 2014:1 to 2015:12 were used to assess the predicting power of the model. ARIMA (4, 1, 6) has been found to be parsimonious model to predict the future values of the consumer price index as a measure of inflation. Nyoni (2018) model and forecast Zimbabwe's inflation using monthly time series data set from 2009:7 to 2018:7 and applied the Autoregressive and Generalized Autoregressive Conditional hetroskedasticity models and it has been found that generalized autoregressive conditional heteroscedasticity has a more predicting power of future inflation rate than the autoregressive model. Similarly, Fwarga, Orwa and Arthiany (2017) model the rates of inflation in Kenya using monthly datasets from 1990:1 to 2015:12 by applying the Generalized Conditional Heteroscedasticity (GARCH) and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) models find the

EGARCH models as the best model to forecast inflation rates in Kenya. Nyoni and Nathaniel (2018) also apply Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) and Generalized Conditional Heteroscedasticity (GARCH) models in modeling and forecasting annual inflation rates using annual data from 1960 to 2015, the study finds that ARMA (1,0, 2 ) is the optimal and best model to predict future inflation and the study predicts that inflation is likely to rise to 17 percent at the end of year 2021. Similarly, Fwarga, Orwa and Arthiany (2017) model the rates of inflation in Kenya using monthly datasets from 1990:1 to 2015:12 by applying the Generalized Conditional Heteroscedasticity (GARCH) and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) models find the EGARCH models as the best model to forecast inflation rates in Kenya. Nyoni and Nathaniel (2018) also apply Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) and generalized conditional heteroscedasticity (GARCH) models in modeling and forecasting annual inflation rates using annual data from 1960 to 2015. The study finds that ARMA (1,0,2 ) is the optimal and best model to predict future inflation and the study predicts that inflation is likely to rise to 17 percent at the end of year 2021. Ngailo, Luvanda and Massawe (2014) apply GARCH model to analyze and forecast future value of inflation rate in Tanzania using monthly data from 1997M1 to 2012M12, they found that GARCH (1,1) is the appropriate model in forecasting inflation in Tanzania. Molebatsi and Raboloko (2016) apply GARCH and ARIMA forecasting techniques on Botswana monthly consumer price index for the period from 2005M1 to 2014M12 and finds that the general autoregressive conditional heteroscedasticity model (GARCH) performs better than the ARIMA model.

Feridun and Adebisi (2005) examine the influence of monetary aggregates in explaining inflation in Nigeria, using Mean Absolute Percentage Error to forecast inflation in addition to the use of Autoregressive Integrated Moving Average methods using monthly time series data from 1986:1 to 1998:4 and the results revealed that monetary aggregates such as money supply and interest rates are important in forecasting inflation in Nigeria. Chukwuemeka, Emmanuel and Michael (2013), apply periodogram and fourier series to model inflation rate in Nigeria, using composite monthly inflation series from 2003:1 to 2011:12. The Fourier series is applied in fitting and forecasting the inflation rate for the next thirteen months and the forecast values compares favourably with the real values.

Ikoku and Okany (2017) also apply Autoregressive Integrated Moving Average method using inflation rate from January 2009 till December, 2014 and the study

find ARIMA (3, 1, 1) is the parsimonious model to forecast inflation rates in Nigeria when compared with autoregressive AR(1) model. Adubisi, David, James, Awa and Terna (2018) use Autoregressive Integrated Moving Average (ARIMA) to analyze and predict 12 month all year average inflation in Nigeria, using monthly time series data from 2006:1 to 2017:12 and the study found that ARIMA (1 2 1) is the parsimonious model that has passed all the diagnostic tests and use in forecasting the inflation from January, 2017 to December, 2017.

David and Raymond (2016) employ Autoregressive Integrated Moving Average (ARIMA) also known as Box and Jenkins (1976) modeling technique to analyze and predict yearly Consumer Price Index (CPI), on a time series dataset for Nigeria from 1950 to 2014. The results from the study found that ARIMA (3, 1, 0) is the best fitting model to describe CPI data series in Nigeria. Based on the estimated model, the future annual CPI in Nigeria for a period of 6 years from 2015 to 2020 was predicted. The forecasts showed a steady increase in the annual values of CPI in Nigeria. However, the results have shown that ARIMA (0, 1, 0) and ARIMA (0, 1, 13) have been suitable for modeling urban and rural inflation rates in Nigeria.

Osuolale, Ayanniyi, Adesina and Mathew (2017) also apply ARIMA models to forecast Nigeria's inflation rates for the periods 2006 to 2015. They identified that ARIMA (0, 1, 1) as been the best model to forecast inflation rates from 2016 to 2018. Norbert, Similarly, Zardi (2017) model and forecast inflation in Tunisia using various forecasting techniques of Vector Autoregressive (VAR), Bayesian vector autoregressive method, dynamic factor models, and forecast combination methods on a quarterly data from 2000Q1 to 2015Q4. Finding from the study indicates that forecast that utilized combination of methods leads to decline in forecast errors when compared to individual forecast models such as Autoregressive Integrated Moving Average method (ARIMA) and Vector Autoregressive (VAR) method.

Bokhari and Feridun (2006) also model and forecast inflation time series dataset for the period from 1991 to 2004 in Nigeria applied the Vector Autoregressive (VAR) method and Autoregressive Integrated Moving Average Method (ARIMA), findings from the study indicates that forecast from the ARIMA model super cedes that of the vector autoregressive method. Doguwa and Alade (2013) analyze and predict inflation in Nigeria, for the monthly dataset from July 2001 to September, 2013 of the consumer price index using the Seasonal Autoregressive Integrated Moving Average Method (SARIMA) and Seasonal Autoregressive Integrated Moving Average Method (SARIMAX) finding from the study reveals that

SARIMA model is better in forecasting core inflation in Nigeria than SARIMAX model.

### **Methodology**

This paper forecasts core inflation in Nigeria using the Autoregressive Integrated Moving Average model developed by Box & Jenkins (1976) commonly known as Box-Jenkins. The choice of the method is informed by the desire to have an idea of the forecast ability of the method. The study uses monthly dataset for the study covering the period from 2009:1 to 2018:12. The dataset was obtained from the Central Bank of Nigeria (CBN) and National Bureau of Statistics (NBS).

### **Variable Measurement**

The variable used in the study is measured following the works of Kelukume and Salami (2014). The inflation rate is measured as the change in consumer price index expressed as percentage.

### **ARIMA Model**

The Autoregressive Integrated Moving Average (ARIMA) is a model that combines the differenced values of the lags of autoregressive and moving average terms. It consists of the autoregressive and moving average models.

### **Autoregressive Moving average (ARMA) Models**

Autoregressive moving average (ARMA) models are a combination of both p autoregressive terms and q moving average terms, it is also called ARMA (p,q) models and expressed as follows

$$Y_t = \mu + \sum_{i=1}^p \lambda_i Y_{t-i} + \epsilon_t + \sum_{i=1}^q \theta_i \epsilon_{t-i} \text{-----}(1)$$

The ARMA (p, q) model is expected to be stationary with zero mean and constant variance, if it is not stationary, it needs to be made stationary, either by removing trend from the series by way of adding time trend in the regression and estimating the residuals. Another way of making the ARMA (p, q) model stationary is by way of differencing the series. The variable  $Y_t$  is integrated of order 1 that is I (1), if taking the first difference produces a stationary process.

The ARIMA (p, d, q) denotes an ARMA model with p autoregressive terms, q moving average terms and difference in the order of d.

The ARIMA (p, d, q) denotes an ARIMA model with p autoregressive terms, q moving average terms and difference in the order of d. To develop ARIMA modeling, the method of Box and Jenkins (1976) method is used and the stages are explained as thus; information gathering, model specification, and estimation of the model, diagnostic test and prediction.

Box - Jenkins method requires about 50 or more observations and if there are more than 50 observations there is the need to test for the structural breaks, if structural break exists, then the sample can be break into subsamples, alternatively a dummy variable can be incorporated into the model to account for structural break. The main identification tools are the plot of the correlelogram which consist of Autocorrelation Function (ACF), the Partial Autocorrelation Function (PACF), and the use of standard tests such as the augmented Dickey and Fuller (1971, 1981), Zivot and Andrews tests for unit root.

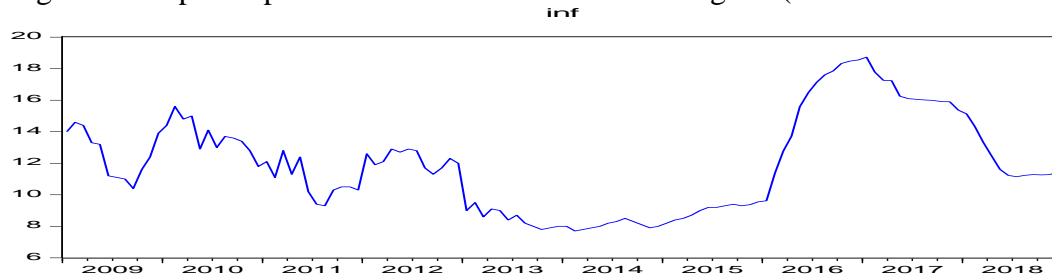
### **Zivot and Andrews (1992) Unit Roots Test with One structural Break**

Zivot and Andrews (1992) unit root test is an alternative to the traditional tests for unit root (Augmented Dickey Fuller, Phillips Perron etc) that takes into consideration the possibility of one structural break that is determined endogenously. The alternative hypothesis of the test is there is unit root with structural break that is endogenously determined and the null hypothesis is rejected when the test statistic is less than the critical values of the test statistic at 1, 5 and 10 percent level of significance. The breakpoint is determined at a point where the t statistic from Augmented Dickey Fuller unit root test is at minimum. This is the break date where there is strong evidence against the null hypothesis of a unit root.

## **Results and Discussion**

### **Data Presentation**

Figure 1: Graphical presentation of inflation trend in Nigeria (2009m1 to 2018m12)



Months

The graph of the inflation series in figure 1 shows that the inflation series contains unit root as it indicates an irregular movement in its trends. This is further confirmed by the Augmented Dickey - Fuller test for unit roots in the results presented in the Table 1 which shows that the series is not stationary at its level value given that the absolute value of the test statistic is less than the absolute critical values at 1, 5 and 10 percent levels of significance respectively.

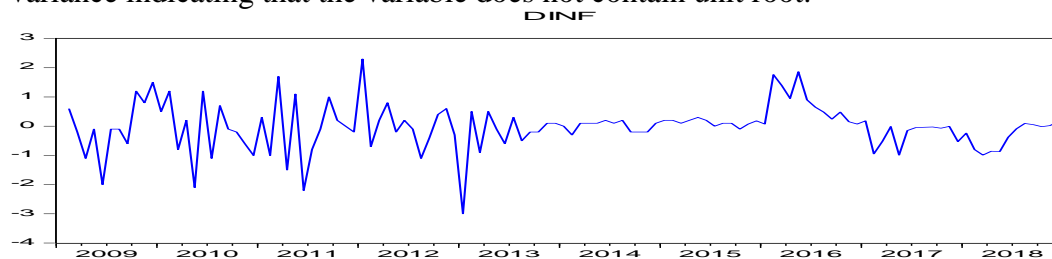
**Table 1: Stationary Test Results using Augmented Dickey Fuller**

Variable				
Inflation	Intercept		Intercept and Trend	
	Level	First Difference	Level	First Difference
	-2.2325	-5.0509	-2.3362***	-5.0411***

Source: Computed by the Author using Eviews 9.0

Note: \*\*\*,\*\*,\* denotes significance at 1,5 and 10 percent level respectively.

The plot of the first difference of the series which is presented in figure 2 shows that it becomes stationary after differencing as depicted by the plot of the first difference of the series which indicates that the variance of the series seems to be very effective. The time plot of the series seems to be stationary in both mean and variance indicating that the variable does not contain unit root.



### Months

The unit roots test for stationarity of the series at its first difference of the series shows it to be stationary at its first difference as indicated in Table 1 as the absolute value of the test statistic is greater than the absolute critical values at 1, 5 and 10 percent significant levels. To check for the presence of structural breaks in the series so that if identified a dummy variable can be included or the data divided into

sub samples. The Table 2 shows the test for unit root with structural break for the inflation series at both level and first difference.

**Table 2: Zivot and Andrews (1992) Unit Root Test Results for Inflation with structural break**

Variable				
Inflation	Intercept		Intercept and Trend	
	Level	First Difference	Level	First Difference
	-3.2648	-5.5041***	-4.6889*	-11.8616***
Break Date	2015m11	2016m02	2015m11	2017m01

Source: Computed by the Author using Eviews 9.0.

Note: \*\*\*, \*\*, \* denotes significance at 1, 5 and 10 percent level respectively. The result in Table 1 indicates that the value of the inflation series is not stationary at its level value using test for unit roots with structural break also since the absolute value of the test statistic is lower than the absolute critical values with the break period identified as 2015M10. The result confirms what is obtained using the traditional method of testing for unit root (Augmented Dickey- Fuller Test). Since the series non stationarity in level form is confirmed, the paper also conducts test for unit root with structural break for the first difference of the inflation series and the results is also presented in Table 2. The results from Table 2 indicates that the first difference of the inflation series is stationary, i.e it does not contain unit root as the absolute value of the test statistic is greater than all the absolute critical values at 1,5 and 10 percent level of significance with the period of break as 2017:01.

Having identified 2017:01 as the break date in the data, it becomes stationary after first differencing. Therefore the data is divided into two sub samples that is from 2009M01 to 2016M12 and 2017M1 to 2018M12. The sample 2009M01 to 2016M12 is selected for the analysis since it is the one that has more than 50 observations as recommended for modeling a time series it should have a minimum of 50 observations.

Having identified that the series is  $I(1)$  that is it is stationary at first difference and it contains structural break, the next step is the identification of the ARMA Model. In other words, identifying the number of Autoregressive and Moving Average terms to be included in the models to be estimated and used as the basis for forecasting the inflation in Nigeria. The autocorrelation and partial autocorrelation function of the series is used to determine the autoregressive and moving average terms and that both the autocorrelation and autocorrelation function move in the same pattern, thus indicating that it follows an ARMA (p, q) model and it is earlier found out to be integrated of order 1. The lags that are significant that is out of the standard error bounds on both the Autoregressive and moving average terms are lags 2, 12 and 13. Possible combinations are (2,1,2), (2,1, 12), (12,1,2), (12,1,12) (13,1,2), (13,1,12), (2,1,13) and (12,1,13) were estimated and the best selected based on a number of models selection criterion such as the model having the most significant coefficient, having highest adjusted  $R^2$ , lowest volatility (variance) and having the least values of the Akaike and Schwartz information criterion. The result of the estimated tentative models is presented in Table 3

**Table 3: Results from estimated Tentative Models for the sub sample**

Model	Significant coefficients	Adjusted $R^2$	Volatility (variance)	Akaike Information Criterion	Schwartz Information Criterion
(2,1, 2)	0	0.1268	0.5218	2.257	2.350
(2,1,12)	2	0.2354	0.4570	2.1474	2.2401
(12,1,2)	2	0.1920	0.4829	2.1883	2.2817
(12,1,12)	1	0.2672	0.4379	2.2419	2.3353
(2,1,13)	3	0.3149	0.40585	2.0704	2.1871
(12,1,13)	2	0.1337	0.5221	2.2576	2.861
(13,1,2)	2	0.1694	0.5006	2.2744	2.2328
(13,1,12)	3	0.2958	0.4170	2.0923	2.2090

Source: Computed by the Author using Eviews 9.0

The results from Table 3 shows that on the basis of the criteria for the appropriate model selection, model **(2,1,13)** is the best model for the sub sample data as it has 2 significant coefficients, highest Adjusted R<sup>2</sup> value, least values of volatility (variance), Akaike and Schwartz information criteria after considering the break date of 2017m01.

The result in Table 4 indicates the results of the estimated tentative models for the whole sample that is from 2009m01 to 2018m12. Based on the correlogram (as shown in the appendix II) both the autocorrelation function and partial autocorrelation function indicates significant spikes at lags 2, 12 and 13 respectively. Hence it follows an ARIMA process of integrated order 1. Possible Arima combinations are (2,1,2), (2,1, 12),(12,1,2) , (12,1,12) (13,1,2), (13,1,12),(2,1,13) and (12,1,13) were estimated and the best selected based on a number of models selection criterion such as the model having the most significant coefficient, highest adjusted R<sup>2</sup>, lowest volatility (variance), the least values of the Akaike and Schwartz information criterion. The result of the estimated tentative models is presented in Table 4

**Table 4: Results from estimated Tentative Models for the whole sample**

Model	Significant coefficients	Adjusted R <sup>2</sup>	Volatility (variance)	Akaike Information Criterion	Schwartz Information Criterion
(2,1, 2)	0	0.1178	0.6023	2.3966	2.4767
(2,1,12)	2	0.2052	0.5427	2.3113	2.3915
(12,1,2)	2	0.1823	0.5583	2.3315	2.4116
(12,1,12)	1	0.2262	0.5284	2.4309	2.5111
(2,1,13)	2	0.1713	0.5658	2.3412	2.4138
(12,1,13)	2	0.1427	0.5854	2.3908	2.4709
(13,1,2)	2	0.1711	0.5659	2.3439	2.4241
(13,1,12)	2	0.1733	0.5645	2.3678	2.4480

Source: Computed by the Author using Eviews 9.0

Table 4 shows the results of the estimated models using the whole sample after considering the break date of 2017m01. Based on the model selection criterion of highest number of significant coefficients and adjusted  $R^2$  as well as lowest values of volatility (variance), Akaike and Schwartz information criterion, model **(2, 1, 12)** is the adequate and parsimonious model that is fitted to the data in forecasting inflation.

### Model Checking

Before the interpretation and the use of the fitted model, some diagnostic checks are conducted to find whether the model is specified correctly and is devoid of autocorrelation and that there is no ARCH effect. The results of the Diagnostic tests are presented in Table 5.

**Table 5: Results of Autocorrelation Test**

Test	Test Statistic value	Probability
ARCH (Ljung- Box)	1.0608	0.3052

The results show the Ljung - Box test for white noise of the residuals of the for the selected model and based on the probability values on all the lags is greater than 0.05 which indicates that it is not significant to reject the null hypothesis that the residuals are white noise and the results is presented in the appendices. Similarly, a test for the stability of the estimated models were conducted using the AR and MA roots which require all be within the unit circle to confirm that ARMA process is both covariance stationary and invertible, the graph is presented in the appendices.

### Forecasting

The next stage in ARIMA modeling is the use of the identified appropriate model to forecast future value of the series under investigation. The ability to do so will further testify the validity of the model. The two identified and estimated models using the whole and sub sample data were used to forecast the future values of the inflation rates and comparison made to identify the best fitted model to forecast future values of inflation and the summary of the two models is presented in Table 6

**Table 6: Forecast properties of the estimated models**

Models/	(2,1,13)	(2,1,12)
Roots Mean Square Error (RMSE)	4.2222	5.0198
Mean Absolute Error	3.6751	4.3593
Mean absolute percentage Error	37.1511	46.1825

Source: Computed by the Author using E views 9.0

On the basis of the least RMSE, MAE and MAPE the model (2,1,13) which used the sub sample data that considers structural break in the data performs better in predicting the future values of the inflation because the values of RMSE, MAE and MAPE are lower than the one that utilized the whole sample data. Therefore, it is used to forecast future value (six months) of the inflation and is presented in Table 7

**Table 7: Actual and Forecast Values of Inflation for six months periods**

Month	Actual value of Inflation	Forecast Values of Inflation
July,2018	14.82	14.23
August,2018	14.82	14.14
September,2018	14.82	14.28
October,2018	14.82	14.26
November, 2018	14.82	14.28
December, 2018	14.82	14.44

Source: Computed by the Author using E views 9.0

The result in Table indicates that whereas the actual inflation is 14.82 in the month of July and December, 2018. The forecast values are 14.23 and 14.44 percent respectively, which shows that the forecast underestimates the actual values of the inflation rates.

## Conclusions and Recommendations

This paper models and forecast inflation rate in Nigeria using monthly time series data set from the period of January, 2009 to December, 2018 employed the Box and Jenkins (1976) Autoregressive Integrated Moving Average method. The study examines the performance of two models without and with the presence of structural break. The study identifies ARIMA (2, 1, and 13) as the appropriate and parsimonious model that fits the data, having met all the model selection criteria and passed diagnostics tests and the model was used in forecasting future values of the inflation. Findings from the study supports the works of Nyoni and Nathaniel (2018) who found that ARIMA has a better predicting power of future values of inflation. The study however, contradicts the work of Mobatsi and Roboloko (2016) who found GARCH method of forecast better than ARIMA modeling. The study recommends that to adequately cushion the negative effects of inflation on the economy there is the need to have an insight of the future value of inflation with a view to designing appropriate policy measures to cushion the effects of inflation on the economy. Future studies on macroeconomic variable should consider the possibility of structural breaks in econometric modeling.

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## Appendices

### Appendix I : Corelogram of the residuals for the whole sample

Sample: 1 120

Included observations: 119

Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	0.064	0.064	0.5063	
. .	. .	2	0.014	0.010	0.5316	
. .	. .	3	-0.023	-0.025	0.5988	0.439
. .	. .	4	-0.001	0.002	0.5990	0.741
. .	. .	5	0.027	0.027	0.6880	0.876
* .	* .	6	-0.070	-0.074	1.3052	0.860
. .	. .	7	-0.017	-0.008	1.3409	0.931
. .	. .	8	0.040	0.046	1.5518	0.956
. .	. .	9	-0.033	-0.043	1.6982	0.975
. .	. .	10	0.028	0.031	1.8041	0.986
. .	. .	11	0.048	0.053	2.1146	0.990
** .	** .	12	-0.299	-0.319	14.140	0.167
. .	. .	13	0.010	0.059	14.154	0.225
. .	. .	14	0.019	0.044	14.201	0.288
. .	. .	15	0.015	-0.028	14.233	0.358
* .	* .	16	-0.115	-0.123	16.066	0.309
* .	. .	17	-0.108	-0.057	17.698	0.279
. .	. .	18	0.039	0.004	17.915	0.329
. *	. *	19	0.111	0.114	19.687	0.291
* .	* .	20	-0.093	-0.097	20.954	0.282
. .	. .	21	-0.019	-0.046	21.009	0.336
. .	. .	22	-0.056	-0.042	21.472	0.370
. .	. .	23	-0.032	-0.003	21.627	0.421
. .	* .	24	-0.044	-0.156	21.925	0.464
. *	. **	25	0.130	0.217	24.517	0.376
. *	. *	26	0.102	0.086	26.116	0.347
. .	. .	27	0.046	0.020	26.447	0.384
. .	* .	28	-0.047	-0.146	26.802	0.420
. .	. .	29	-0.008	-0.047	26.813	0.474
. .	. .	30	0.016	0.039	26.856	0.526

* .	. .	31	-0.109	0.009	28.806	0.475
. .	. .	32	0.065	0.001	29.505	0.491
. .	* .	33	-0.053	-0.118	29.979	0.518
. .	. .	34	0.021	0.005	30.053	0.565
. .	. .	35	0.005	0.052	30.056	0.614
. .	* .	36	-0.055	-0.173	30.577	0.636

## Appendix II:

### Corelogram of the residuals for the Sub sample

Date: 01/17/21 Time: 16:06

Sample: 2009M01 2017M01

Included observations: 96

Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. *	. *	1	0.101	0.101	1.0127	
. .	. .	2	0.048	0.038	1.2424	
* .	* .	3	-0.093	-0.103	2.1221	0.145
* .	* .	4	-0.084	-0.068	2.8481	0.241
. .	. .	5	0.003	0.028	2.8491	0.415
. .	. .	6	-0.059	-0.065	3.2132	0.523
. .	. .	7	-0.010	-0.015	3.2232	0.666
. .	. .	8	-0.001	0.005	3.2234	0.780
* .	* .	9	-0.084	-0.095	3.9879	0.781
. .	. .	10	-0.000	0.005	3.9879	0.858
. .	. *	11	0.064	0.077	4.4362	0.880
. .	. .	12	0.036	0.001	4.5777	0.918
. **	. **	13	0.292	0.279	14.228	0.221
. .	. .	14	0.072	0.039	14.830	0.251
. .	. .	15	-0.003	-0.043	14.830	0.318
* .	* .	16	-0.198	-0.161	19.431	0.149
* .	* .	17	-0.145	-0.068	21.918	0.110
. .	. .	18	0.009	0.033	21.928	0.146
. *	. *	19	0.109	0.141	23.378	0.137
* .	* .	20	-0.075	-0.129	24.076	0.153
. .	. .	21	-0.017	-0.027	24.111	0.192
. .	. .	22	-0.023	0.035	24.180	0.235
. .	. .	23	0.017	0.007	24.217	0.283
. .	* .	24	-0.017	-0.081	24.257	0.334
. *	. *	25	0.165	0.193	27.843	0.222
. *	. .	26	0.133	0.012	30.215	0.178
. .	. .	27	0.071	0.035	30.907	0.192
* .	* .	28	-0.116	-0.110	32.770	0.169
* .	. .	29	-0.117	-0.005	34.688	0.147

. .	. *	30	-0.019	0.081	34.742	0.177
* .	. .	31	-0.072	-0.045	35.486	0.189
. *	. .	32	0.075	-0.051	36.311	0.198
* .	* .	33	-0.079	-0.083	37.233	0.204
. .	. .	34	-0.007	0.033	37.240	0.240
. .	. .	35	-0.008	0.058	37.251	0.280
. .	* .	36	-0.056	-0.119	37.741	0.302

### Appendix III:

#### Stability Test of the Estimated Models

Inverse Roots of AR/MA Polynomial(s)

