MODELING INFLATION RATES IN NIGERIA: BOX-JENKINS' APPROACH

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ABSTRACT: *This study modeled the inflation rates in Nigeria using Box Jenkins' time series approach. The data used for the work ware yearly collected data between 1961 and 2013. The empirical study revealed that the most adequate model for the inflation rates is ARIMA* (0, 0, 1). *The fitted Model was used to forecast the Nigerian inflation rates for a period of 12 years. Based on these results, we recommend effective fiscal policies aimed at monitoring Nigeria's inflationary trend to avoid damaging consequences on the economy.*

KEYWORDS: ARIMA, ACF, PACF, Inflation, Forecasting.

INTRODUCTION

A high and sustained economic growth in conjunction with low inflation rate is the central objective of macroeconomic policy. Low and stable inflation along with sustainable budget deficit, realistic exchange rate and appropriate real interest rate are among the indicators of a stable macroeconomic environment. Thus, as an indicator of stable macroeconomic environment, the inflation rate assumes critical importance (Fatukasi, 2014).

It is therefore important that inflation rates be kept stable even when it is low. The primary focus of monetary policy both in Nigeria and elsewhere has traditionally been the maintenance of a low and stable rate of aggregate price of inflation as defined by commonly accepted measures such as the consumer price index (Ret and Sheffarin, 2003).

Forecasting and modeling inflation rates could be done using time series analysis, which is a sequence of observations on a single entity reported or measured at regular time intervals. Modeling provides not only a defined description of time series but also an important step towards predicting or controlling the series. The Box-Jenkins' Autoregressive integrated moving average (ARIMA) modeling approach enables us to identify a tentative model, estimate the parameters and perform diagnostic checking or residual analysis.

This paper outlines the practical steps needed in the use of autoregressive integrated moving average (ARIMA) time series models for forecasting Nigeria's inflation rates.

METHODOLOGY

In this work, we shall consider the first step in developing a Box-Jenkins' model, which is to determine if the series is stationary and if there is any significant seasonality that needs to be modeled. Stationarity can be examined from a run sequence plot as it showcases constant location and scale. Alternatively, an autocorrelation plot is capable of revealing any case of stationarity. The autocorrelation at lag p is the correlation between the pairs (Y_t, Y_{t-p}) given by $r_p = \frac{\sum_{t=1}^{n-p}(Y_t - \bar{Y})(Y_{t-p} - \bar{Y})}{\sum_{i=0}^{n}(Y_t - \bar{Y})^2}$, and it ranges from -1 to +1.

On the other hand, non stationarity is often indicated by an autocorrelation plot with very slow decay. Differencing approach is recommended to achieve stationarity, often differencing is used to account non-stationarity that occurs in the form of trend and or seasonality. The difference, $x_t - x_{t-1}$, can be expressed as (1-B) x_t or ∇ = 1- B. Thus $\nabla x_t = (1-B)x_t = x_t - x_{t-1}$.

Our goal for model identification is to detect seasonality and identify the order, if it exists. However, it may also be helpful to apply a seasonal difference to the dataset and generate the ACF and PACF plots. This may help in the model identification of the non-seasonal components of the model (Box and Jenkins (1976). All the AR(p) , MA(q) and ARMA(p, q) models that will be presented below are based on the assumption that the time series can be written as:

$X_t = \delta_t + w_t$, where δ_t is the conditional mean series, i.e. $\delta_t = E[X_t|X_{t-1}, X_{t-2}, \ldots]$ and w_t is a disturbance term.

AR, MA, ARMA, and ARIMA Models

- An AR (1) model is given by: $x_t = \delta + \varphi_1 x_{t-1} + w_t$, where $w_t \sim iid\ N(0, \sigma_w^2)$. In this case, the maximum lag = 1. Thus, the AR polynomial is; $\Phi(B) = 1 - \phi_1 B$ or $(1-\phi_1 B)x_t = \delta + w_t$.

- A MA (1) model is given by: $x_t = \mu + w_t + \theta_1 w_{t-1}$ and could be written as $x_t = \mu + (1 + \theta_1 B)w_t$. A factor such as $1 + \theta_1 B$ is called the MA polynomial, and it is denoted as $\Theta(B)$. It has the following properties: -

  (i) The mean is: $E(x_t) = \mu$.

  (ii) The variance is: $Var(x_t) = \sigma_\omega^2(1 + \theta_1^2)$.

  (iii) The autocorrelation function (ACF) is: $\rho_1 = \frac{\theta_1}{1+\theta_1^2}$, $\rho_h = 0$ for $h \geq 2$.

  Generally, we can write an MA model as $w_t - \mu = \Theta(B)w_t$.

- An ARMA (Autoregressive moving average) model can be denoted by ARMA (p, q) and may be defined by the equation; $x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_p - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t$.

- ARIMA (p, d, q) where p, d, and q denote the order of auto-regression, order of differencing and moving average, respectively. Given a time series process $\{X_t\}$, ARIMA (p, d, q) can be defined as; $\Phi(B)\nabla^d X_t = \Theta(B)\mathcal{E}_t$.

In general, an autoregressive process, ARIMA (p, 0, 0), can be denoted as; $x_t = \nu + \phi_1 x_{t-1} + \phi_2 x_{t-2}, + \ldots + x_{t-p} + \varepsilon_t,$ The ACF declines exponentially and the PACF spikes on the first P lags for moving average process. ARIMA (0, 0, q) can be defined as;

$x_t = \nu - \theta_1 \varepsilon_{t-1} - \theta_1 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t,$ The ACF spikes on the first q lags and the PACF declines exponentially. For fixed processes ARIMA (p, d, q), decline on both ACF and PACF. If the ACF and PACF decline slowly (i.e. has autocorrelations with values greater than 1.6 for more than five consecutive lags) the process is probably not stationary and should therefore be differenced.

ANALYSIS OF RESULTS

- The sequence plots of the data (Appendices A1 and A2) shows that there is no trend and seasonal variation, and as such it does not require differencing.
- Appendix B is the autocorrelation function (ACF) of the data while Appendix C shows the partial autocorrelation function (PACF) of the dataset. Both cut off at lag 1, and every other lag falls within the confidence interval signifying stationarity in the dataset. From these plots, it can be concluded that the data are being described by the moving average (MA) of order, q = 1. Based on the diagnostic check, ARIMA (0, 0, 1) is suggested as the appropriate model.
- The residual plot in Appendix D for the ACF and PACF of the model, which serves as a diagnostic check of the model, reveals that it is within specification as it shows no significant autocorrelations. All the residuals are white noise indicating that the model fits the data adequately. It is also observed that all the coefficients are within the limits of $\pm$ 1.96√N, where N = 53, is the number of observations. Also, the Normal probability plot is well-shaped and so the assumption of normally distributed residuals is in order.

From the results in Appendix E, we have that p = 0, d = 0, q = 1,

$\theta_1 = -0.6392$ with a standard error of 0.1079 and t = -5.93, which is highly significant.

CONCLUSION

The Box – Jenkins' procedure was applied on the stationary data series and we identified the corresponding ARIMA (0, 0, 1) process with the aid of the series correlogram (Appendices B and C). The Root Mean Square Error (RMSE) which determines the efficiency of the model was estimated at 0.116, indicating that the model is quite efficient. The predicted series of inflation rates and the graph for 2014 – 2025 are as shown in Appendix F with the following accuracy measures:- MAPE: 131.872, MAD:11.752, and MSD: 256.058. However, we recommend effective fiscal policies aimed at monitoring Nigeria's inflationary trend to avoid damaging consequences on the economy with time.

REFERENCES

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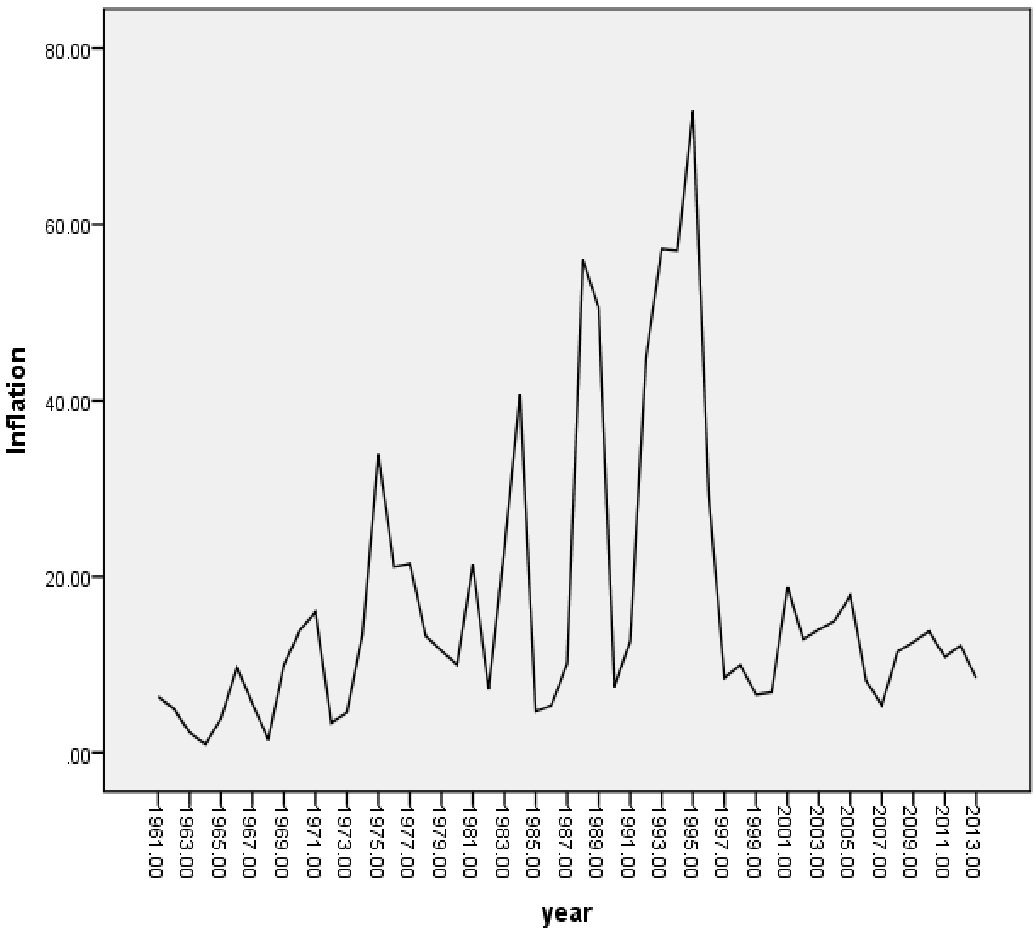
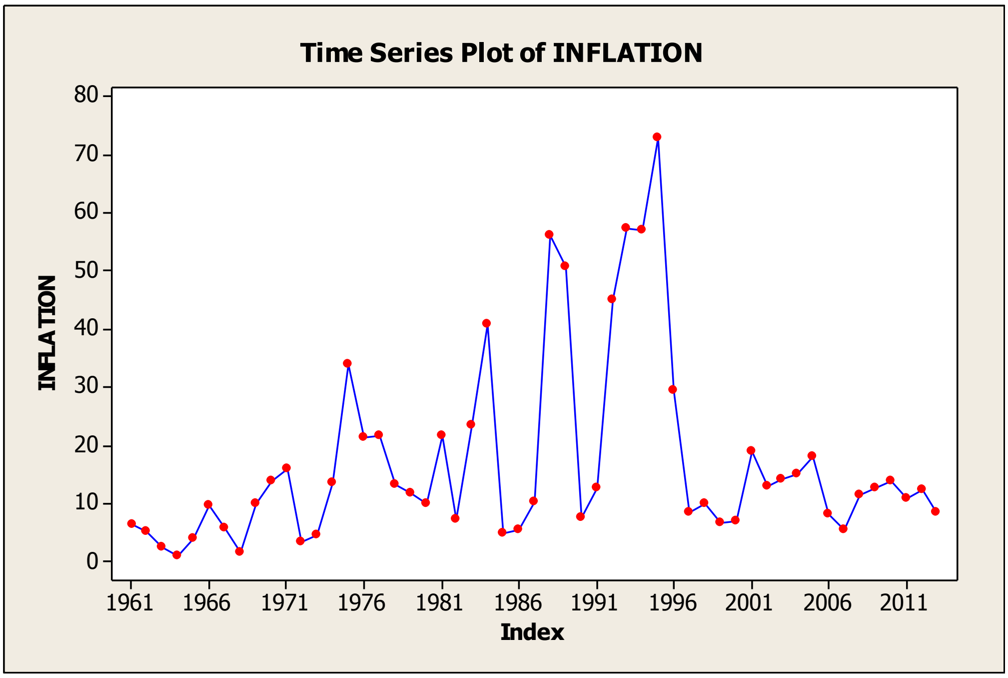
Ret. A. S., and Shaffain, P. M. (2003). Economic: Principle in action, New Jersey, Pearson Prentice Hall. pp. 234.

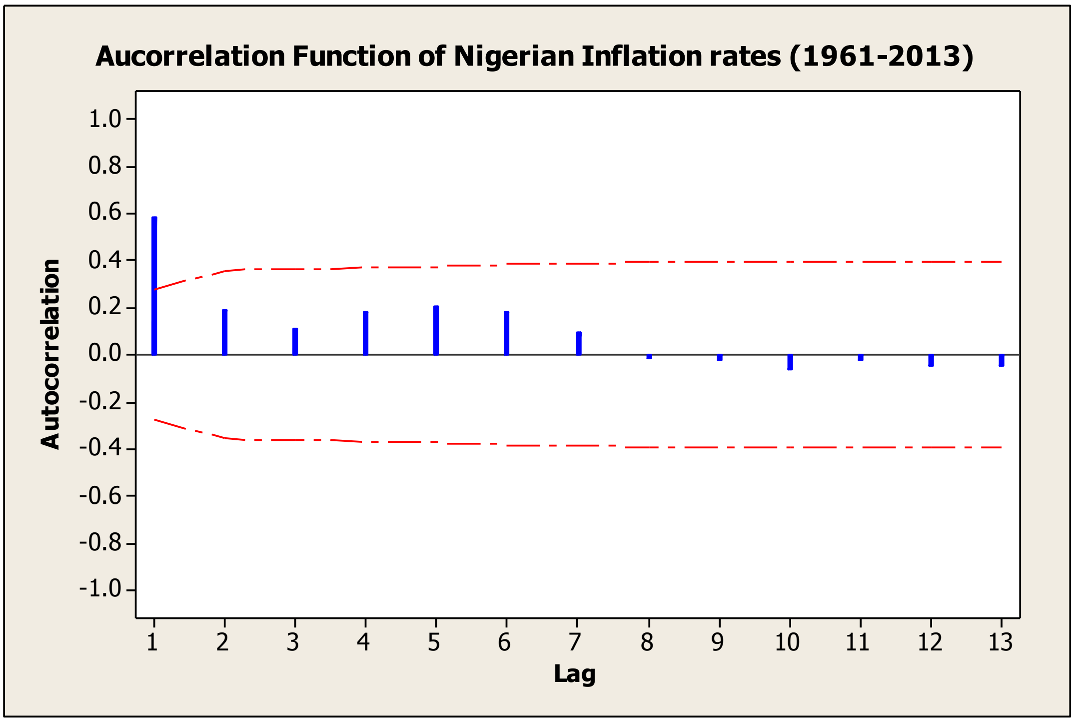
APPENDIX A1: SEQUENCE PLOT



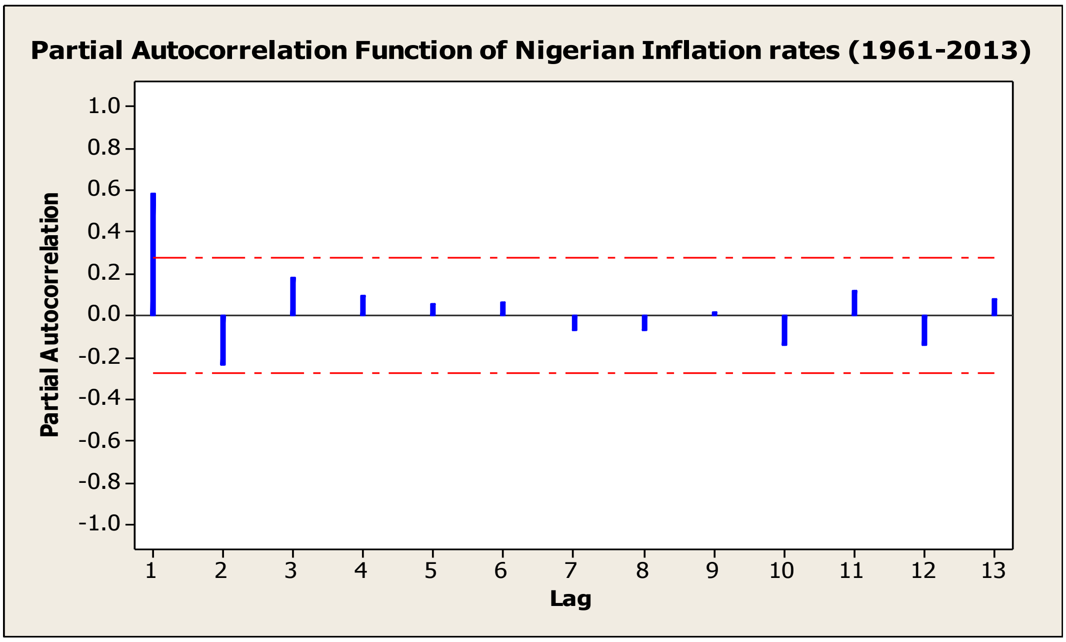
APPENDIX A2


Time Series Plot of INFLATION
INFLATION
80
70
60
50
40
30
20
10
0
1961
1966
1971
1976
1981
1986
1991
1996
2001
2006
2011
Index

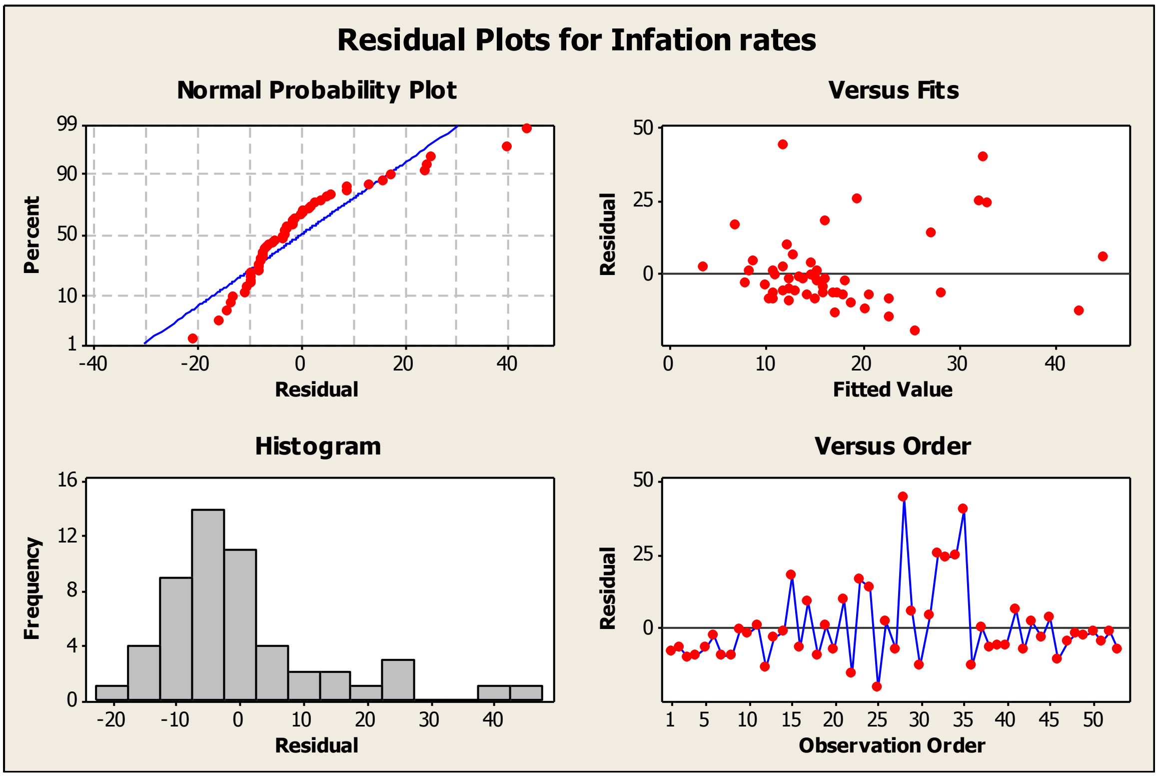
APPENDIX B


Aucorrelation Function of Nigerian Inflation rates (1961-2013)
Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1
2
3
4
5
6
7
8
9
10
11
12
13
Lag

APPENDIX C

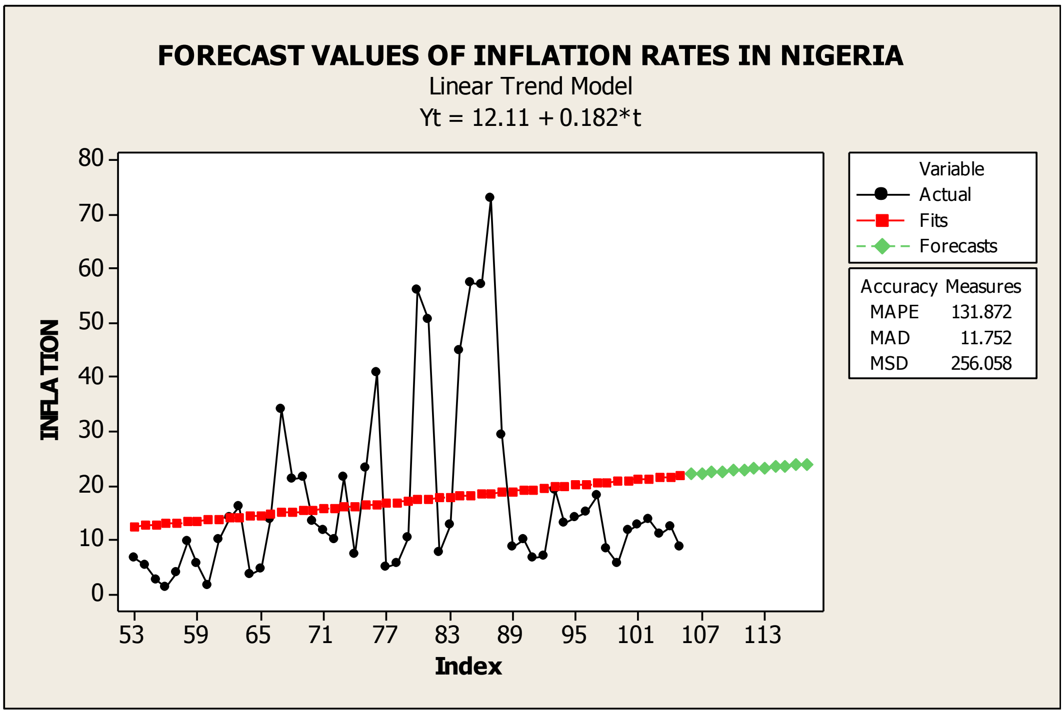


APPENDIX D



APPENDIX E

Period	Forecast
2014	19.9701
2015	19.1018
2016	23.4868
2017	35.6577
2018	25.7382
2019	32.6617
2020	27.8678
2021	8.0601
2022	9.9678
2023	10.9787
2024	38.2083
2025	39.1419



APPENDIX E

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
MA 1	-0.6392	0.1079	-5.93	0.000
Constant	16.866	2.958	5.70	0.000

Mean 16.866 2.958

Number of observations: 53

Residuals: SS = 8876.73 (backforecasts excluded)

MS = 174.05 DF = 51

Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-Square	9.5	17.6	27.9	30.1
DF	10	22	34	46
P-Value	0.489	0.727	0.760	0.966