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APPLICATION OF TIME SERIES MODEL ON CONSUMER PRICE INDEX (CPI)

[1]Aliyu Baba Masaya & [2]Ibrahim Usman Bura
Corresponding author:aliyubabamasaya@gmail.com,brhmusman@gamil.com
[1]Department of Computer Science, Yobe State University, Yobe, Nigeria
[2]Department of Environmental Science, School of Basic Science and Research, Sharda University, India

ABSTRACT
This work examines time series analysis on consumer price index (CPI) in Nigeria for the period 2003 to 2016 on yearly basis. The main objective of the study was to determine the pattern, the adequacy and also to develop a model for forecasting the consumer price index (CPI). A secondary data was collected from the Central Bank of Nigeria website. The statistical software used to analyze the data was the MINITAB version 17.0. It was found that as the year increases the CPI also increases. The analysis also reveals that the fitted values were highly reliable. The SARIMA (1,1,1) (1,0,1)$_{12}$ model fitted well into our data and could be used to forecast the consumer price index (CPI) for the future.

Keywords: Consumer Price Index, Auto-correlation Function (ACF), Partial auto-correlation Function (PACF), Auto-Regressive Integrated Moving Average (ARIMA), Seasonal Auto-Regressive Integrated Moving Average (SARIMA).

INTRODUCTION
Numerous works have investigated the relative accuracy of alternative inflation forecasting models. One type of practice has been to compare the accuracy of survey respondents' inflation forecasts relative to univariate time series models. Another approach is the methodology found in Fama (1975) and their extensions Fama and Gibbons (1984). This approach uses extracts from observed nominal interest rates, which is the market's inherent expectation of inflation. Fama and Gibbons (1984) found that the interest-rate model yields inflation forecasts with a lower error variance than a univariate model. This conclusion was based on a univariate time series modeling of the real interest rates. Numerous researchers such as Johnson et al (1977), Schwartz (1986), Babula et al (1995), Oyinlola (2008), Apergis and Rezitis (2011), Dewbre et al (2008), Busicchia (2013), Smirlock (1986), Kim and Shukla (2006), have examined the influence of exchange rate movements on Agricultural trade (prices, supplies, and demands). But there still remain some disagreements on the magnitude of the effects. Johnson et al (1977) compared the impact of exchange rate versus the impact of foreign commercial policy in the pricing of united state wheat. Johnson et al employed a deterministic short run forecasting model to examine the international pricing of wheat, their result show that foreign commercial is created to insulate consumers from increasing prices was more influential in domestic price of wheat than united state policy. Schwartz (1986) compared the effect of changes in the exchange rate in a simple competitive versus a noncompetitive for wheat. In the simple competitive case and tinder a floating exchange rate in one country will cause a short run adjustment Babula et al (1995) found no Co integration between exchange rate price, sales and shipments with respect to united state corn exports. But estimates obtained using both structural econometric models and time series methods generally showed varying degrees of exchange rate impacts on agricultural prices and quantity traded. Oyinlola (2008) empirically investigated the impact of exchange raw movements and tariff rate reduction on disaggregated import prices of the corn economy like Nigeria undergoing structural change using (CM). The paper observes that in the short run, exchange rate exhibits positive and more than complete price through to significant import prices of consumer and capital product groups. According to Apergis and Rezitis (2011) higher food prices translate into higher inflation. So the link among the two is obvious and will depend on the process of price transmission in which many factors are involved, Apergis and Rezitis also note that the fact that persistent food price increases will translate into higher inflation can lead

to higher wages and inflationary expectations, as well as reduced real consumption, savings and investments, which in turn can contribute to slow down aggregate demand. Dewbre at al (2008) the impacts of food commodity prices on consumers focuses on international food prices of commodities, these impacts are best measured by changes in the food component of the consumer price index (CPI),
which accounts for changes in the prices paid for food products by consumers. Heady and Fan (2010) agree on the fact that the food CPI approximates better welfare costs, especially if it is deflated to measure real food price movements. Yet, Dorward (2011) states that there is a "downward bias in estimated real food-price changes for low-income groups when these are calculated using a CPI calculated for higher-income groups". Busicchia (2013) examines food price fluctuations and developments related to international shocks and how food price inflation is managed in Australia, France and the UK. While food consumer prices did not undergo a sharp rise in these countries, they remained high even though world agricultural commodity prices decreased in 2009. And he notes that in the EU the rise of international agricultural commodity prices was rapidly followed by rises in food producer and consumer prices but the easing of international commodity prices did not spill over domestic food producer and consumer prices. (Commodities typically make up only a small share of processed food in developed countries, so the volatile or high agricultural commodity prices are expected to be translated into consumer food prices to a lower degree, due to the fact that the share of agricultural raw materials in food production costs is small (European Commission (EC), 2008). The share of the commodity in final consumer food prices is lower, as the extent of processing increases (Dewbre et al 2008). Malliaris and Malliaris (1995) presented a decomposition of inflation and its volatility. According to the traditional quantity theory of money, the rate of inflation is decomposed into three components: the rate of change in the money supply, plus the rate of change in the velocity of circulation, minus the rate of change in real output. They derived a generalization of this decomposition by postulating that the rate of change of money supply, velocity, and output follow diffusion equations. Using stochastic calculus techniques, two expressions are obtained decomposing inflation and its volatility as a sum of several economically important terms. Two sets of U.S. data are used to illustrate these decompositions with actual numbers.

TIME SERIES ANALYSIS

Time series analysis has an area of considerable activities in recent years. Traditional method of time series analysis is mainly concerned with decomposing the variations in a series in component representing trend, seasonal variation and cyclical changes. Any remaining variation is attributed to irregular fluctuations. And type of Time series analysis. This approach is not always the best but is particularly valuable when is denoted by trend and seasonality. However, this method will be used to study the nature of the trend that occurs in the prices of commodities in the concerned months and to determine the type of model that is generated using the provided data. Time series is an ordered sequence of value of a variable at equally spaced time intervals. This also occurs frequently when looking at industrial data. Time series analysis comprises method for analyzing time series data in order to extract meaningful statistics and other Characteristics of the data.

TYPES OF TIME SERIES ANALYSIS

* Time series forecasting is the use of model to predict future value based on previously observed value
* Descriptive analysis to determine the trend or pattern in a time series using graph or other tools.
* Spectral analysis is also required to as frequency domain and aims to separate periodic or cyclical components in a time series
* Explanative analysis studies the cross correlation or relationship between two time series and the dependence of one on another.

TIME SERIES ANALYSIS TECHNIQUES

Time Series can be defined as an ordered sequence of values of a variable at equally spaced time intervals. The motivation to study time series models is twofold:

- Obtain an understanding of the underlying forces and structure that produced the observed data
- Fit a model and proceed to forecasting, monitoring or even feedback and feed forward control.

Time Series Analysis can be divided into two main categories depending on the type of the model that can be fitted. The two categories are:

- Kinetic Model: The data here is fitted as $x_t = f(t)$. The measurements or observations are seen as a function of time.
- Dynamic Model: The data here is fitted as $x_t = f(x_{t-1}, x_{t-2}, x_{t-3} \ldots)$.

The classical time series analysis procedures decomposes the time series function $x_t = f(t)$ into up to four components

* **Trend:** a long-term monotonic change of the average level of the time series.
* **The Trade Cycle:** a long wave in the time series.
* **The Seasonal Component:** fluctuations in time series that recur during specific time periods.
* **The Residual component** that represents all the influences on the time series that are not explained by the other three components.

The *Trend* and *Trade Cycle* correspond to the smoothing factor and the *Seasonal* and *Residual* component contribute to the cyclic factor. Often before time series models are applied, the data needs to be examined and if necessary, it has to be transformed to be able to interpret the series better. This is done to stabilize the variance. For example, if there is a trend in the series and the standard deviation is directly proportional to the mean, then a logarithmic transformation is suggested. And in order to make the seasonal affect addictive, if there is a trend in the series and the size of the seasonal effect tends to increase with the mean then it may be advisable it transform the data so as to make the seasonal effect constant from year to year. Transformation is also applied sometimes to make the data normally distributed.

TYPES OF MODELS

The specific combination of trend, cyclical, or seasonal components that defines the underlying pattern of a time series is observed in the presence of random error. The forecast is based on the underlying pattern delineated from the random error or noise that obscures this pattern. Isolating the pattern is a central goal of a time series analysis. The stable, predictable component of a time-series is the specific combination of trend, cyclical, and seasonal components that characterize the particular time series. How do these components combine to result in a value of *Yt*. One of two models accounts for the underlying pattern, an additive model or a multiplicative model. The additive model expresses *Yt*as the sum of the trend, cyclical, seasonal, and error components.

Additive Model of Time Series Data

$$\mathbf{Y}_t = \mathbf{T}_t + \mathbf{C}_t$$

The cyclical, seasonal, and error components are each a fixed number of units above or below the underlying trend.

Multiplicative Model of Time Series Data

$$Y_t = T_t \times \mathbf{C}_t \times \mathbf{S}_t \times \mathbf{I}_t$$

$\mathbf{Y}_t$= Data (Is the observation) and

$\mathbf{T}_t$, $\mathbf{C}_t$, $\mathbf{S}_t$ and I_t are respectively, the trend, cyclical, seasonal and irregular variations at time t.

The multiplicative model expresses the C, S, and I components as percentages above or below the underlying trend. Each percentage is a ratio above or below the baseline of 1. The trend component T is expressed in the original units of Y, which is multiplied by each of the C, S, and I ratios to yield the actual data. With the multiplicative model, larger trends magnify the influence of the remaining components. For the additive model, the influence of a given value of C, S, or I is the same for all values of T.

ESTIMATION OF TREND

It is necessary that we distinguish one factor from another and measure its influence after identifying the factors which may cause the fluctuation in our data.
Estimation of trend can be achieved in several possible ways including:

a) **The Freehand Method:** it consists of fitting trend or curve simply by looking at the plotted scattered diagram on the graph, the trend line is drawn by the eye in such a way that it appears to lie evenly between the recorded point, it can be used to estimate T, however, this has glaring disadvantage of depending too much on individual judgment.

b) **The Semi-Average Method:** In this method, the time series data is divided into two equal parts, and then the average of each part is taken. If the number of observation is odd, the central observation is omitted. The two averages are then plotted at the mid-points of the time interval or period covered by the respective part and joined together to produce the trend life.

c) **The Moving Average Method:** Attempts is made to average out of appropriate orders, the effects of cyclical, seasonal and irregular pattern in the time series data. An average taken at the end of each successive time period and placed opposite the midpoint of the group to which it refers.

   The moving average method is particularly useful when estimating the trend of seasonal variation but its disadvantages lies in the following:

   - It may generate cycles or other movement patterns which were not present in the actual or original data.
   - Data at the beginning and the end of a series are lost; also trend values do not correspond of individual items of data.
   - It requires choosing suitable period as a basis of calculation. As it is strongly affected by extreme values, solution to this is the weighted average.

d) **The Least Squares Method:** This is the technique by which a line or curve is filled to the time series data such that the sum of squares of errors made between the observed scores or data and the corresponding estimate in the line is least. This least square method is in the form of regression co-efficient $Y = a + bx$ where a and b are computed values.

ESTIMATION OF SEASONAL VARIATION

Once a trend has been estimated, the seasonal variation can be determined depending on the model we assume i.e additive model or multiplicative model.
The actual observation (Y) and the corresponding trend (T) i.e $S = Y - T$
Then the average of these seasonal variations are then taken, in which the sum of these averages must be added up to zero, because variations around the basic trend line should
Cancel each other out and up to zero. The sum of these average seasonal variations re called seasonal components, seasonal indices and seasonal adjustments.
If we assume the multiplicative model, the actual observation value is expressed as a percentage of the corresponding trend value to obtain the seasonal variation, it is expressed mathematically as $Y = T \times S$ then $S = Y/T$.
For a 4-point moving average, the sum of the average seasonal variation must be equal to 400. For 5-point moving average, it will equal to 500 and so on.

FORECASTING FOR TIME SERIES DATA

The ultimate aim of time series is to forecast for future values. The trend and seasonal variation can be isolated and estimated.
Procedure:
a. The first step is to estimate the future trend values (T) using whatever method.
b. The estimated trend values ($\vec{T}$) are then adjusted with corresponding average seasonal variation (S).

Thus, forecasted future value is given as
Y = T + S..........................(assuming additive model)
Y = $\frac{T \times S}{100}$............................(assuming multiplicative model)
Where Y = forecasted value
T = estimated or forecasted trend value
S = average seasonal variation

METHODOLOGY

Introduction

The yearly consumption price index of Nigeria is a series of observation collected periodically which suggests a time series. The aim is to build model on time series data which invariably make the yearly inflation rate of Nigeria appropriate and suitable for demonstrating such process.Modeling in time series involves having a relatively large number of observations to adequately perform its analysis.

Source of Data

The study made use of secondary data collected between 2003 - 2016 from Central Bank of Nigeria (CBN). Retrievable from the data and statistics publication of CBN website www.centralbank.org.

Models

Models for time series data have many forms and represent different^ stochastic processes when model variations in the level of a process, three broad classes of practical importance are the autoregressive (AR) models, integrated (I) and moving average (MA) models. These three classes depend linearly on previous data points. Combinations of these ideas produce autoregressive moving averages (ARMA) and autoregressive integrated moving averages (ARIMA) models.

Table 1: How to Determine the Model by Using ACF and PACF Patterns

MODEL	ACF	PACF
AR(p)	Dies down	Cut off after lag q
MA (q)	Cut off after Lag P	Dies down
ARMA (p,q)	Dies down	Dies down

Time Series Model

Before an appropriate model can be identified for any time series, the condition known as Stationary must be satisfied. Basically, three models exist as stationary in nature; namely

- Moving Average (MA);
- Auto-Regressive (AR) and
- Auto-Regressive Moving Average Models (ARMA).

When a "regular differencing "process is applied together with auto-regressive and moving average models, a non-stationary model referred to as Auto-regressive Integrated Moving Average (ARIMA) resulted. The "I" indicates "Integrated" and; referencing the differencing procedures.

Auto-Regressive Process

This is a model in which the current value of the series is expressed as a finite linear aggregate of previous value of the process and a random shock Z_t. It is known as auto- regressive because the current value of the series can regress on its past values. Let Y_t, Y_{t-1}, $Y_{t-2,}$... Denote the value of a process at equally spaced times T_0, T_1, T_2, etc.
Thus,
$y_t = f(Y_{t-1}, Y_{t-2}, Y_{t-3}, \ldots \varepsilon_t)$. We say that the process (Y_t) is autoregressive of order **p(AR(p))** If there exist constant
$a_1 \ldots a_p$ Such that $\sum_{k=1}^{p} a\, X_{t-k} + \varepsilon_t$
A common representation of an autoregressive model where it depends on p of its past values called as **AR(p)** model is represented below:

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_4 Y_{t-3}, \ldots \beta_p Y_{t-p} + \varepsilon_t$$

Where $\beta_1, \beta_{1,} \ldots \beta_p$ are autoregressive parameters and (ε_t) is a white noise process with mean, zero and constant variance,δ^2.

Identification of Auto-Regressive Process

Deciding whether or not an auto- regressive model can fit a given time series data will depend on the nature exhibited by the estimated auto-correlation function and partial auto-correlation function of such series. Upon inspection, if the auto-correlation functions decrease exponentially whereas partial auto-correlation function "cut-off after some point, then an auto-regressive model will go just well
with the series. The "cut-off point will now determine which "order" the AR process will take, suppose the "cut-off occur at k =p, the appropriate model is **AR(P)**.

MOVING AVERAGE PROCESS

A moving average model is one when Y_t depends only on the random error terms which follows a white noise process i.e.

$$Y_t = f(\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-3}, \ldots)$$

A common representation of a moving average model where it depends on q of its past values is called MA (q) model and is represented below:

$$Y_t = \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \varphi_3 \varepsilon_{t-3} + \ldots \varphi_q \varepsilon_{t-q}$$

The error terms £, are assumed to be white noise processes with means zero and variance 82.
Identification of a Moving Average Process
This is the first problem to be looked into in the analysis of time series. The series autocorrelation function and partial auto-correlation function is calculated. The inspection should indicate the model. For a MA (q) process, if the correlation "cut-off after some points say k = q, then the appropriate model is MA model of order q. if the correlogram "cut-off after k = 1, then MA (1) is suitable for the series.
Another aid for interpreting ACF and PACF is to calculate the 95% confidence limit given by $\pm\ 2/\sqrt{n}$ where n is the number of observation in the series. Observed value of rk (sample autocorrelation) and kk which falls outside this limit are significantly different from zero at 5% level. For a MA series, the value of the PACF will appear to be decreasing progressively but will "cut-off. On the other hand the values for k will "cut-off at some-point. The correct order of MA (q) series is the value of q beyond which the sampled value of rk is not significantly different from zero.

AUTO-REGRESSION MOVING AVERAGE (ARMA)

A very practical way to fit model to a time series data is to fit a model which has the fewest parameter and greatest degree of freedom among all models that fit the data, that is, parsimony, such a model is the Auto-Regression Moving Average, usually written as ARMA. The auto-regressive moving average includes both auto-regressive and moving average. It's given as

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_4 Y_{t-3} + \ldots + \beta_p Y_{t-p} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \varphi_3 \varepsilon_{t-3} + \ldots \varphi_q \varepsilon_{t-q}$$

An ARMA (p, q) model is a combination of AR (p) and MA(q) models and is suitable for univariate time series modeling. In an AR (p) model the future value of a variable is assumed to be a linear combination of p past observations and a random error. MathemType equation here.atically the AR (p) model can be expressed as

$$Y_t = \sum_{i=1}^{p} \varphi_1 \varepsilon_{t-1} + \ \varepsilon_t = \ \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \ldots + \varphi_1 \varepsilon_{t-p} + \varepsilon_t$$

Here Y_t and £t are respectively the actual value and random error (or random shock) at time Period t, φ_i (i =l,2,...p) are model parameters. The integer constant p is known as the order of the model. Sometimes the constant term is omitted for simplicity. Usually For estimating parameters of an AR process using the given time series, the Yule Walker equations are used.
Just as an AR(p) model regress against past values of the series, an MA(q) model uses past errors as the explanatory variables. The MA(q) model is given by

$$Y_t = \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t = \mu + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \dots + \varphi_q \varepsilon_{t-q} + \varepsilon_t$$

Here u is the mean of the series, φ_j(j = 1,2,...,q) are the model parameters and q is the order of the model. The random shocks are assumed to be a white noise process, i.e. a sequence of independent and identically distributed (i.i.d) random variables with zero mean and a constant variance δ^2. Generally, the random shocks are assumed to follow the typical normal distribution. Thus conceptually a moving average model is a linear regression of the current observation of the time series against the random shocks of one or more prior observations.

Identification of Auto-Regressive Moving Average

The auto-correlation and partial auto-correlation function provides a clue for identifying an ARMA process. If the estimated auto-correlation and partial auto-correlation functions tail off, a mixed process is suggested. Furthermore, the auto-correlation function for a mixed process, containing a pth order auto-regressive component and a qth order moving average component, is mixture of exponentials and damped waves after the q-p lags. Conversely, the partial autocorrelation function for a mixed process is dominated by a mixture of exponential and damped since waves after the first p-q lags.

THE AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL (ARIMA) The order of the autoregressive component is p, the order of differencing needed to achieve stationary is d, and the order of the moving average component is q. In general the ARIMA process (8) is of the form $Z_t = \sum_{k=1}^{p} \alpha_k Z_{t-k} - \sum_{k=1}^{q} \theta\, e_{t=k} + \mu + e_t$

SEASONAL AUTOREGRESSIVE MODELS

A purely seasonal time series is the one that has only seasonal AR or MA parameters. Seasonal autoregressive models are built with parameter called seasonal autoregressive (SAR) parameters. The SAR parameters represent the autoregressive relationships that exist between time series data separated by multiples of the number of periods per season. A general AR model with P SAR parameter is given by $Y_t = \sum_{i=1}^{p} \alpha_{is} Y_{t-is}$ is where Y_{t-s} is of order s, Y_{t-2s} is of order 2s and Y_{t-ps} is of order ps. A model with one SAR parameter is written as

$$Y_t = \alpha_s Y_{t-s} + e_t$$

Seasonal moving Average (SMA) models are built with seasonal moving average (SMA) parameters, and the general SMA model with Q parameters is given by:

$$Y_t = \sum_{i=1}^{Q} \theta_{is} e_{t-is} + e_t$$

The general mixed SAR and SMA model is given by

$$Y_t = \sum_{i=1}^{p} \alpha_{is} Y_{t-is} + \sum_{i=1}^{q} e_{t-is} + e_t$$

The order the seasonal ARMA process is given in terms of both Ps and Qs.

SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA) MODELS

An important tool in modeling non stationary seasonal processes is the seasonal difference. The seasonal difference of period s for the series $[X_t]$ is denoted by $\nabla_s x_t$ and is defined as:

$$\nabla_s x_t = x_t - x_{t-s}$$

For a series of length n, the seasonal difference series will of length n-s that is s data values are lost due to seasonal differencing. In a non- stationary seasonal model, a process $\{x_t\}$ is said to be multiplicative seasonal ARIMA model with non-seasonal(regular)order p, d and q,seasonal orders P, D and Q and seasonal period s if the differenced series:

$$w_t = \nabla^d \nabla_s^D x_t$$

Satisfies an ARMA (p x q) (P x Q) s model with seasonal period s. we say that $\{x_t\}$ is an ARIMA (p,d,q)(P,D,Q)s model with seasonal period s. the seasonal part of a Seasonal ARIMA model has the same structure as the non-seasonal part: it may have an AR factor, an MA factor, and\or an order of differencing. In the seasonal part of the model, all of these factors operate across multiples of lag s (the number of periods in a season).

DATA ANALYSIS

The data was analyzed using statistical package named Minitab and the version is 17.0 and Excel Spreadsheet The statistical technique or tool employed for this study is time series analysis, which involves understanding the historical pattern, judge upon the status and making forecasts of the future development for CPI. Since the best method of finding model in any circumstance depends on the 'shape' taken by the past data, it seems reasonable to plot that data as the first step i.e. **Time series of past data → Suitable method →Best fitting model →Forecast.** The first step is therefore to produce a **scatter-plot** against time (otherwise known as Historigram or time plot) leaving room for forecasts in the near future.

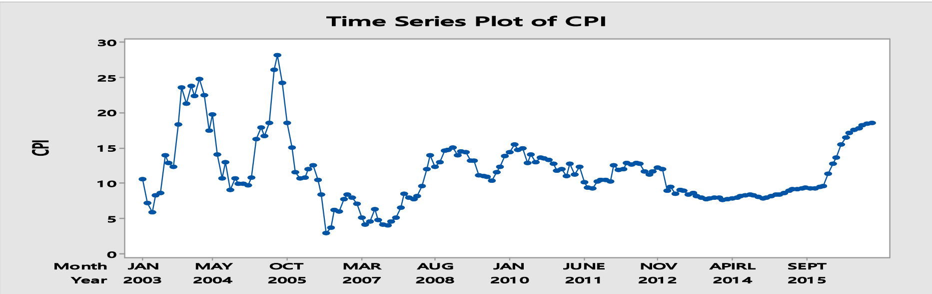

Figure 1: Time plot of the original series

The time plot of CPI shows presence of non – stationary in the series due to the fact that mean and variance are not at fixed level

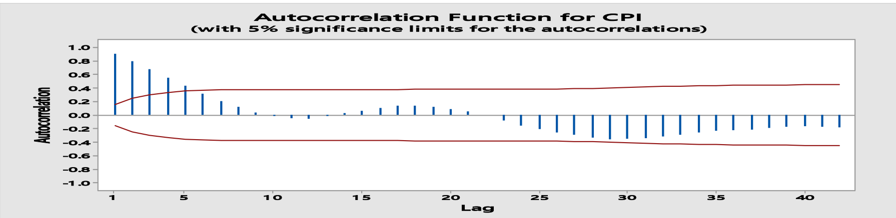

Figure 2: Plot of Autocorrelation function before difference

The ACF shows a pattern typical for a non- stationary series, since there is large significance ACF for the first 5 time lag and slow decrease in the size of the autocorrelation. Also there exist several spike beyond the confidence line limit which also shows a non stationarity of the series.

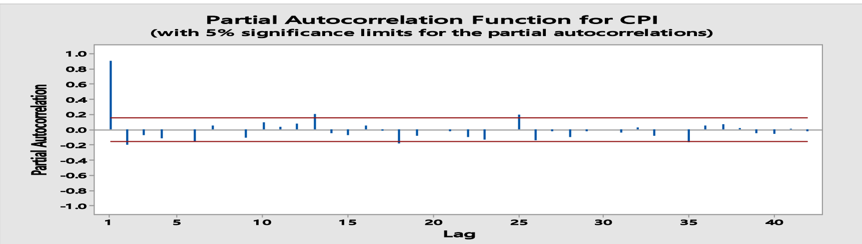

Figure 3: The plot of partial autocorrelation function before difference
Comment: This is also typical of non-stationary series, the PACF at time lag 1 is approximately close to one.

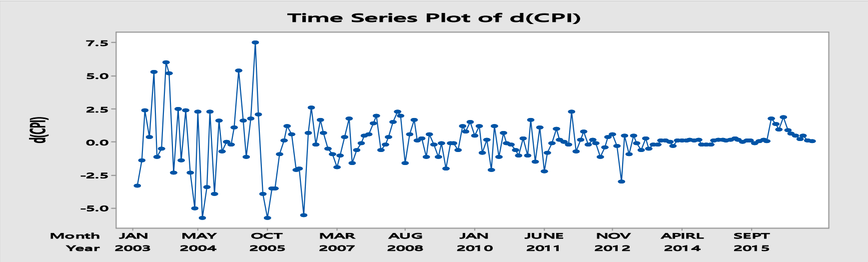

Figure 4: Time plot of differencing
Comment: The time plot of CPI shows present of stationary in but there is presence of seasonality.

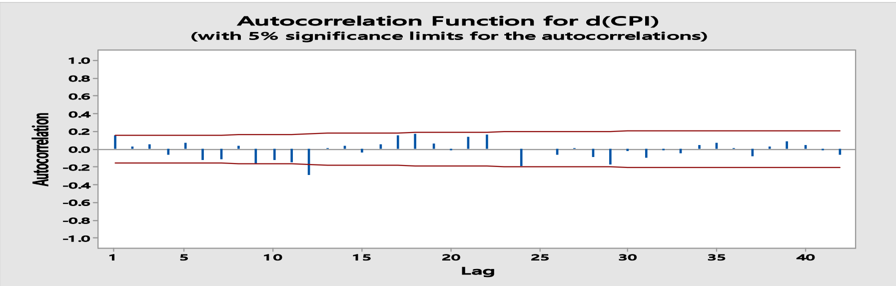

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Figure 5: The plot of autocorrelation function after first difference

Comment: The plot of ACF shows that the spike at lag 1 almost significant and there is a significant spike at lag 12 which confirms the presence of non-seasonal and seasonal Moving Average.

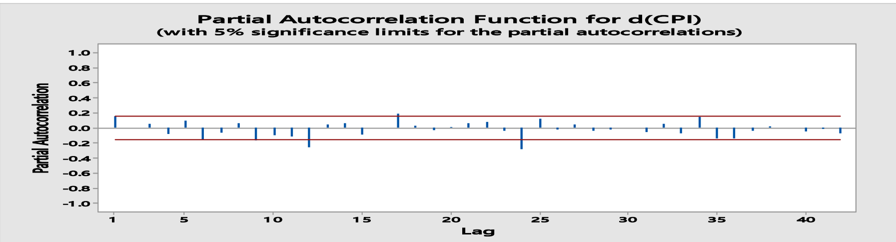

Figure 6: The plot of partial autocorrelation function after first difference

Comment: The plot of the partial autocorrelation function shows almost a significant spike at lag 1, then significant spikes at lags 12 and 24 which, suggest non seasonal and seasonal auto regressive model. Based on the plot of auto correlation and partial auto correlation functions, we try SARIMA (1,1,1) $(1,0,1)_{12}$

ESTIMATION STAGE

This involves starting with a preliminary estimate and refining the estimate iteratively until the sum of squared errors is minimized. Parameters that are significantly different from zero are drop from the model. The Ljung- Box statistics should give non- significant values for efficient model. Hence, the following parameters were estimated for **SARIMA (1,1,1)** $\mathbf{(1,0,1)_{12}}$ based on the plot of correlogram and partial correlogram.

FINAL ESTIMATES OF PARAMETERS

Type	Coef	SE Coef	T	P

AR	1	0.1076	0.0770	1.40	0.164
SAR	12	0.1550	0.0772	2.01	0.046
MA	1	0.9975	0.0007	1496.58	0.000
SMA	12	0.9658	0.0377	25.62	0.000
Constant		0.0007130	0.0002193	3.25	0.001

Differencing: 1 regular difference
Number of observations: Original series 167, after differencing 166
Residuals: SS = 294.622 (backforecasts excluded)
MS = 1.830 DF = 161

MODEL DIAGNOSTIC

Diagnostic checking of a fitted model to a given time series data is necessary in case there is serious inadequacy in the model. Diagnostic checking helps us to know how the model should be modified in the next iterative cycle.

MODIFIED BOX –PIERCE (LJUNG – BOX) CHI- SQUARE STATISTIC

Lag	12	24	36	48
Chi-Square	14.9	27.3	39.8	44.9
DF	7	19	31	43
P-Value	0.038	0.097	0.134	0.393

Comment:

The result in Table 1 confirm that all the parameters including the constant are significantly different from zero, because they have p-values that are significantly smaller than .05. In addition, the Box –Pierce Chi- Square p-values are non- significant (p >0.05) indicating that the model fits the data well and the residuals appeared to be uncorrelated. Therefore, the appropriate model is **SARIMA(1,1,1) (1,01) $_{12}$**. Furthermore, the model contains minimal parameters. The model for this data is;

$$Y_t = 7.0\epsilon04 + 0.1076y_{t-1} + 0.1550y_{t-12} + 0.9975\varepsilon_{t-1} + 0.9658\varepsilon_{t-12}$$

INTERPRETATION: The seasonal ARIMA of order (1,1,1) (1,0,1) $_{12}$ is the most significant model hence it retained to be the model for the study. Hence there is very strong reliability on the model. The model can be used for policy making to predict the future for consumer price index in Nigeria.

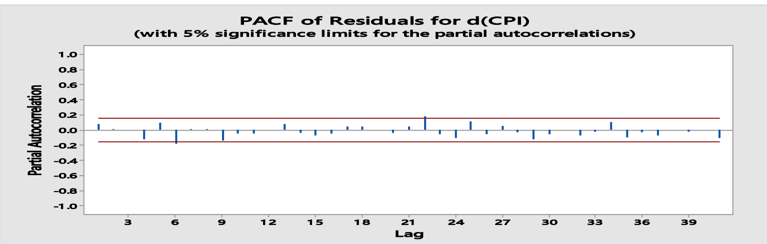

Figure 7

Comment : the plot of ACF and PACF of the residuals forms what is regarded as white wise i.e ARIMA (0,0,0) which indicates that the adequacy of the model fit is good and okay.

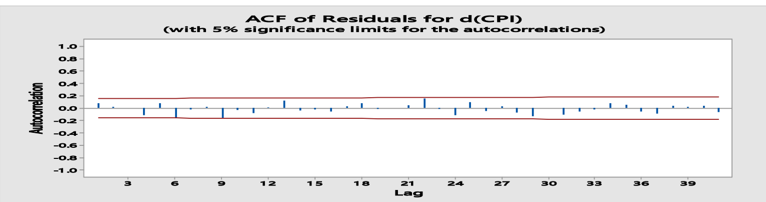

Figure 8
Comment : The result obtained basically shows that the model is good for policy making since all the coefficient of the ACF rapidly decay to a constant and also all the spike lies within the upper and lower limit.

FORECASTS

Forecasts from period 168

Period	Forecast	Lower (95% Limits)	Upper (95% Limits)	Actual
JAN2018	0.06953	-3.35268	3.49173	
FEB2018	-0.16139	-3.59127	3.2s6849	
MAR2018	-0.14732	-3.57728	3.28264	
APR2018	-0.02168	-3.45163	3.40828	
MAY2018	-0.16591	-3.59587	3.26404	
JUN2018	0.01114	-3.41881	3.44110	
JUL2018	0.08733	-3.34263	3.51728	
AUG2018	0.06210	-3.36786	3.49206	
SEP2018	0.06928	-3.36067	3.49924	
OCT2018	-0.03594	-3.46590	3.39402	
NOV2018	0.05555	-3.37441	3.48551	
DEC2018	0.03811	-3.39185	3.46807	
JAN2019	0.07724	-3.36875	3.52323	
FEB2019	0.04224	-3.40393	3.48841	
MAR2019	0.04522	-3.40095	3.49139	
APR2019	0.06550	-3.38067	3.51167	
MAY2019	0.04393	-3.40224	3.49010	
JUN2019	0.07218	-3.37399	3.51835	
JUL2019	0.08479	-3.36138	3.53097	
AUG2019	0.08168	-3.36449	3.52785	
SEP2019	0.08359	-3.36258	3.52977	
OCT2019	0.06808	-3.37809	3.51425	
NOV2019	0.08306	-3.36311	3.52923	
DEC2019	0.08116	-3.36501	3.52733	

COMMENTS

The above forecast value for Jan 2018 to December 2019. It revealed that there is slight increase in all-share to be traded by the investors for year Jan 2018 to December 2019.

SUMMARY OF ANALYSIS

The date for the analysis was collected from the central bank of Nigeria website which is www.centralbank.org. From the analysis the yearly consumer price index for the period showed a seasonal autoregressive integer moving average. The SARIMA model was used to forecast the yearly consumer price index.From the analysis figure 1 the time plot of the original series shows presence of non-stationry in the series due to the fact that the mean and the variance are not at fixed level.

Figure 2 the ACF shows a pattern typical for a non- stationary series, since there is large significance ACF for the first 5 time lag and slow decrease in the size of the autocorrelation. Also there exist several spike beyond the confidence line limit which also shows a non-stationary of the series before difference. Figure 3 the plot of partial autocorrelation function before difference, This is also typical of non-stationary series, the PACF at time lag 1 is approximately close to one before difference.

Figure 4 the time plot of differencing show that the time plot of CPI shows the present of stationary in but there is presence of seasonality Figure 5 the plot of ACF shows that the spike at lag 1 almost significant and there is a significant spike at lag 12 which confirms the presence of non-seasonal and seasonal Moving Average after first differencing. Figure 6 the plot of the partial autocorrelation function shows almost a significant spike at lag 1, then significant spikes at lags 12 and 24 which, suggest non seasonal and seasonal auto regressive model. Based on the plot of auto correlation and partial auto correlation functions, we try SARIMA (1,1,1) $(1,0,1)_{12}$ after first differences. Box-pierce (ljung-box) chi-square statistics confirm that all the parameters including the constant are significantly different from zero, because they have p-values that are significantly smaller than .05. In addition, the Box –Pierce Chi- Square p-values are non- significant ($p > 0.05$) indicating that the model fits the data well and the residuals appeared to be uncorrelated. Therefore, the appropriate model is **SARIMA(1,1,1) (1,01) $_{12}$.**

CONCLUSION AND RECOMMENDATION

Since the seasonal ARIMA of order (1,1,1) (1,0,1) $_{12}$ is the most significant model hence it retained to be the model for the study. Hence there is very strong reliability on the model. The Stochastic model can be used for policy making to predict the future for consumer price index in Nigeria.

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