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Research Article

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Time Series Analysis of Monthly Consumer Price Index (CPI) for Nigeria (2009-2020)

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Abstract The study is aimed to model monthly CPI and forecast for the general CPI in Nigeria. This is with a view to select the best model that fit the CPI and forecasting the future values. Time series plot analysis was used in the study to observe the pattern of fluctuations in CPI from January 2009 to December 2020 where we observed that the series have a trend pattern, after taken Second difference the series become stationary. The ARIMA (2, 2, 1) serve as the best model for the CPI and for forecasting the general CPI future value in Nigeria. A 12 Months forecast has also been made in other to know the expected value of the general CPI in Nigeria. It was recommended that Labor policy should promote competition and mobility in the work force populace. Instead, government regulations often hold workers back and cartelize the labor market.

Keywords Difference, Forecast, Index, Model and Stationary

1. Introduction

The method developed by Box, Jenkins and Reinsel (2008) that based on the modeling of time series by autoregressive integrated moving average (ARIMA) processes, is one of the two approaches utilized in this study. The second approach being the frequency domain, which assumes that the time series is best regarded as a sum or linear superposition of periodic sine and cosine waves of different periods or frequencies. See, for example, Pollock (1999) and Khuri (2003). In other words, Consumer price index (CPI) is the most common economic indicator and measures the changes in prices of a group of goods over time. Therefore, it measures shifts in the purchasing power of money. The consumer price index (CPI) is an important indicator of macroeconomic analysis and decision-making, general price level detection and regulation, and national economic accounting. It is not only an important indicator of the extent of inflation, but also a reduction indicator in the national economic accounting. This study will use the monthly CPI data from 1994-2010 to describe the internal driving mechanism of CPI, and predict CPI on this basis.

Therefore, in this study, we fitted ARIMA model. The error levels of the models will be critically assessed to select the best which will guide in policy implementation in Nigeria.

David and Raymond (2016) fitted a Univariate Autoregressive Integrated Moving Average (ARIMA) model of Box and Jenkins modeling technique to model and forecast annual Consumer Price Index (CPI) for Nigeria from 1950 to 2014. ARIMA (3, 1, 0) model was the best fit model to describe CPI data series in Nigeria.

Udegbunam and Onu (2016) modeled Nigeria's urban and rural inflation using consumer price index (CPI) monthly data from January 2001 to December 2015. The results revealed that ARIMA (0, 1, 0) and ARIMA (0, 1, 13) were the best fit model for Urban and Rural inflation rates in Nigeria. Osarumwense and Waziri (2013) similarly, explored the univariate non- linear time series analysis on the inflation data from January, 1995 to December, 2011. Hybrid (GARCH (1,0) + ARMA (1,0)) model was the best fit and 24 months forecast from January, 2012 to 2014 was made.

Etuk (2012) fitted a Multiplicative Seasonal Autoregressive Integrated Moving Average (ARIMA) model, (1, 1, 0)(0, 1, 1)12 to forecast monthly inflation rate in Nigeria; Using all items (Year on change) inflation rate from 2003 to 2011. Ekpenyong and Udoudo (2016) modeled and forecasted monthly all-items (year-on-year change) inflation rates in Nigeria from 2000 to 2015, using a seasonal ARIMA (0, 1, 0) (0, 1, 1) model. This model was found to be very appropriate in predicting the 12-months inflation rates with minimal standard deviation. Osuolale et al. (2017) applied ARIMA models to modeling and forecasting Nigeria's inflation rates for the periods 2006 to 2015. They found that ARIMA (0, 1, 1) was suitable for forecasting inflation rates for the next three years which indicates a parallel trend from January, 2016 to December, 2018.

2. Material and Methods

The model used in this study is the popular Box-Jenkins Autoregressive Integrated Moving Average (ARIMA). The three stages of modeling as suggested by Box and Jenkins namely identification, estimation and diagnostic checking were strictly explored. For model identification, test the stationary of the original data was assessed using time series plot, autocorrelation function (ACF), and unit root test was equally applied objectively test for Stationarity. If the series is not stationary, then we need to difference of the series until to get stationary. After the Stationarity was attained, the information criteria of Akaike, Bayesian and Schwartz were used to select the best fit model. The model having the smallest criteria value is considered the best. Estimation of the model was done by the least square method. In the diagnostic checking phase, the model residual analysis was performed. Thereafter, forecast was made using the best fit model.

AIC= $\log [\left(\hat{\sigma}^2{}_{p,q}\right) + \frac{(p+q)2}{n}$

BIC=$\log [\left(\hat{\sigma}^2{}_{p,q}\right) + \frac{(p+q)\log(n)}{n}$

SIC= $\log [\left(\hat{\sigma}^2{}_{p,q}\right) + \frac{(p+q)2\log(\log(n))}{n}$

Where n is the number of observations, p is the number of parametres in the model and $\hat{\sigma}^2{}_e$ is the sum of the sample squared residuals. The model parameter that minimizes AIC, BIC and HQIC is chosen as the best for the model penalty functions and helps greatly in the identification when the BO-Jenkins approach seems to be unclear on the choice of the paramatres selection.

3. Results and Discussions

Different time series techniques were utilized in order to obtain the best model for the Consumer price index (CPI) and forecast for the future values. The data used in this analysis are secondary data obtained from National bureau of statistics Bulletin. Similarly, the data was analyzed to check for trend of CPI in Nigeria and also to build a forecasting using ARIMA model for future prediction, Autocorrelation and partial autocorrelation functions (ACF and PACF) included. The model obtained is subjected to model diagnostics in order to determine its efficiency and then finally used for the forecast.

Data Presentation

The CPI data used in this research work was collected from statistical Bulletin for the period of 11 years (2009-2020) covering 132 months.

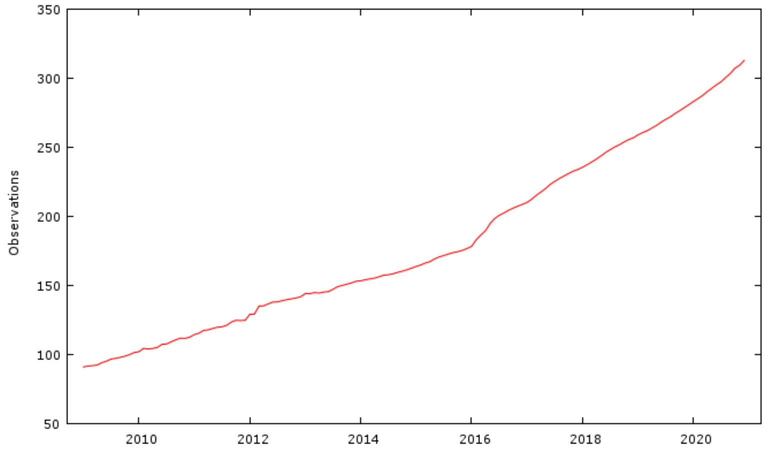

Figure 1: A plot of the CPI data

From the above plot we observe that the original CPI data exhibits both trend and seasonality. From the trend of the data there is increase in the inflation of recent years. Also, even though the mean value of each month seems quite different. The series is not stationary in term of the mean and variance, this portrait that there is variability between the patterns of the series. In short, if a time series is stationary, its mean, variance and auto covariance (at various lags) remain the same no matter at what point we measure them.

Plot of Autocorrelation Function (ACF) and Partial Autocorrelation (PACF) Function

Autocorrelation (ACF) and partial autocorrelation (PACF) function factor plot which can help to identify the pattern in the stationary series of CPI, the idea is to identify the presence of AR and MA component in the residuals.

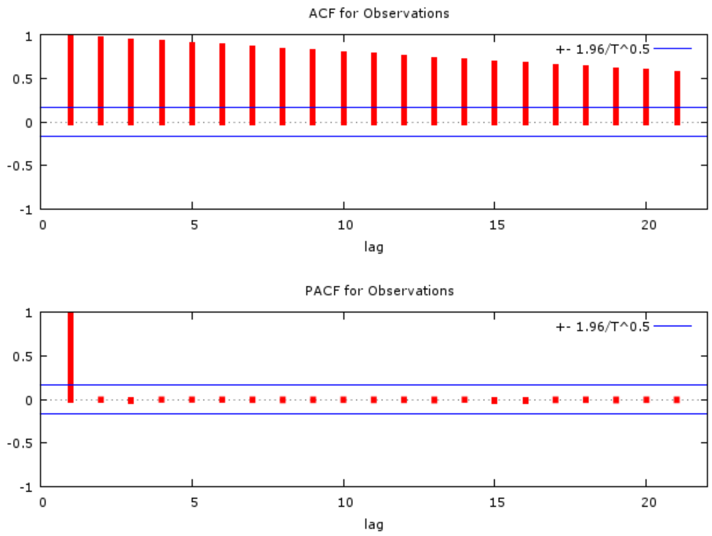

Figure 2: ACF and PACF OF CPI Data before differencing

From the plot of (ACF) and (PACF) above we notice that there is point in the plots outside the significant zones, therefore we conclude that the data is non stationary.

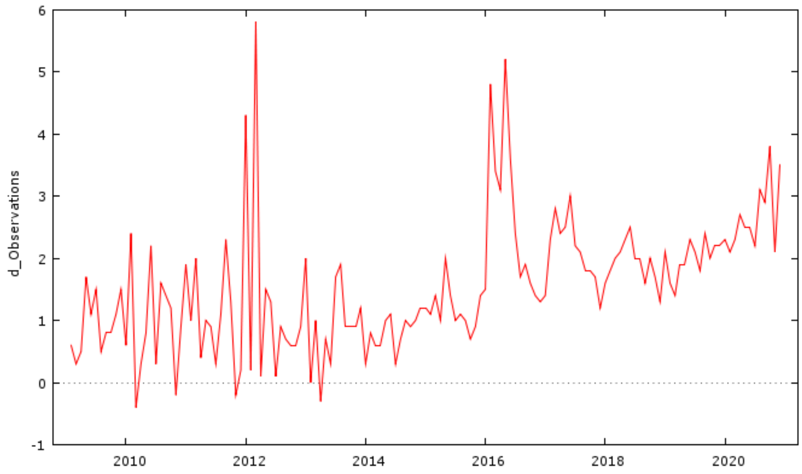

Figure 3: Time plot of the first Difference of Consumer Price Index (CPI)

It can be observed that the time plot of the data at first differencing also non stationary, in both mean and variance. Since some the coefficients are outside the 95% C.I

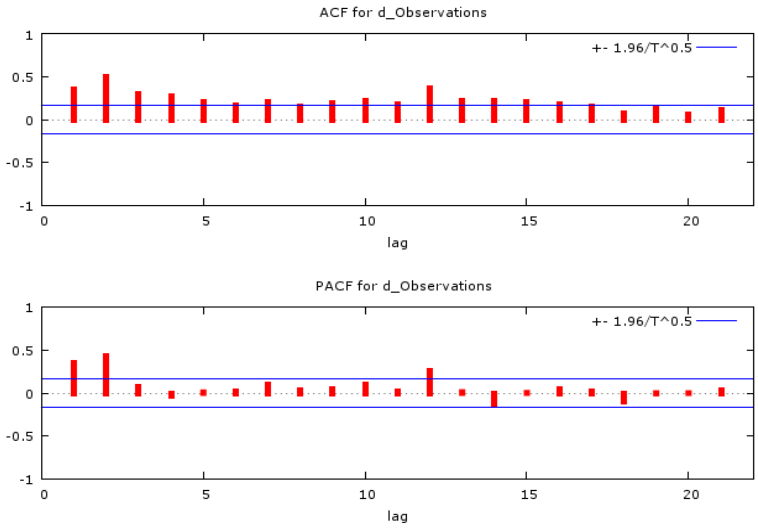

Figure 4: ACF and PACF after First Differencing

The autocorrelation function and ACF and PACF clearly show that the data is not stationary even after the first difference.

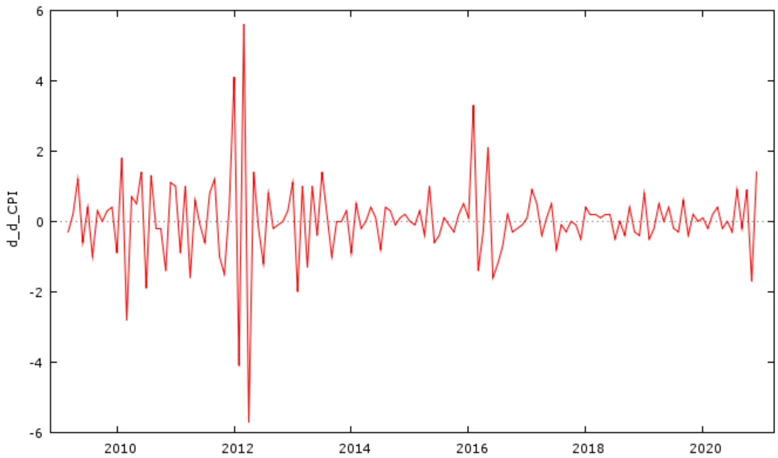

Figure 5: Time plot after second differencing

It can be observed that the time plot of the data at second differencing is stationary, in both mean and variance.

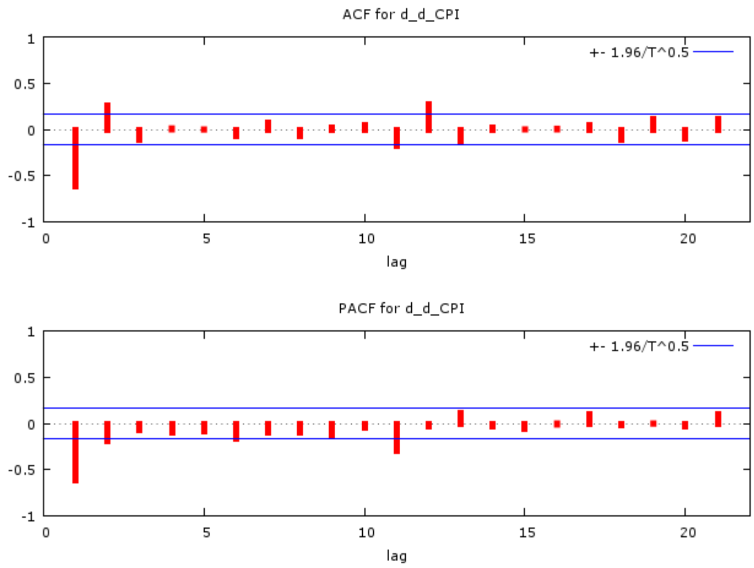

Figure 6: ACF AND PACF after Second Differencing

Stationarity Test

A stationary time series is one whose properties do not depend on the time at which the series is observed, Scott (2007). Thus, time series with trends, or with seasonality, are not stationary. The trend and seasonality will affect the value of the time series at different times. On the other hand, a white noise series is stationary - it does not matter when we observe it, it should look much the same at any point in time. Some cases can be confusing a time series with cyclic behavior (but with no trend or seasonality) is stationary. This is because the cycles are not of a fixed length.

Augmented Dickey-Fuller Test (ADF)

Hypothesis

H_0: The series is not stationary

H_1: The series is stationary

Level of significance: 0.05

Decision rule: Reject H_0 if p-value $\leq \alpha$

Table 3.1: Augmented Dickey-Fuller Tests

Dickey-Fuller	Lag order	P-value	Test statistics
At level	4	1	0.044396
First difference	4	0.03958	-2.95245
Second difference	4	$1.965e^{-010}$	-7.08351

Conclusion: We observe that the series is not stationary at level and after first difference but is stationary after second differencing because the

P-value < ($1.965e^{-010}$<0.05) then we accept null hypothesis H_o and conclude that it is stationary.

3.5: KPSS Test for Level Stationarity

Hypothesis

H_0: The series is stationary

H_1: The series is not stationary

Significance level = 0.05

Decision rule: Reject null hypothesis if p-value is $\leq \alpha$

Table 3.2: KPSS Test for Level Stationarity

Level of significance	10%	5%	1%	Test statistics
At levels	0.120	0.148	0.216	0.708803
First difference	0.120	0.148	0.216	0.104172
Second difference	0.120	0.148	0.216	0.0202132

Conclusion: By looking at the table 3.2 above, we can observe that, the test statistics for the KPSS test, is not stationary, at level and after first differencing, because are greater than asymptotic critical values at all level of significance, but less than KPSS test after second differencing therefore, we fail to reject null hypothesis and conclude that the series is stationary.

Table 3.3: Model Selection

S/n	Model	Const.	Φ_1	Φ_2	Φ_3	θ_1	Θ_2	Θ_3	SIC	AIC	HQIC
1.	ARIMA(1,2,1)	0.017	-0.3492	-	-	-0.4459	-	-	387.85	376.03	380.83
2.	ARIMA(2,2,1)	0.013	0.1075	0.359	-	-1	-	-	**377.63**	**362.85**	**368.86**
3.	ARIMA(1,2,2)	0.016	-0.65	-	-	-0.201	-0.356	-	390.77	375.99	381.99
4.	ARIMA(2,2,2)	0.013	0.165	0.349	-	-1.067	0.067	-	382.47	364.73	371.94
5.	ARIMA(3,2,2)	0.02	-0.502	0.430	0.262	-0.410	-0.594	-	387.01	366.32	374.73
6.	ARIMA(2,2,3)	0.013	0.366	0.083	-	-1.275	0.545	-0.269	386.38	365.69	374.10
7.	ARIMA(3,2,3)	0.022	-0.460	0.356	0.245	-0.444	-0.488	-0.067	391.86	368.22	377.82

From the above table 3.3, it has been noticed that the ARIMA (2,2,1) has the minimum value of AIC, SIC and HQIC, therefore it served as the best model, to fit the CPI of the general price in Nigeria.

Table 3.4: A Forecast of inflation (From January – December 2021)

Month	Observe values	Predicted values
January	282.9	282.9
February	285.0	285.1
March	287.3	287.1
April	290.0	289.6
May	292.5	292.4
June	295.0	295.2
July	297.2	297.6
August	300.3	299.6
September	303.2	303.0
October	307.0	306.0
November	309.1	310,1
December	312.6	312.3

The above table 3.4shows the forecast of CPI values from January to December 2021, we can conclude that the inflation is stable and may be decrease.

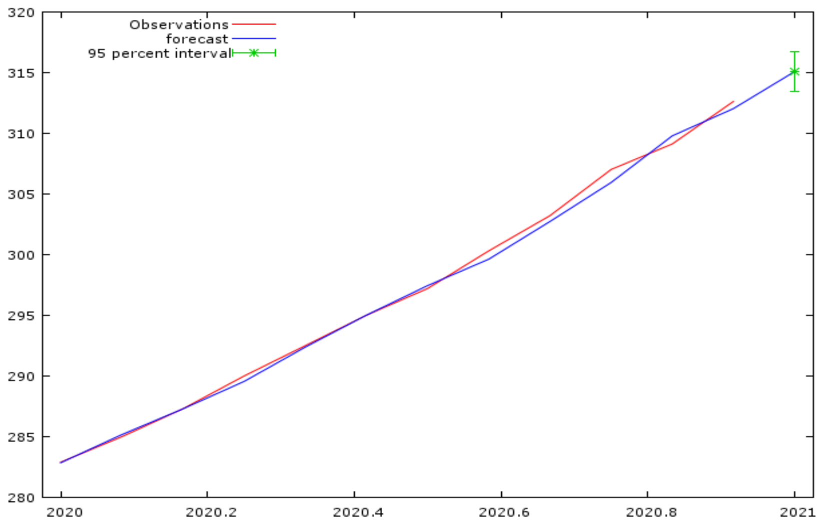

Figure 7: Forecast Plot From ARIMA (2,2,1) With Zero Mean

From the forecast plot above the graph has obviously shows that there may be a decreasing in future years due to the pattern of the series, the impression we get from the graph is that the predicted series seems to be "trending" upward and then down ward.

4. Conclusion

This study is an attempt to select the best and accurate model among various ARIMA models which possess a high power to fit the CPI and high predictability for forecasting the future value from January 2009 to December 2020. The main focus was to figure out the best model for the CPI and forecast the monthly fluctuation in the future value, for this purpose, different ARIMA model were fitted and the candid model was selected based on various diagnostic, selection and evaluation. The integration order d (I (d)) was found to be 2 is (I (2)). ARIMA (2, 2, 1) was found to be the most appropriate model to describe and forecast the CPI values. The model found to be adequate and best describe the monthly CPI. The ADF test and forecast indicate that the model is adequate.

5. Recommendations

From the discussion made so far and the result obtained from the analysis, the following recommendations are made:

It is recommended that government should have policy and programs control over Consumer Price Index (CPI) to address the issue of inflation for economic growth.

It is recommended that the ARIMA model with least AIC, SIC and HQIC is the best for describing the CPI data and forecasting the future values.

It is recommended that Housing and Investments Landlords to use the CPI forecasts to determine future rent increases in contracts.

It is recommended that Labor policy should promote competition and mobility in the work force. Instead, government regulations often hold workers back and cartelize the labor market.

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