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ARIMA MODELLING OF FOOD INFLATION RATE IN NIGERIA

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ABSTRACT

This paper fit a time series model to the monthly food inflation rate price in Nigeria from 2014 to 2018 and also provided a year forecast for the likely food inflation rate in Nigeria. The study attempts to outline the practical steps which need to be undertaken to use autoregressive integrated moving average (ARIMA) time series models for forecasting Nigeria's food inflation rate. Inspecting the ACF and the PACF at the lag, k = 1,2,3…, we discovered that the tentative model is a subset of ARIMA(3,1,3), and the model ARIMA(1,1,2) was preferred base on the AIC &BIC. Then the ACF plot of the residuals shows that the residuals of the model is stationary, and the normal quantile plot indicates that the residuals is normally distributed. Finally, we compared the forecasts for the months of January, February, March, April, June & July to the original values in 2019, and RMSE of 2.999.

***Keyword**: Food Inflation Rate, ARIMA, Time Series, Forecasting*

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1 Introduction

Inflation is a general rise in the price of goods and services in a particular economy, resulting in a fall in the value of money. When the price rises, each unit of currency buys fewer goods and services. Consequently, inflation reflects a reduction in the purchasing power per unit of money. Adams, Awujola &Alumgudu (2014) considered inflation to be a major economic problem in transition economies and thus fighting inflation and maintaining stable prices is the main objective of monetary authorities like CBN. The negative consequences of inflation are well known, it can result in a decrease in the purchasing power of the national currency leading to the aggravation of social conditions and living standards. High prices can also lead to uncertainty making domestic and foreign investors reluctant to invest in the economy. Moreover, inflated prices worsen the country's terms of trade by making domestic goods expensive on regional and world markets. Okuneye (2001) stated that agricultural production, food insecurity, lack of sensitization programs etc. affect the prices of food. Furthermore, he defined food inflation as a condition whereby there exists increase in wholesale price index of essential food item relative to the general inflation of the consumer price index. Various research shows that level inflation is negatively correlated with economics growth in developing countries. The issue of food inflation has been a critical one for economy planners. Between mid-2007 and mid-2008 the food price index of the World Bank increased by almost 86% (Wright, 2009). The causes for the sudden rise in international food prices ranged from higher energy. In Sub-Saharan Africa the greatest impact of rising food prices was evident in poverty levels. Wodon and Zaman (2010) found that an increase in food prices by just 50 per cent resulted in a 4.4 per cent increase in the poverty headcount in Sub-Saharan Africa.

Mordi *et al*. (2007), in their study of the best models to use in forecasting inflation rates in Nigeria identified areas of future research on inflation dynamics to include re-identifying ARIMA models, specifying and estimating VAR models and estimating a P-Star model, amongst others that can be used to forecast inflation with minimum mean square error. Imimole and Enoma (2011) conducted a research on the impact of exchange rate depreciation on inflation in Nigeria using auto regression distributed lag (ARDL) and co integration procedures. Evidence from the estimate results suggested that exchange rate depreciation, money supply and real gross domestic product were the main determinants of inflation in Nigeria. Odunsaya and Atanda (2010)

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critically examined the dynamic and simultaneous inter-relationship between inflation and its determinants in Nigeria within the period 1970-2007. The Augumented Engle-Granger (AEG), cointegration test and error correction model were employed. The estimated result indicated that substantial benefits occurred when moving from high or moderate rate to low level of inflation. Omekara *et al* (2013) applied Periodogram and Fourier Series Analysis to model all-items monthly inflation rates in Nigeria from 2003 to 2011. Their main objectives was to identify inflation cycles, fit a suitable model to the data and make forecasts of future values. To achieve these objectives, monthly all-items inflation rates for the period was obtained from the Central Bank of Nigeria (CBN) website. Periodogram and Fourier series methods of analysis are used to analyze the data. Based on their analysis, it was found that inflation cycle within the period was fifty one (51) months, which coincides with the two administrations within the period. Further, appropriate significant fourier series model comprising the trend, seasonal and error components is fitted to the data and this model is further used to make forecast of the inflation rates for thirteen months. These forecasts compare favorably with the actual values for the thirteen months. Olajide *et al* (2012) forecast the inflation rate in Nigeria using Jenkins approach. The data used for this paper was yearly data collected for a period of 1961-2010. Differencing method were used to obtain stationary process. The empirical study reveals that the most adequate model for the inflation rate is ARIMA (1,1,1). The root mean square error (RMSE) which determine the efficiency of the model was estimated at 12.55, this indicate that the model built is efficient. Using an ARIMA (1,1,1) model of annual value series of inflation rate for 2011 is estimated to be 16.27%.The model developed was used to forecast the year 2011 inflation rate. Based on this result, they recommend effective fiscal policies aimed at monitoring Nigeria's inflationary trend to avoid the consequences in the economy. Adams *et al* (2014) fit a time series model to the consumer price index (CPI) in Nigeria's Inflation rate between 1980 and 2010 and provided five years forecast for the expected CPI in Nigeria. The Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) models was estimated, and the best fitting ARIMA model was used to obtain the post-sample forecasts. They discovered that the best fitted model is ARIMA (1, 2, 1), Normalized Bayesian Information Criteria (BIC) was 3.788, stationary R2 = 0.767 and Maximum likelihood estimate of 45.911. The model was further validated by Ljung-Box test (Q = 19.105 and p>.01) with no significant autocorrelation between residuals at different lag times. Finally, five years forecast was made, which showed an average increment of about 2.4% between 2011 and 2015 with the highest CPI being estimated as 279.90 in the 4th quarter of the year 2015. Ekpeyong and Udoudo (2016) paper consider the analyses and forecasting of the monthly All-items (Year-on-Year change) Inflation Rates in Nigeria. The data used for this study are monthly All-items Inflation rates from 2000 to 2015 collected from the Central Bank of Nigeria. Analyses reveal that the Inflation rates of Nigeria are seasonal and follow a seasonal ARIMA Model, (0, 1, 0) x (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.

This study aim to fit an appropriate time series model for the food inflation rates of Nigeria using Box-Jenkins methodology. Hence, the specific objectives include: to specify the order of the ARIMA model for food inflation rates in Nigeria, estimating the coefficient in the specified model, diagnostic check of the specified model and forecasting food inflation rates in Nigeria. The R statistical programming software will be used in displaying the plots and computing the results of method of analysis.

2 Methodology

Box–Jenkins method is a methodology which uses a variable past behavior to select the best forecasting model from a general class of models. There are four stages involved in this methodology, this includes; order selection, estimating the coefficient, diagnostic checking and forecasting

2.1 Data collection

This work used the monthly food inflation rate (Year on Year change). All the data were collected from Central Bank of Nigeria statistical bulletin. They were collected for the period of January, 2014 to June, 2019. The values from the year 2019 wil be use to test the model.

2.2 Time series

A time series $\{Y_t\}$ is a set of observations y_t indexed in time order t. If the observations in a time series are recorded at successive equally spaced points in time it is called a *discrete-time time series*. (Brookwell and Davis, 2002). These kind of time series will be dealt with in this thesis as the data points are recorded once every month.

2.3 The stationarity condition

When performing different time series techniques one often assumes that some of the data's properties do not change over time. The most fundamental assumption is that the data is stationary. Stationarity is an important condition for ARIMA models. In practice, the mean and variance should be constant as a function of time before performing the analysis. Otherwise, past effects would accumulate and the values of successive y_t's would approach infinity making the process non-stationary. For a first order nonstationarity, the observations with ARIMA models should be sieved first by differencing the observations *d* times, using $\Delta^d y^t$ instead of y_t as the time series to obtain stationary data. This is usually done with the transformation

$$\Delta Y_t = Y_t - Y_{t-1} \tag{1}$$

2.4 The ARIMA model

If a time series does not exhibit the features connected to stationarity one looks for transformation of the data to generate a new series with the desired properties. If the data requires differencing to become stationary one talks about the class of autoregressive integrated moving average (ARIMA) models. These models are a generalization of the class of ARMA models discussed previously and with $\Delta Y_t = Y_t - Y_{t-1}$ an ARIMA(p,1,q) takes the following form:

$$\Delta Y_t = \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} + \ldots + \phi_p \Delta Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \tag{2}$$

2.5 Autocorrelation and partial autocorrelatyion function

The autocorrelation function (ACF) is considered when the linear dependence between $\{Y_t\}$ and its past values $\{Y_{t-1}\}$ is of interest. The autocorrelation coefficient between $\{Y_t\}$ and $\{Y_{t-1}\}$ is denoted $\rho(l)$ which under the weak assumption of stationarity is a function of l only

$$\rho(l) = \frac{Cov(Y_t, Y_{t-l})}{Var(Y_t)} \tag{3}$$

The partial autocorrelation function (PACF) is a function of ACF and is the extent of correlation between a variable and a lag of itself that is not explained by correlations at all lower-order-lags. Considering the AR model.

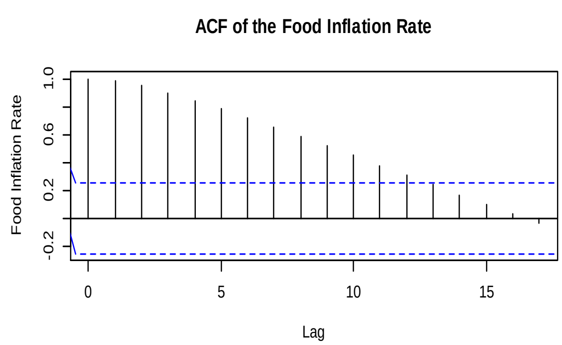

Fig.5: autocorrelation function of the food inflation rate

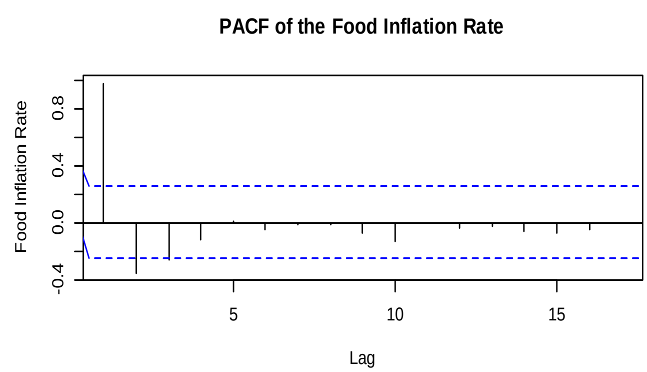

Fig.5: the partial autocorrelation function of the food inflation rate

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2.6 Applying the ARIMA technique: Box-Jekins methodology

Modelling the data as $Y_t = \sum_{v\geq 0} \alpha_v \varepsilon_{t-v}$, where (ε_t) is a white noise. We would also have to determine infinitely many parameters α_v , $v \geq 0$. By the *principle of parsimony* it seems, however, reasonable to fit only the finite number of parameters of an ARMA (p,q)-process. So far, the above centered on the Box and Jenkins methodology with its benchmark model.

The Box-Jekins program consist of four steps: Order selection: choice of the parameters p and q , estimation of coefficients—the coefficients $\phi_1, \phi_2, ..., \phi_p (\phi_p \neq 0)$ and $\theta_1, \theta_2, ..., \theta_p$ are estimated, diagnostic check—the fit the ARMA (p, q)-model with the estimated coefficients is checked, and forecasting—the prediction of future values of the original process.

2.6.1 Order selection

The objective of this method is to select a subclass of the family of ARIMA models appropriated to represent a time series. We identify a set of stationary ARMA processes to represent the stationary process, i.e, we choose the order (p, q). These plots are from the autocorrelation and autocorrelation function. The summary of the patterns of the theoretical ACFs and PACFs of some common models is given by Box-Jenkins (1994) are given in table 1:

Table 1: Behavior of the ACF and PACF for causal and invertible pure ARMA models

Process	ACF	PACF
AR(p)	Decrease exponentially	Cuts off after lag P
MA(q)	Cuts off after lag q	Decrease exponentially or sine wave pattern.
ARIMA(p,q)	No cut off	No cut off

Source: Box-Jenkins (1994)

The order q of a moving average MA (q)-process can be estimated by means of the empirical autocorrelation function $r(k)$ i.e., by correlogram. The order p of an AR (p)-process can be estimated in an analogous way using the empirical partial autocorrelation function $\hat{\alpha}(k), k \geq 1$. The choice of the orders p and q of an ARMA (p, q)-process is a bit more challenging. In this case we take the pair (p, q) , minimizing some function, which is based on the estimate $\hat{\sigma}^2_{p,q}$ of the variance of ε_0 .

Popular functions are:

Akaike's Information Criterion:

$$AIC(p,q) := \log(\hat{\sigma}^2_{p,q}) + 2\frac{p+q+1}{n+1} \tag{4}$$

Bayesian Information Criterion:

$$BIC(p,q) := \log(\hat{\sigma}^2_{p,q}) + \frac{(p+q)\log(n+1)}{n+1} \tag{5}$$

Brokwell and Davis (1991) discussed the AIC and BIC for a Guassian processes $\{Y_t\}$. The variance estimate $\hat{\sigma}^2_{p,q}$ will in general become arbitrarily small as $p+q$ increases. The additive terms in the above criteria serve, therefore, as penalties for large values, thus helping to prevent overfitting of the data by choosing p and q too large.

2.6.2 Estimation of Coefficients

Suppose we fixed the order p and q of an ARMA (p,q)-process $\{Y_t\}_{t\in}$,with $Y_1,\ldots Y_n$ now modelling the data $y_1,\ldots y_n$ In this step, we will use the maximum likelihood estimate of the parameter $\phi_1,\ldots,\phi_p,\theta_1,\ldots,\theta_p$ in the model. The method in deriving the maximum likelihood estimator of the parameters is discussed by Falk, *et al.* (2006).

2.6.3 Diagnostic Check

Brockwell and Davis (1991) summarized the Portmanteau-test of Box and Pierce (1970) which checks, whether estimated residuals $\hat{\varepsilon}_t, t=1,\ldots,n$, behave approximately like realizations from a white noise process. To this end he considers the pertaining empirical autocorrelation function.

$$\hat{r}_\varepsilon(k) = \frac{\sum_{j=1}^{n-k}(\hat{\varepsilon}_j - \bar{\varepsilon})(\hat{\varepsilon}_{j+k} - \bar{\varepsilon})}{\sum(\hat{\varepsilon}_j - \bar{\varepsilon})^2}, \quad k = 1,\ldots,n-1 \tag{6}$$

Where $\bar{\varepsilon} = \frac{\sum_{j=1}^{n}\hat{\varepsilon}_j}{n}$, and checks, whether the values $\hat{r}_\varepsilon(k)$ are sufficiently close to zero. This decision is based on

$$Q(K) = n\sum_{k=1}^{K}\hat{r}_\varepsilon(k), \tag{7}$$

Which follows asymptotically for $n\to\infty$ a χ^2-distribution with $K-p-q$ degrees of freedom if (Y_t) is actually an ARMA(p,q)-process. The parameter K must be chosen such that the sample size $n-k$ in $\hat{r}_\varepsilon(k)$ is large enough to give a stable estimate of the autocorrelation function. The ARMA(p,q) model is rejected if the $p-value\ 1-\chi^2_{K-p-q}(Q(K))$ is too small, since in the case the value $Q(K)$ is unexpectedly large. To accelerate the convergence to the χ^2_{K-p-q} distribution under the null hypothesis of an ARMA(p,q)-process, so we replace the Box-Pierce statistic $Q(K)$ by the Box-Ljung statistic (Ljung and Box (1978))

$$Q^*(K) = n\sum_{k=1}^{K}\left(\left(\frac{n+2}{n-k}\right)^{1/2}\hat{r}_\varepsilon(k)\right)^2 = n(n+2)\sum_{k=1}^{K}\frac{1}{n-k}\hat{r}_\varepsilon(k) \tag{8}$$

2.6.4 Forecasting

Cryer and Chan (2008) stated the minimum mean square error forecast based on the available history of the series up to time t, namely $Y_1, Y_2, \ldots, Y_{t-1}, Y_t$, which we would use to forecast the value of Y_{t-l} that will occur l time the lead time for the forecast, and denote the forecast itself as $\hat{Y}_t(l)$ is given by

$$\hat{Y}_t(l) = E(Y_{t+l} \mid Y_1, Y_2, \ldots, Y_t) \tag{9}$$

The prediction limits is given as

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$$\hat{Y}_t(l) \pm z_{1-\frac{\alpha}{2}} \sqrt{Var(e_t(l))} \tag{10}$$

2.6.4.1 Root mean square error

Since we aim at forecasting, we need a measure of the models' adequacy. The root mean square error (RMSE) measures the actual deviation from the predicted value to the observed value.

$$RMSE\left(\hat{Y}_t(l)\right) = \sqrt{MSE\left(\hat{Y}_t(l)\right)} = \sqrt{\frac{1}{n}\sum_{l=i}^{n}(\hat{Y}_t(l) - Y_t(l))^2} \tag{11}$$

3.0 Results and Discussion

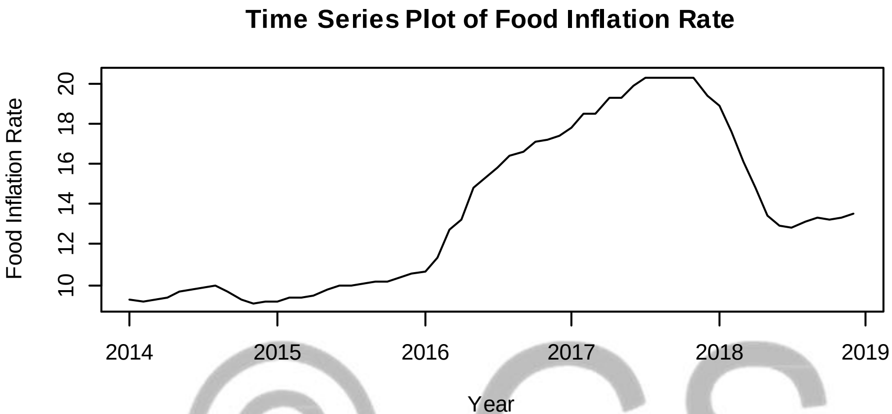

Fig.1: Time series plot of Monthly Food Inflation Rate.

The time series plot of the monthly food inflation rate is shown in Figure 4.1 above. A critical study of the plot reveals that there is an upward increase over time from 2014-2018. The plot suggest presence of trend

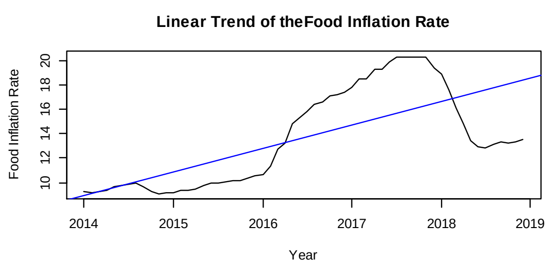

Fig. 2: *The linear trend analysis plot for food inflation rate.*

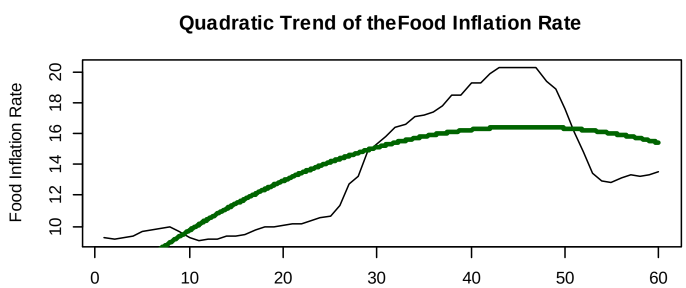

Fig. 3: *The quadratic trend analysis plot for food inflation rate.*

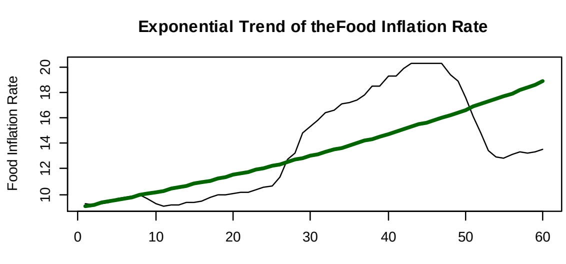

Fig. 4: *The growth curve trend analysis plot for food inflation rate*

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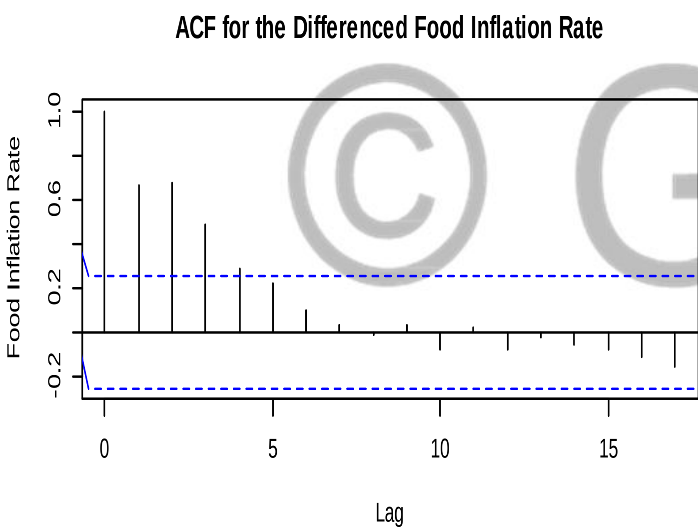
Trend	R-squared	Adjusted R-squared
Linear	0.4951	0.4864
Quadractic	**0.6188**	**0.6054**
Exponential	0.5574	0.5497

Table 2: Accuracy measures for the best trend curve

Source: Researcher's computation

Table 2 summarize the trend analysis in Fig 2,.3&4, the quadratic trend has the maximum R-squared and Adjusted R-squared; Since the quadratic curve explains about 61% of the variation, it is suitable trend curve for the given food inflation rates in Nigeria. The trend analysis plots above shows that the trend is significant which indicates there is presence of trend in the series. Therefore, suggesting that the series is not stationary.

3.1 Selecting the appropraite model



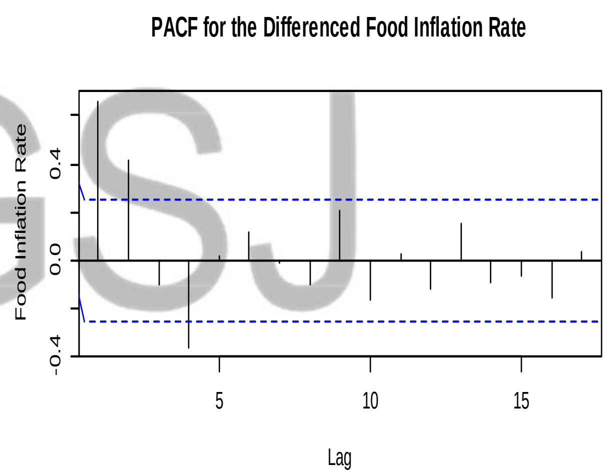


Fig.6: the differenced ACF of the food inflation rate

Fig.7: the differenced PACF of the food inflation rate

Inspecting the ACF and the PACF at the lags, k = 1,2,3…, it appears that the ACF cut off after lag 2 and the PACF shows a significant cut-off after lag 3. Based on Table 3.1, this result indicates that we should consider fitting a model with both p > 0 and q>0 for the non-seasonal components. Hence, we will consider p = 2 and q=3. Thus, a tentative model obtainable from the ongoing preliminary analysis as shown from the ACF and PACF is a subset of ARIMA (3,1,3).We will consider fitting the eigth models suggested by these observations and computing the AIC& BIC for each.

Model	AIC	BIC
ARIMA(1,1,2)	**53.36285**	**61.673**
ARIMA(1,1,3)	54.63788	65.02556
ARIMA(2,1,1)	60.72058	69.03073
ARIMA(2,1,2)	54.93042	65.3181
ARIMA(2,1,3)	54.01048	66.4757
ARIMA(3,1,1)	58.25763	68.64532
ARIMA(3,1,2)	53.85925	66.32447
ARIMA(3,1,3)	55.73835	70.28111

Table 3: AIC BIC of the selected models

Source: Researcher's computation

Based on the least AIC and BIC, the ARIMA (1,1,2) model is the appropriate model that fit the food inflation rate in Nigeria.

3.2 Estimated parameters of ARIMA(1,1,2) model

```
Call:

arima(x = TA, order = c(1, 1, 2), method = "ML")

Coefficients:

          ar1       ma1      ma2

        0.6656  -0.2391  0.5310

s.e.    0.1668   0.2141   0.1402

sigma^2 estimated as 0.1233:  log likelihood = -22.68,   aic = 53.36
```

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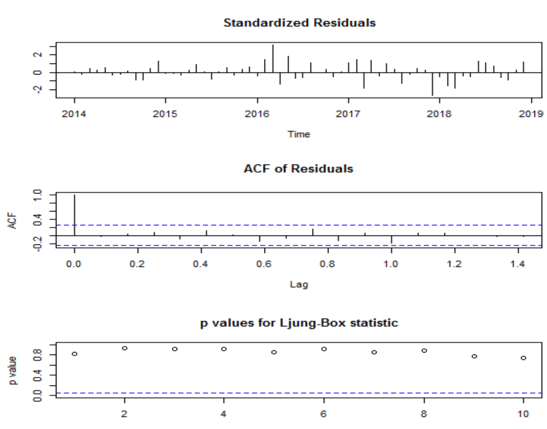
Source: R output

The fitted model for the food inflation rate is $y_t = 0.3344 y_{t-1} - 0.6656 y_{t-2} + \varepsilon_t + 0.2391\varepsilon_{t-1} - 0.5310\varepsilon_{t-2}$

3.3 Diagnostic plot



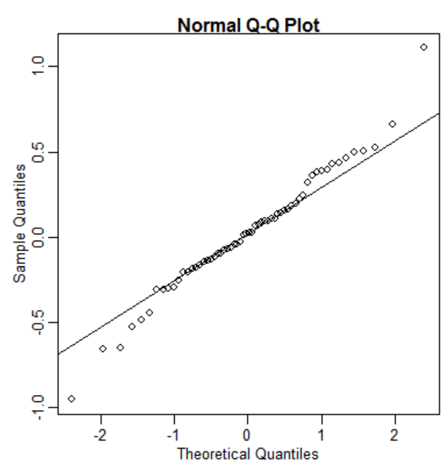


Fig.8: Diagnostics plots of the fitted model

From the plot in fig.8 above, the ACF of the residuals shows no significant peaks at any given lag, indicating that the residuals of the model is stationary. The normal quantile plot above shows that almost all of the sample quantiles of the residuals falls in the same line with the theoretical quantiles which indicates that the residuals is normally distributed. Since the residuals is stationary and normally distributed, we conclude that the model selected is adequate. We also note, however, presence of a few outliers.

3.4 Forecast

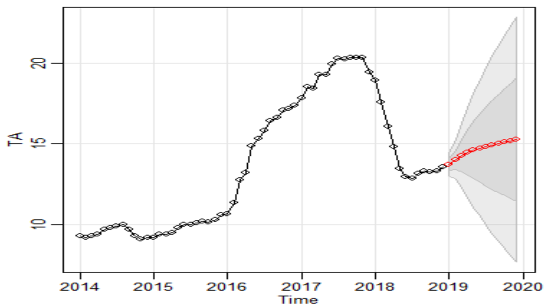


Fig.9: Forecasts and limits for the monthly food inflation rate

Forecasts for the next 12 months and its limits are shown in fig. 9 and the values are given in table 4 below. From the plot in fig.9 above, we can deduce that the monthly food inflation rate is gradually increasing from the period of 2018-2019.

Table 4: Forecasts for the year 2019

Month	Forecast	Lower limit	Upper limit
Jan	13.6938	13.3432	14.0444
Feb	14.0262	13.4160	14.6363
Mar	14.2702	13.2763	15.2642
Apr	14.4563	13.0663	15.8463
May	14.6045	12.8354	16.3735
Jun	14.7277	12.6042	16.8512
Jul	14.8346	12.3819	17.2873
Aug	14.9309	12.1726	17.6891
Sep	15.0201	11.9774	18.0628
Oct	15.1047	11.7961	18.4132
Nov	15.1863	11.6282	18.7444
Dec	15.2659	11.4724	19.0594

Source: Researcher's computation

3.4.1 Root mean square error

Table 5: RMSE and SE of the forecast and actual of the year 2019

Month	Forecast	Actual value	Square Error
Jan	13.6938	11.37	5.4000
Feb	14.02618	11.31	7.3776
Mar	14.27021	11.25	9.1217
Apr	14.45632	11.37	9.5254
May	14.60446	11.4	10.2686
Jun	14.7277	11.22	12.3040
	RMSE		2.9999

Source: Researcher's computation

4 Conclusion

The time series plot of the monthly food inflation rate in Fig. 1 reveals that there is a steady process between 2014 and 2017, then there is downward decrease over time from 2017-2018. The trend analysis plots above shows that the trend is significant which indicates there is presence of trend in the series. Therefore, suggesting that the series is not stationary. After Inspecting the ACF and the PACF, we consider that a tentative model obtainable is a subset of ARIMA (3,1,3). On the basis of the AIC& BIC, ARIMA(1,1,2) is the model preferred for fitting the series. Finally, we compared the forecasts for the months of January, February, March, April and June to the original values in 2019, and we got a RMSE of 2.999.

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