PREDICTING PEAK TIME INFLATION IN NIGERIA USING SARIMA MODEL

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ABSTRACT: *The often-disturbing adverse effects of inflation in developing economies such as Nigeria necessitates developing dynamic inflation forecasting models for appraising shocks on macroeconomic variables. This work utilizes the Box-Jenkins methodology to develop Seasonal Autoregressive Integrated Moving Average (SARIMA) model to predict peak time inflation in Nigeria's inflation time series from January 2001 to December 2015 obtained from National Bureau of Statistics, Abuja. A test of parameter estimates was performed on the suggested models and, using the AIC and BIC criteria, SARIMA(1,1,2)(2,0,1)12 model was identified as the most fitted model. The diagnostic test of the residuals using ACF and PACF of residual plots showed that they follow white noise process. 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. The information contained here can be useful to ensure monetary and fiscal policies that will stabilize the economy.*

KEYWORDS: Peak Time Inflation, Sarima Model, Consumer Prices, Purchasing Power of Money, Nigeria

INTRODUCTION

Inflation as defined by [1] is the persistent increase in the level of consumer prices or a persistent decline in the purchasing power of money. Inflation can also be expressed as a situation where the demand for goods and services exceeds their supply in the economy [2]. In real term, inflation means that money cannot buy as much as it could have bought previously. A chief measure of inflation is the inflation rate, the annualized percentage change in a general price index (normally the consumer price index) over time.

High inflation is known to have many adverse effects; it imposes welfare costs on the society; impedes efficient resource allocation by obscuring the signaling role of relative price changes; discourages savings and investment by creating uncertainty about future prices. It also inhibits financial development, hits the poor excessively, reduces a country’s international competitiveness, and perhaps more importantly, reduces long-term economic growth [3]. Overall, businesses and households are thought to perform poorly in periods of high and unpredictable inflation [4]. Even though some evidence suggests that moderate inflation helps in economic growth [5], the overall weight of evidence so far clearly indicates that inflation is inimical to growth. Inflation-targeting countries such as Nigeria need dynamic inflation forecasting models that are capable of stimulating the impact of shocks to monetary policy on macroeconomic variables.

Empirical researches have been carried out in the area of forecasting inflation using seasonal autoregressive integrated moving average (SARIMA) model propounded by [6]. [7]

examined the most appropriate short-term forecasting method for Ghana's inflation. They utilized SARIMA and Holt-Winters approaches to obtain short-term out of sample forecast. From the results, they concluded that an out of sample forecast from an estimated SARIMA $(2,1,2)(0,0,1)_{12}$ model far supersedes any of the Holt-Winters' approach with respect to forecast accuracy. Several other works that echo the superiority of SARIMA modeling framework over other Box-Jenkins time series modeling paradigms, particularly short-term periods abound(see, for instance, [8];[9]; [10];[11]; [12]; and [13].

This work seeks to further lend credence to the suitability of engaging SARIMA model to predict the monthly inflation rates in Nigeria using monthly inflation rates data from January 2001 to December 2015 obtained from National Bureau of Statistics Abuja so as to unravel the peak in the inflation series which was not considered by other works.

METHODS

A process$\{X_t\}$ is said to be ARIMA (p,d,q) if $\Delta^d X_t = (1-B)^d X_t$ is ARMA (p,q). In general, we will write the model as

$$\phi(B)(1-B)^d X_t = \theta(B)\, Z_t\ ;\ \{Z_t\} \sim WN(0,\sigma^2) \quad (1)$$

where Z_t follows a white noise (WN). Here, we define the lag operator by

$B^k X_t = X_{t-k}$ and the autoregressive operator and moving average operator are defined as follows:

$$\left.\begin{aligned} \phi(B) &= 1-\phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \\ \theta(B) &= 1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \end{aligned}\right\} \quad (2)$$

$\phi(B) \neq 0$ for$|\phi| < 1$, the process $\{X_t\}$ is stationary if and only if $d = 0$, in which case it reduces to an ARMA (p,q) process.

The SARIMA model is an extension of ARIMA model which comes in when the periodic component of the series repeats itself after s observations. The SARIMA model is sometimes called the multiplicative seasonal autoregressive integrated moving average model denoted by ARIMA $(p,d,q)(P,D,Q)_S$, this can be written in its lag form as

$$\left.\begin{aligned} \phi(B)\Phi(B)^s(1-B)^d((1-B)^D X_t &= \theta(B)\Theta(B)^S \\ \phi(B) &= 1-\phi_1 B - \phi_2 B^2 - \cdots \phi_p B^p \\ \Phi(B)^S &= 1-\Phi B^s - \Phi_2 B^{2s} - \cdots - \Phi p B^{ps} \\ \theta(B) &= 1-\theta_1 B - \theta_2 B^2 - \cdots - \theta q B^q \\ \Theta(B^s) &= 1-\Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta q B^{sq} \end{aligned}\right\} \quad (3)$$

where,

p, d and *q* are the order of non-seasonal AR, differencing and MA respectively.

P, D and Q are the order of seasonal AR, differencing and MA respectively.

X_t represents time series data at period t (monthly inflation rates)

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Z_t represents white noise error (random shock) at period t.
B represents backward shift operator $B^k X_t = X_{t-k}$
S represents seasonal order ($s = 12$ monthly data).

Consider a seasonal ARIMA $(0,1,1)(0,1,1)_{12}$ model. This is specified as

$$\left.\begin{aligned} &(1-B^{12})(1-B)\ X_t = (1-\theta_1 B)(1-\Theta B^{12})\, Z_t \\ &X_t = X_{t-1} + X_{t-12} + X_{t-13} + \theta_1 Z_{t-1} - \Theta_1 Z_{t-12} + \theta_1 \Theta_1 Z_{t-13} \end{aligned}\right\} \quad (4)$$

Where

X_t = inflation rate at successive period

Z_t= represents white noise error (random shock) at period t and is independent and identically distributed

Estimation of Model Parameters

The parameters of the model will be estimated using the conditional least squares. For the model estimates, we consider the model with the least Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc) and Bayelsian Information Criterion (BIC) with the following statistic:

$$AIC = n \log\left(\frac{RSS}{n}\right) + 2k,\ AIC_c = AIC + \frac{2(k+1)(k+2)}{n-k-2},\ BIC = \{ln(\hat{\sigma}_e^2)\} + k\{ln(n)\} \quad (5)$$

where RSS is the estimated residual of fitted model, n is the residual sample size and k is the total number of estimated parameters in the fitted model and $\hat{\sigma}_e^2$ is the error variance.

Unit Root Test

There are several statistical tests in testing for the presence of unit root in a series. The augmented Dickey Fuller and the Phillip Perron test of unit root whose statistics are respectively given below.

$$X_t = \alpha_0 + \rho_1 X_{t-1} + \sum_{j=2}^{p-1} \beta_j \nabla X_{t-1} + z_t \qquad Z_p = n(\hat{\rho}_n - 1) - \frac{1}{2}\frac{n^2\hat{\sigma}^2}{s_n^2}(\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \quad (6)$$

Model Identification

The first technique to determine values for p,d,q and P,D, Q is to compute the sample ACF and PACF from the data and compare this to known properties of the ACF for ARIMA models. The theoretical PACF has nonzero partial autocorrelation at lags 1,2,..p and has zero partial autocorrelations at all lags for any non seasonal ARIMA (p,d,q) process. The ACF and PACF has spikes at lags ks and cuts off after lags ks at the seasonal level .for seasonal MA component the ACF shows a significant spikes at seasonal lags while for seasonal AR components the PACF shows a significant spike at the seasonal lags.

Diagnostic Checking

The goodness of fit of a statistical model to a set of data is judged by comparing the observed values with the corresponding predicted values obtained from the fitted model. The

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assumption of the SARIMA model is that the residuals of the models should be white noise. The ACF should be approximately zero if the residuals are white noise. The ljung box statistic proposed by [6] can still be used to check if a given observable series is linearly independent. The test statistic is given as:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-2} \quad (7)$$

Where $\hat{r}_k^2$ is the estimated autocorrelation of the series at lag *k*, and *m* is the number of lags being tested.

Another diagnostic test to be considered is the Durbin-Watson test whose statistic is as given:

$$d = \frac{\sum_{i=2}^{n}(z_i - z_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \quad (8)$$

Peak Time Forecast

Consider the same model of the form $(p,d,q)(P,D,Q)_s$ then

$$\phi(B)\Phi(B)^s(1-B)^d((1-B)^D X_t = \theta(B)\Theta(B^S)Z_t \quad (9)$$

And the peak time is the point for which the k-step ahead forecast is maximum. Thus, this is given as

$$\hat{X}_{t+k,s} = [\,\phi(B)\Phi(B)^s(1-B)^d((1-B)^D]^{-1}\theta(B)\Theta(B^S)Z_{t+k} \quad (10)$$

Where peak is as defined below

$$\text{Max}\ \hat{X}_{t+k,s} = [\,\phi(B)\Phi(B)^s(1-B)^d((1-B)^D]^{-1}\theta(B)\Theta(B^S)Z_{t+k} \quad (11)$$

RESULTS/DISCUSSIONS

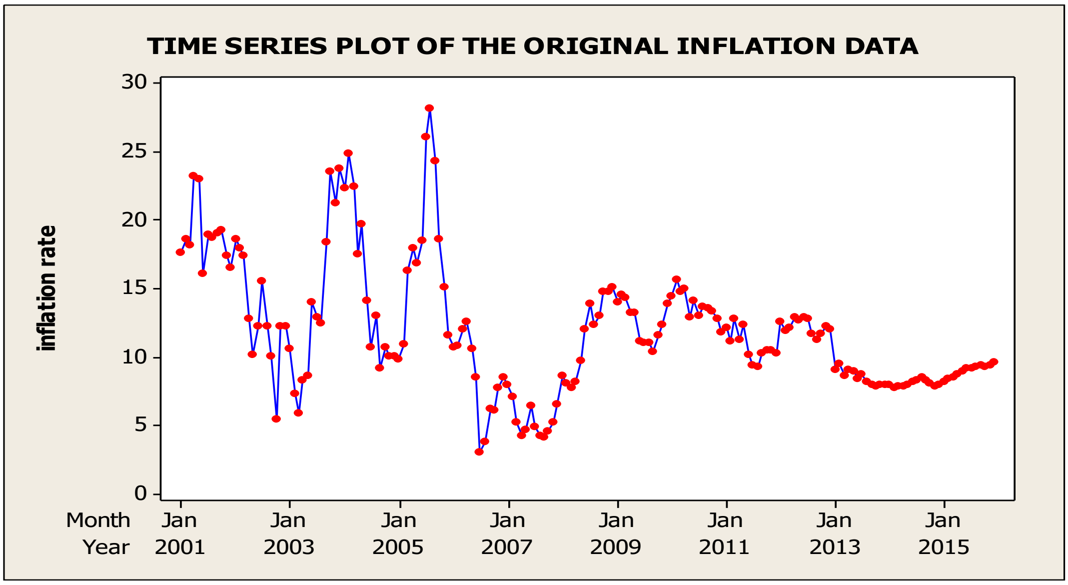

Figure 1: Monthly Inflation Rates of Nigeria. 2001:1 to 2015:12

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Table 1: Augmented Dickey-Fuller Test for Unit Root of the Inflation Rates

Null Hypothesis: NIGERIA_S_INFLATION_DATA has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.384774	0.1541
Test critical values:	1% level	-2.577945	
	5% level	-1.942614	
	10% level	-1.615522	

*MacKinnon (1996) one-sided p-values.

Table 2: Phillip-Perron Test for Unit Root of the Inflation Rates

Null Hypothesis: NIGERIA_S_INFLATION_DATA has a unit root
Exogenous: None
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.381403	0.1550
Test critical values:	1% level	-2.577945	
	5% level	-1.942614	
	10% level	-1.615522	

*MacKinnon (1996) one-sided p-values.

For the Augmented Dickey-Fuller (ADF) and the Phillips-Perron unit root tests in Tables 1 and 2 respectively, the null hypothesis that the series contains a unit root will not be rejected.

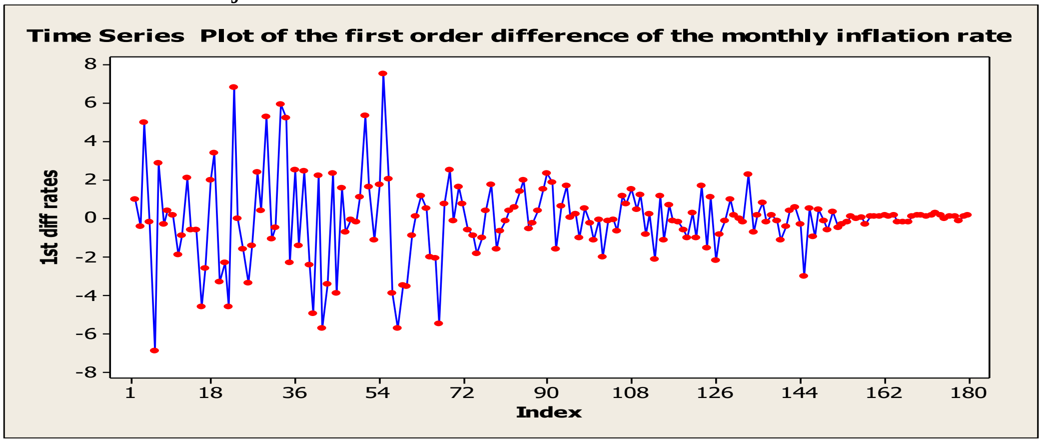

Figure 2: First Order Difference of the Inflation Rates

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Table 3: ADF Test for Unit Root of the First Difference Inflation Rates

Null Hypothesis: D(NIGERIA_S_INFLATION_DATA) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.43027	0.0000
Test critical values:	1% level	-2.578018	
	5% level	-1.942624	
	10% level	-1.615515	

*MacKinnon (1996) one-sided p-values.

Table 4: Phillip-Perron Test for Unit Root of the Inflation Rates:
Null Hypothesis: D(NIGERIA_S_INFLATION_DATA) has a unit root

Exogenous: None
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-12.40268	0.0000
Test critical values:	1% level	-2.578018	
	5% level	-1.942624	
	10% level	-1.615515	

*MacKinnon (1996) one-sided p-values.

Having satisfied that the series is stationary at level in the seasonal part, Figure 2 shows the first non-seasonal differencing. But For the Augmented Dickey-Fuller (ADF) and the Phillips-Perron unit root tests of the first differenced series in Tables 3 and 4 respectively, since the absolute value of the computed test statistics are more than the critical values at 1%, 5% and 10%, we would reject the null hypothesis that the series contains a unit root.

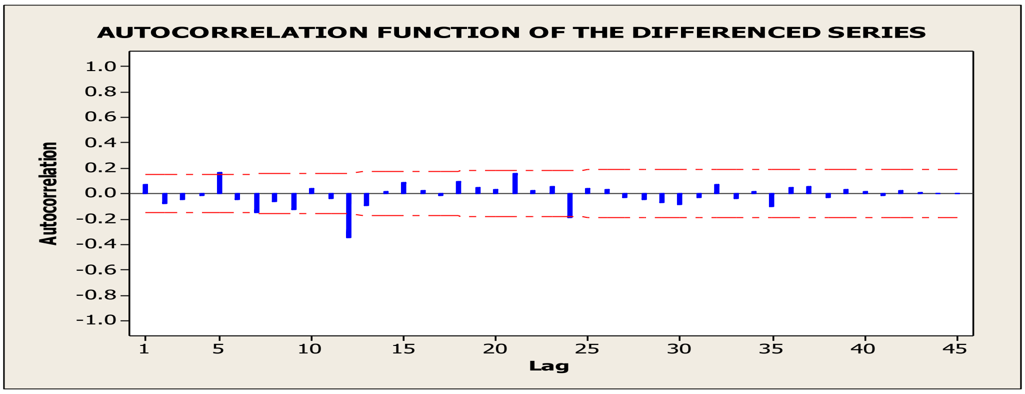

Figure 3: ACF of First Order Difference

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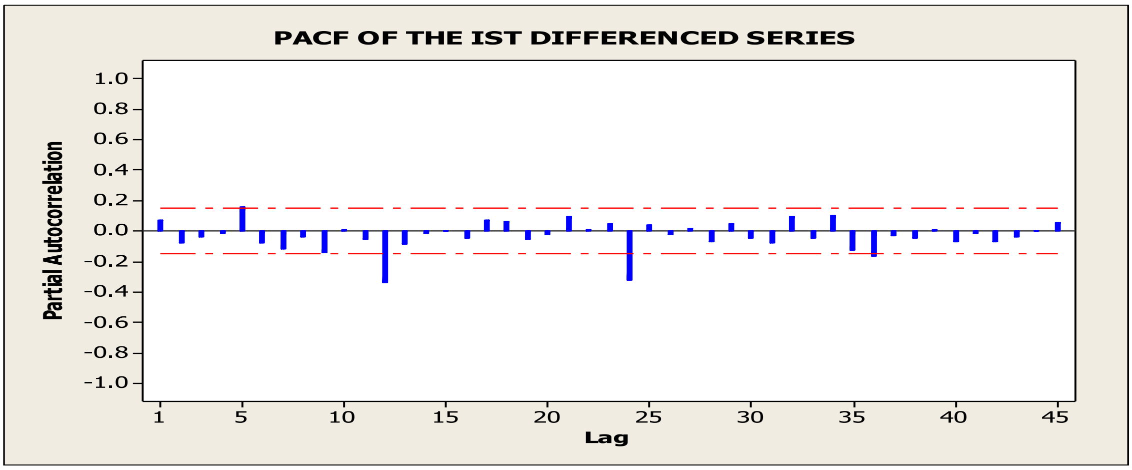

Figure 4: PACF of First Order Difference

Identifying the model using figure 3 and 4, both ACF and PACF tail off at lag 1, suggesting that $q = 1$ and $p = 1$ would be needed to describe these data as coming from a non-seasonal moving average and autoregressive process respectively. Also looking at the seasonal lag, the ACF spike at seasonal lag 12 while the PACF spike at seasonal lag 12 and 24 and then drops to zero for other seasonal lags suggesting that $Q = 1$ and $P = 2$ would be needed to describe these data as coming from a seasonal moving average and autoregressive process. Hence ARIMA $(1,1,1)(2,0,1)_{12}$ could be possible model for the series. However other significant models entertained in this study include ARIMA $(1,1,2)(2,0,1)_{12}$,ARIMA $(1,1,1)(2,0,1)_{12}$ and ARIMA$(0,1,0)(0,0,2)_{12}$

Table 5: Estimates of Parameters of SARIMA $(0,1,0)(0,0,2)_{12}$

Dependent Variable: D(INFLATION_RATES)
Method: Least Squares
Date: 06/23/16 Time: 09:59
Sample (adjusted): 2001M02 2015M12
Included observations: 179 after adjustments
Convergence achieved after 12 iterations
MA Backcast: 1999M02 2001M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(12)	-0.803003	0.071519	-11.22776	0.0000
MA(24)	-0.159743	0.071291	-2.240731	0.0263

R-squared	0.444866	Mean dependent var	-0.044693
Adjusted R-squared	0.441730	S.D. dependent var	2.079989
S.E. of regression	1.554115	Akaike info criterion	3.730800
Sum squared resid	427.5034	Schwarz criterion	3.766413
Log likelihood	-331.9066	Hannan-Quinn criter.	3.745241
Durbin-Watson stat	1.816004		

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Table 6:Estimates of Parameters of SARIMA (1,1,1)(2,0,1)12

Dependent Variable: D(INFLATION_RATES)
Method: Least Squares
Date: 06/23/16 Time: 10:07
Sample (adjusted): 2003M03 2015M12
Included observations: 154 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 2002M02 2003M02

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.557068	0.110837	-5.026000	0.0000
SAR(12)	0.170377	0.070991	2.399970	0.0176
SAR(24)	-0.104741	0.063656	-1.96543	0.0120
MA(1)	0.818633	0.066318	12.34414	0.0000
SMA(12)	-0.973712	0.013519	-72.02566	0.0000

R-squared	0.521150	Mean dependent var	0.015119
Adjusted R-squared	0.508295	S.D. dependent var	1.874642
S.E. of regression	1.314530	Akaike info criterion	3.416765
Sum squared resid	257.4705	Schwarz criterion	3.515367
Log likelihood	-258.0909	Hannan-Quinn criter.	3.456817
Durbin-Watson stat	1.904166		

Table 7:Estimates of Parameters of SARIMA (1,1,2)(2,0,1)12

Dependent Variable: D(INFLATION_RATES)
Method: Least Squares
Date: 06/23/16 Time: 10:44
Sample (adjusted): 2003M03 2015M12
Included observations: 154 after adjustments
Convergence achieved after 45 iterations
MA Backcast: 2002M01 2003M02

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.858601	0.043143	19.90110	0.0000
SAR(12)	0.155963	0.071919	2.168588	0.0317
SAR(24)	-0.143752	0.064650	-2.223543	0.0277
MA(1)	-0.714808	0.087271	-8.190652	0.0000
MA(2)	-0.279912	0.081253	-3.444967	0.0007
SMA(12)	-0.971366	0.014480	-67.08464	0.0000

R-squared	0.629446	Mean dependent var	0.015119
Adjusted R-squared	0.613549	S.D. dependent var	1.874642
S.E. of regression	1.307489	Akaike info criterion	3.412275
Sum squared resid	253.0099	Schwarz criterion	3.530598
Log likelihood	-256.7452	Hannan-Quinn criter.	3.460338
Durbin-Watson stat	1.981621		

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Model Representation

TABLE 8: AIC and BIC for the entertained SARIMA models

MODEL	AIC	AICc	BIC	DW	R^2	S.E
ARIMA(1,1,1)(2,0,1)$_{12}$	3.417	3.902	527.458	1.816	0.445	1.554
ARIMA(0,1,0)(0,0,2)$_{12}$	3.731	3.960	668.323	1.907	0.521	1.315
ARIMA(1,1,2)(2,0,1)$_{12}$	3.412	3.793	527.022	1.982	0.629	1.307

Among models whose parameter estimates were significant as presented in table 5, 6 and 7, their AIC, AICc, and BIC (as shown in Table 8) were compared and ARIMA (1,1,2)(2,0,1)$_{12}$ was chosen.

Table 9: Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Modified Box-Pierce (Ljung-Box) Chi-Square for SARIMA(1,1,2)(2,0,1)$_{12}$				
Lag	12	24	36	48
Chi-Square	15.2	22.9	28.9	30.1
DF	10	22	34	46
P-Value	0.124	0.408	0.716	0.966

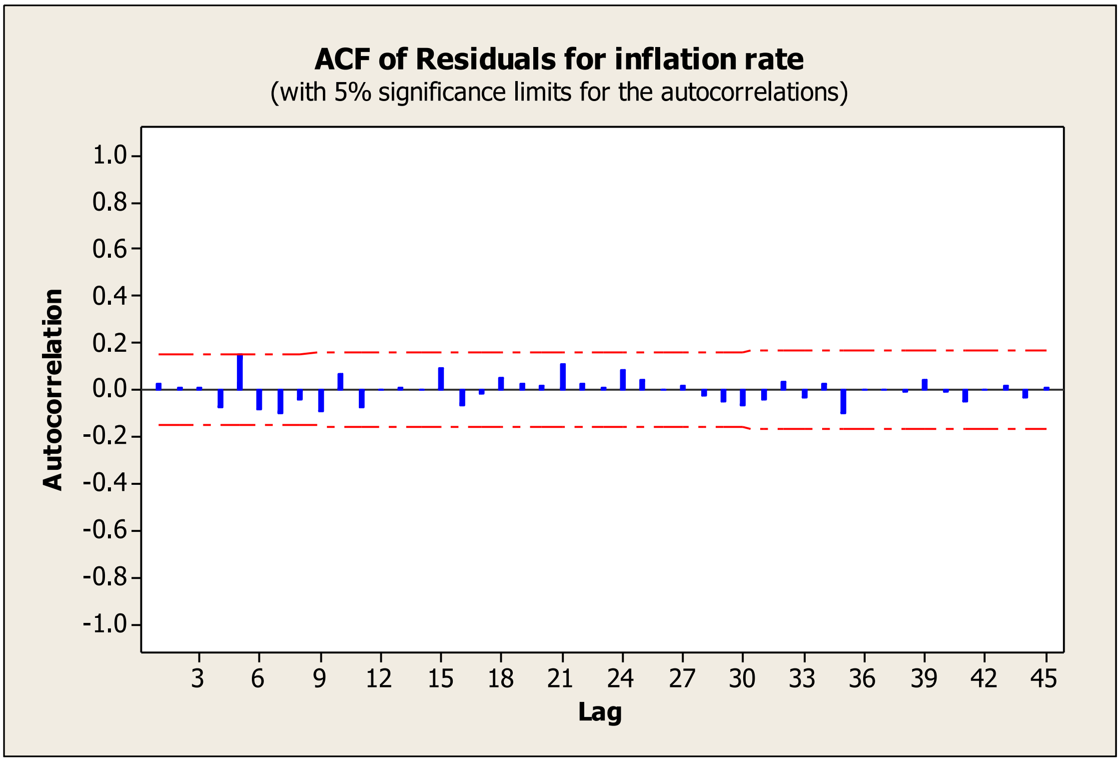

Figure 5: ACF of Residual

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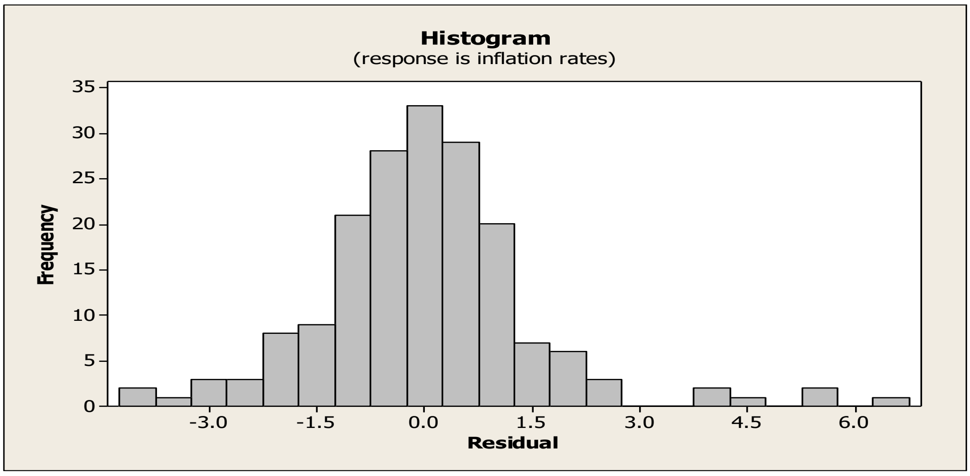

Figure 6: Histogram of Residual

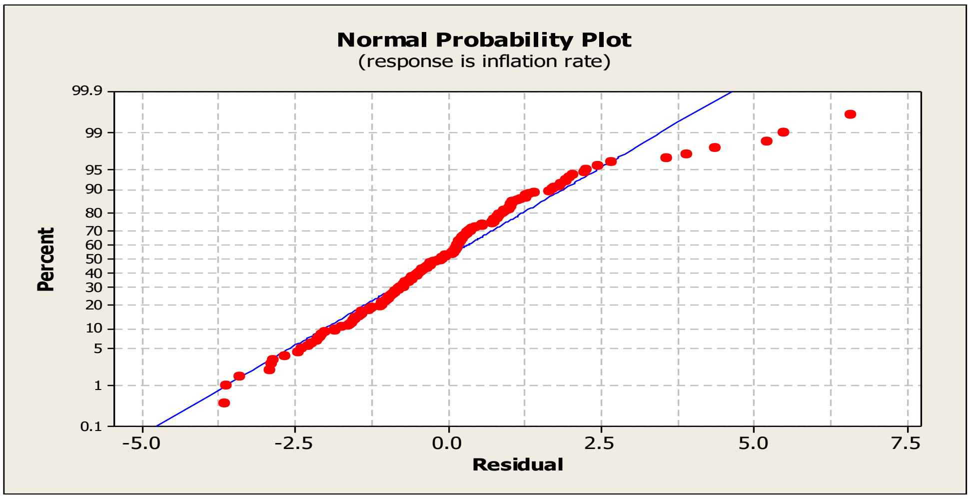

Figure 7: Residual Normal probability Plot

The residuals were checked to find out if they follow a white noise process. The ACF of the residuals as shown in Figure 5 shows that for all the first 45 lags, all sample autocorrelation fall inside 95% confidence bounds indicating that the residuals appear random. In addition, the histogram plot in Figure 6 shows a bell shaped distribution which is an indicator for normality. The Ljung Box test in Table 9 and the plot of residual normality test in Figure 7 further confirms the fit of the model at 95% confidence level.

Forecasting with the Identified Models {ARIMA(1,1,2)(2,0,1)$_{12}$}

The selected model is ARIMA(1,1,2)(2,01)$_{12}$. This model will be used in predicting seasonal (monthly) values of inflation from where the peak value will be identified.

$$(1-B)(1-\phi B)(1-\Phi_1 B^2-\Phi_2 B^{24})X_t=(1-\theta_1 B-\theta_1 B^2)(1-\Theta B^{12})Z_t \quad (12)$$

which is represented as:

$$X_t = X_{t-1} + 0.1560X_{t-12} - 0.1438X_{t-24} + 0.8588X_{t-1} - 0.1339X_{t-13}$$
$$+ 0.1235X_{t-25} - 0.1560X_{t-13} + 0.1438X_{t-25} - 0.8588X_{t-2}$$

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$$+ 0.1339X_{t-14} - 0.1235X_{t-26} + Z_t + 0.9713Z_{t-12} - 0.7148Z_{t-1}$$

$$+ 0.6943Z_{t-13} + 0.2799Z_{t-2} + 0.2719Z_{t-14} \qquad (13)$$

The one step ahead prediction is given as

$$X_{t+1} = X_t + 0.1560X_{t-11} - 0.1438X_{t-23} + 0.8588X_t - 0.1339X_{t-12}$$

$$+ 0.1235X_{t-24} - 0.1560X_{t-12} + 0.1438X_{t-24} - 0.8588X_{t-1}$$

$$+ 0.1339X_{t-13} - 0.1235X_{t-25} + Z_{t+1} + 0.9713Z_{t-11} - 0.7148Z_t$$

$$+ 0.6943Z_{t-12} + 0.2799Z_{t-1} + 0.2719Z_{t-13} \qquad (14)$$

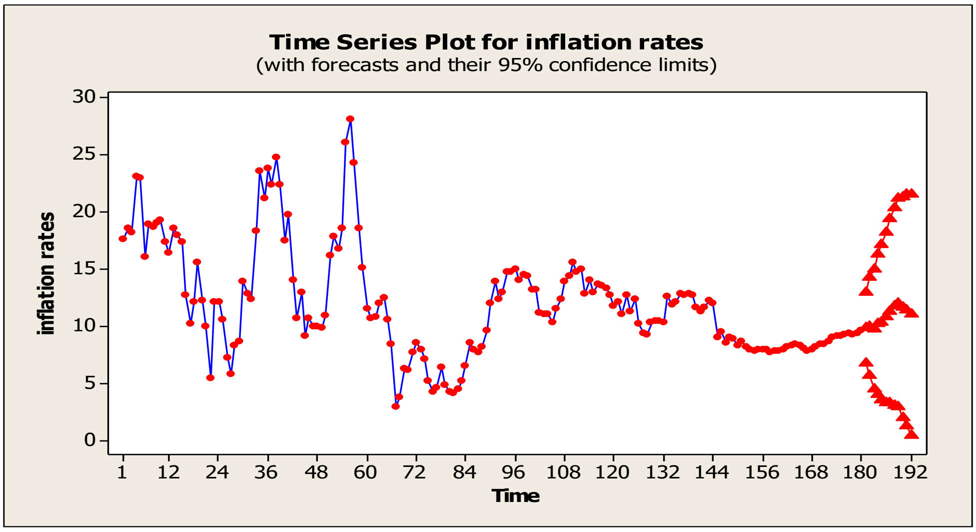

Figure 8: Time Series Plot for Inflation Rates with Twelve Month Forecast and their 95% Confidence Limits

Table 10: ARIMA(1,1,2)(2,0,1)12 Forecasting Results for Monthly Inflation Rates

MONTH	FORECAST%	LOWER BOUND(%)	UPPER BOUND(%)
January	10.17	7.15	13.20
February	10.32	5.85	14.79
March	10.59	4.67	15.57
April	10.65	4.43	16.86
May	10.87	4.02	17.72
June	11.65	4.25	19.04
July	12.45	4.57	20.34
August	13.12	4.80	21.44
September	13.52	4.80	22.24
October	12.95	3.86	22.04
November	12.54	3.09	21.98
December	12.15	2.37	21.92

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CONCLUSION

The results of the forecasts for 2016 show that Nigeria will experience high inflation rates above one digit in the year which will be at its peak in the third quarter of the year and precisely in the month of September. Similarly, the forecast also revealed that the lowest inflation rates will be recorded in the month of January for the year 2016.

Furthermore, comparing the predicted rates of inflation for the first three months with the observed rates, it can be deduced that the predicted values are close to the observed values published by the National Bureau of Statistics. Moreover, all the observed values fall inside the 95% confidence interval which means that ARIMA $(1,1,2)(2,0,1)_{12}$ is adequate for predicting monthly inflation rates of Nigeria. The peak time corresponds with the months of august and September of each year.

In line with these findings vigorous monetary policies and appropriate economic measures be implemented by government and other stakeholders to ensure that single digit inflation value in general and stabilize inflation for the identified peak periods.

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