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Exploring The Predicting Power Of Arima Models Using Nigerian External Debt (2005-2019) Record

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Abstract

The predicting power of ARIMA model was profoundly explored in this paper using Nigerian external debt. The study adopted ex-post-facto research design with sourced data from Nigeri an Debt Management Office Bulletin (2005-2019) editions with Box–Jenkins and forward ste pwise approach. Non-seasonal ARIMA models generally denoted by ARIMA(p,d,q) was also a dopted. ARIMA(0,2,0) was produced by auto.arima function from R software while two model s; ARIMA(1,1,0) and ARIMA(1,1,1) were produced via forward stepwise approach. Findings from the study showed that models with 1 differencing are optimistic about the future unlike t hose with 2 differencing like ARIMA(0,2,0) produced by auto.arima. ARIMA(1,1,0) which is a fine-tuned random walk was shown to be optimistic about the future as seen from the look of t he forecast. This was in agreement with (Robert, 2020) findings. The Akaike Information Crit eria (AIC) of ARIMA(1,1,0) model = 284.03 was smaller than that of ARIMA(1,1,1) model = 285.79 and the smaller the AIC, the better. In vein of these findings, ARIMA(1,1,0) was chose n as the best fitted model. Also, the prediction of external debt from ARIMA(1,1,0) model depi cted a slight upward trend. Researchers were advised among others to stick to the forward ste pwise approach in choosing ARIMA models to avoid wrong predictions/forecasts. Governmen t of the day was advised to perceive the dangers of borrowing and misappropriation of funds t o the economy.

Keywords: ARIMA models, External Debt, Prediction, Time series.

Introduction

Background Information

External debts are debts owed to non-residents which are repayable in currency, goods, or services (DMO, 2018). The problem of external debt by Nigeria goes back to the colonial period, which has its inception in 1958 when the aggregate of US$28 million was contracted for route construction (Adepoju, Salau and Obayelu, 2007). It's been so long now since Nigeria celebrated the repayment of the Paris Club debt. The narrative back then was that paying the debt will free up cash that will be channeled towards capital expenditure and then usher in the economic boom we have craved for decades. It is good to borrow money but when the borrowed money is misappropriated and embezzled, it becomes detrimental to the economy and the poor masses suffer it. Nigeria's external debt hits a 16 year high of $27 billion in December 2019 just higher than the $20.8 billion in external debt level as at 2005 (CBN, 2019). The rising foreign debt profile and the sliding external reserves highlight how vulnerable Nigeria's economy is to external shock. Between the start of 2015 and December 2020, Nigeria's external debt profile has risen from $9.7 billion to $27 billion (CBN, 2019).

It's undoubtedly that any progressive minded nation will not hesitate from forecasting for the future occurrences such as debt, crime rate, unemployment rate, poverty, etc. This could be achievable with the use of one of the five traditional time series forecasting/predicting models (ARIMA). Time-series analysis is a statistical method of analyzing data from repeated observations on a single unit or individual at regular intervals over a large number of observations (Glass, Willson, & Gottman, 1975). Time-series analysis can be viewed as the exemplar of longitudinal designs. The most widely employed approach is based on the class of models known as Autoregressive Integrated Moving Average (ARIMA) models (Glass, Willson, & Gottman, 1975). ARIMA models can address several major classes of research questions, including an analysis of basic processes, intervention analysis, and analysis of the pattern of treatment effects over time (Glass, Willson, & Gottman, 1975). Autoregressive Integrated Moving Average Model (ARIMA) is a generalized model of Autoregressive Moving Average (ARMA) that combines Autoregressive (AR) process and Moving Average (MA) processes and builds a composite model of the time series with the general form denoted as ARIMA (p, d, q) for non-seasonal ARIMA models (Robert, 2020). The model generally fits the non-stationary time series data (Robert, 2020). It is in view of the above preliminary information that this study is set to explore empirically, the predicting power of ARIMA models with reference to Nigerian External Debt from 2005-2019.

Statement of the problem

The hottest debate in Africa's largest economy this year has been the over possibility of Nigeria "losing" its sovereignty to China over external debts and the truth is that any country that keeps borrowing will hardly achieve economic prosperity. This calls for future prediction. It's good that predictions are made but how accurate such predictions are should be of essence, hence this study. Many scholars who adopted ARIMA models because of its predicting ability gave little or no concern to the rules of differencing and insertion of AR and MA terms based on the ACF and PACF plots which is where the predicting power of the models lies. Without being cognizant and appropriating the rules of ARIMA models, the tendency of choosing a wrong model will always be there. When wrong models are chosen, wrong predictions are begotten.

Significance of the study

This study will be of immense benefit to all-and-sundry. The major benefactors are; governments, the public, policy makers and researchers in different fields. It will reveal the trend of Nigerian external debt over the years investigated. This, no doubt will help the government and policy makers in planning and execution. Researchers who have been using ARIMA models but are not cognizant of how to explore the predicting power of the model will be enlightened on how to do so via this study.

Aim and objectives of the study

The aim of this study is to explore the predicting power of ARIMA models in predicting Nigerian external debt from 2020 to 2024. Specifically, the study is set to achieve the following objectives:

- To ascertain the values of Nigerian external debt from 2020-2024.
- To ascertain the trend of Nigerian external debt over the years under investigation.
- To ascertain the predicting power of ARIMA models.

Research Questions

The following questions guided the study namely:

- What are the values of Nigerian external debt from 2020-2024?
- What's the trend of Nigerian external debt over the years under investigation?
- What is predicting power of ARIMA models?

Scope and limitations of the study

The study is limited to the application of ARIMA models in predicting Nigerian external debt from 2020-2024. It did not engage any other traditional time series model and economic variable. However, it explored the predicting power of the model by appropriating the predicting rules.

Review of Related Literature

The review of the available related literature was done under the following three sub-headings: The Conceptual framework, Theoretical framework and the Empirical studies

The Conceptual Framework:

The concept of Time series analysis

Time series analysis had been more generally developed in areas such as engineering and economics before it came into widespread use within social science research. The prevalent methodology that has developed and been adapted in psychology is the class of models known as Autoregressive Integrated Moving Average (ARIMA) models (Box and Jenkins, 1976; Box &

Tiao, 1965, 1975; Box, Jenkins, & Reinsel, 1994).

Time series analysis belongs to the class of new methods of data analysis that require the use of modern high-speed computers. The estimation of the basic parameters cannot be performed by pre-computer methods. ARIMA models have proven especially useful within time series analysis because they provide a basic methodology to model the effects of dependency from the data series and allow valid statistical testing (Glass, Willson, & Gottman, 1975).

Theoretical Framework:

Debt Over-hang Theory

The above theory states that "if there is likelihood that in the future debt will be larger than the country's repayment ability; expected debt service costs will discourage further domestic and foreign investment because the expected rate of return from the productive investment projects will be very low to support the economy as the significant portion of any subsequent economic progress will accrue to the creditor country" (Krugman, 1988). The theory hinges on the fact that a counter-productive effect debt instrument will drastically reduce investment opportunities and low level of output in the economy.

Empirical studies:

Causal relationship between external debt and economic growth:

On the causal relationship between external debt and economic growth, Karagol (2002), investigated the relationship between external debt and economic growth for Turkey during the period 1956-1996. The Granger causality test showed a one-way negative relationship from debt service to economic growth.

Amassoma (2011), examined the causal link between internal, external debt and economic growth in Nigeria. The results showed a long-run relationship between external debt and economic growth in Nigeria. Vector autoregressive result also shows that there is a uni-directional relationship between external debt and economic growth, moving from the latter to the former.

Research Methodology:

Research Design

The study adopted ex-post-facto research design with sourced data from several editions of the Debt Management Office Statistical Bulletin. The data spanned through 15 years annual publication period (2005-2019). The study adopted Box–Jenkins approach and non-seasonal ARIMA models generally denoted by ARIMA(p,d,q), where parameters p, d, and q are non-negative integers, p is the order (number of time lags) of the autoregressive model, d is the degree of differencing (the number of times the data have had past values subtracted), and q is the order of the moving-average model (Ljung and Box, 1978). AIC was used as an error metric to evaluate performance and accuracy of the model and asses the prediction.

The predicting equation of the utilized ARIMA models with constant μ:

ARIMA(1,1,0) : $\hat{Y}_t = \mu + Y_t\text{-}1 + \phi_1 (Y_t\text{-}1)$

ARIMA(1,1,1) : $\hat{Y}_t = \mu + Y_t\text{-}1 + \phi_1 (Y_t\text{-}1) - \theta_1 e_t\text{-}1$

ARIMA(0,2,0) : $\hat{Y}_t = \mu + 2Y_t\text{-}1 - Y_t\text{-}2$ and so on.

Note: The phis (ϕ's) and thetas (θ's) of the selected model are estimated using maximum likelihood techniques, backcasting or backshift operator, etc. The ϕ is for AR, θ is for MA while Y_t-1 is for 1 differencing.

Basic Rules for choosing the best predicting ARIMA models (Forward Stepwise Approach)

Rule1: If the PACF of the differenced series displays a sharp cutoff and/or the lag-1 autocorrelation is positive--i.e., if the series appears slightly "under-differenced"--then consider adding an AR term to the model. The lag at which the PACF cuts off is the indicated number of AR terms.

Rule2: If the ACF of the differenced series displays a sharp cutoff and/or the lag-1 autocorrelation is negative--i.e., if the series appears slightly "over-differenced"--then consider adding an MA term to the model. The lag at which the ACF cuts off is the indicated number of MA terms.

Rule3: It is possible for an AR term and an MA term to cancel each other's effects, so if a mixed AR-MA model seems to fit the data, also try a model with one fewer AR term and one fewer MA term--particularly if the parameter estimates in the original model require more than 10 iterations to converge.

Rule4: If there is a unit root in the AR part of the model--i.e., if the sum of the AR coefficients is almost exactly 1--you should reduce the number of AR terms by one and increase the order of differencing by one. Similarly, an MA(1) model is said to have a unit root if the estimated MA(1) coefficient is exactly equal to 1. When this happens, it means that the MA(1) term is exactly cancelling a first difference, in which case, you should remove the MA(1) term and also reduce the order of differencing by one. In a higher-order MA model, a unit root exists if the sum of the MA coefficients is exactly equal to 1.

Rule5: If there is a unit root in the MA part of the model--i.e., if the sum of the MA coefficients is almost exactly 1--you should reduce the number of MA terms by one and reduce the order of differencing by one. For example, if you fit a linear exponential smoothing model (an ARIMA(0,2,2) model) when a simple exponential smoothing model (an ARIMA(0,1,1) model) would have been sufficient, you may find that the sum of the two MA coefficients is very nearly equal to 1 (Robert, 2020).

Rule6: Models with I differencing is more optimistic about the future than models with 2 differencing (Robert, 2020).

Data Analysis and Results

Fig1: Plot of Autocorrelation Function (ACF)

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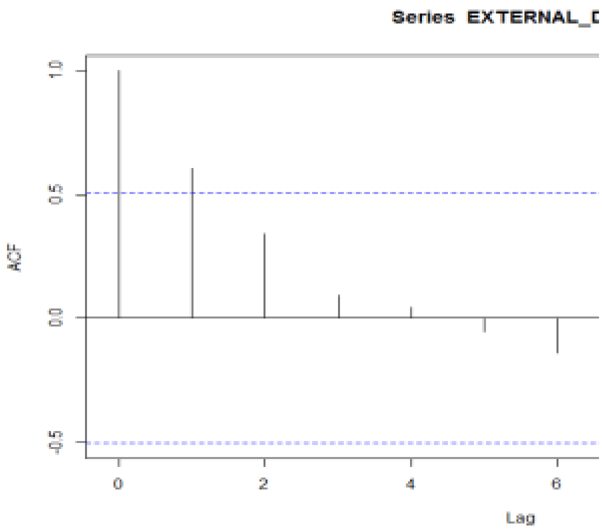
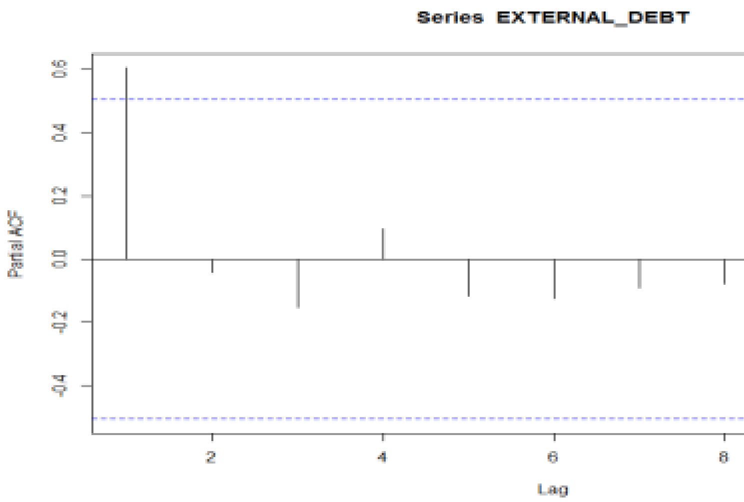


Result

The above ACF plot has two significant spikes at lag-0 and 1, thus indicating two MAs; MA(0) and MA(1). From Rule2, it implies that the MA term can be set as 0 or 1. This means that all the higher-order autocorrelations are effectively explained by the lag-0 and 1 autocorrelation.

Fig2: Plot of Partial Autocorrelation Function (PACF)



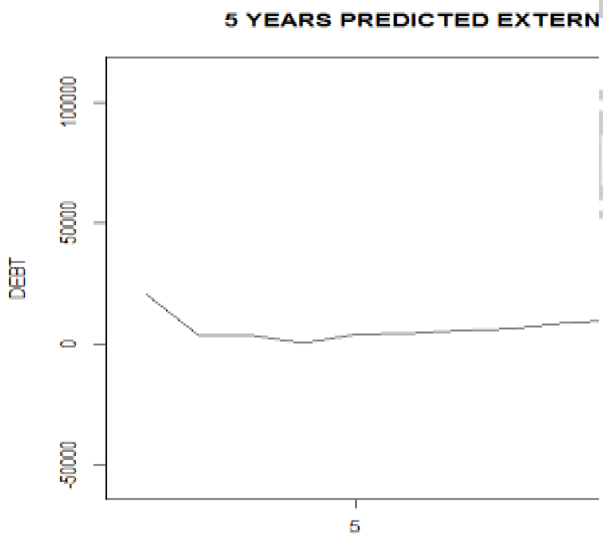
Result:

The above PACF plot has only one significant spike at lag-1, thus indicating AR(1). From Rule1, it implies that the AR term can only be set as 1. This means that all the higher-order partial autocorrelations are effectively explained by the lag-1 partial autocorrelation.

```
#Rcodes and Results produced by au
to.arima command without adhering t
o the position of the spikes at AC
F and PACF as well as the rules fo
r choosing the best models:

> auto.arima(EXTERNAL_DEBT)
Series: EXTERNAL_DEBT
ARIMA(0,2,0)

sigma^2 estimated as 33892774:  lo
g likelihood=-131.15
AIC=264.3   AICc=264.66   BIC=264.
86
> fit=arima(EXTERNAL_DEBT,order=c(
0,2,0))
> fit

Call:
arima(x = EXTERNAL_DEBT, order = c
(0, 2, 0))


sigma^2 estimated as 33892440:  lo
g likelihood = -131.15,  aic = 264
.3
> fit_resid=residuals(fit)
```

```
#Using Box Jekins Approach:
> Box.test(fit_resid,lag=2,type="L
jung-Box")

        Box-Ljung test

data:  fit_resid
X-squared = 2.1367, df = 2, p-valu
e = 0.3436

> x=forecast_EXTERNAL_DEBT=forecas
t(fit,h=5)
> x
   Point Forecast       Lo 80     Hi
80      Lo 95     Hi 95
16        25944.90  18484.064 33405
.74  14534.54  37355.26
17        26280.17   9597.233 42963
.11    765.82  51794.52
18        26615.44  -1300.453 54531
.33 -16078.23  69309.11
19        26950.71 -13913.972 67815
.39 -35546.43  89447.85
20        27285.98 -28045.062 82617
.02 -57335.55 111907.51

> plot(x,main="PREDICTED EXTERNAL
DEBT FROM ARIMA(0,2,0) MODEL")
```

Fig3: Forecast from ARIMA(0,2,0) produced by auto.arima function.



Results

Looking at the plot above, one can observe that model with 2 differencing assumes a time-varying local trend. It's a Linear Exponential Smoothing model (LES) and is not optimistic about the future as seen from the look of the forecast. This is in agreement with (Robert 2020) findings.

```
#checking the Accuracy of the mode
l:
accuracy(forecast_EXTERNAL_DEBT)
                  ME      RMSE
MAE          MPE      MAPE        MASE
ACF1

Training   set   1147.44   5419.754
3188.949     -2.515588     95.25108
0.9864275 -0.3125576
```

Forward stepwise approach: Looking at the ACF plot, one can observe that there are two significant spikes at ACF; one at Lag-0 and the other at Lag-1. Following rule 1 and 2, we fit MA(0) or MA(1) model. Also, the PACF plot showed only one significant spike at Lag-1.

If we fit ARIMA(1,1,0) model that is MA(0), we obtain thus:

```
> fit=arima(EXTERNAL_DEBT,order=c(1,1,0))
> fit

Call:
arima(x = EXTERNAL_DEBT, order = c(1, 1, 0))

Coefficients:
         ar1
      0.3213
s.e.  0.4117

sigma^2 estimated as 28236928:  log likelihood
> fit_resid=residuals(fit)
> Box.test(fit_resid,lag=1,type="Ljung-Box")

        Box-Ljung test

data:  fit_resid
X-squared = 1.1457, df = 1, p-value = 0.2844

> x=forecast_EXTERNAL_DEBT=forecast(fit,h=5)
> x
```

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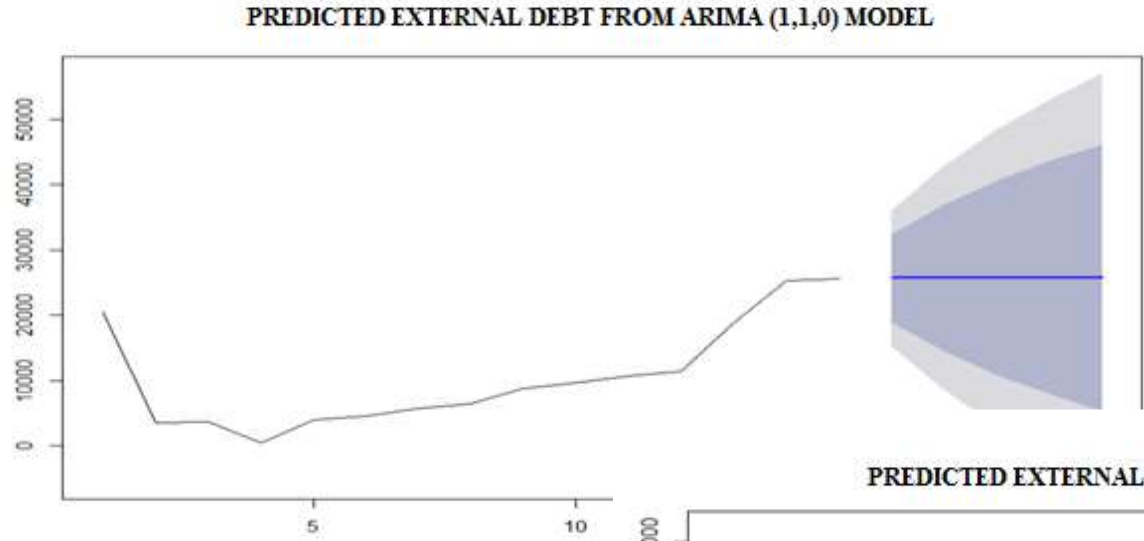
```
   Point Forecast     Lo 80     Hi 80
16       25717.36 18907.392 32527.32 153
17       25751.97 14467.417 37036.52  84
18       25763.09 10881.779 40644.40  3C
19       25766.67  7878.123 43655.21 -15
20       25767.81  5274.088 46261.54 -55

> plot(x,main="PREDICTED EXTERNAL DEBT F
```

Fig4: Forecast from ARIMA(1,1,0) produced via



esults

Looking at the plot above, one can observe that m

he future unlike the one with 2 differencing. It's a

s optimistic about the future as seen from the look

2020) findings. In practice, SES performs better tl

```
#checking the Accuracy of the model:
> accuracy(forecast_EXTERNAL_DEBT)
                   ME     RMSE      MAE
Training set 300.6349 5133.663 3156.998
```

If we fit ARIMA(1,1,1) model that is MA(1), we obtain thus:

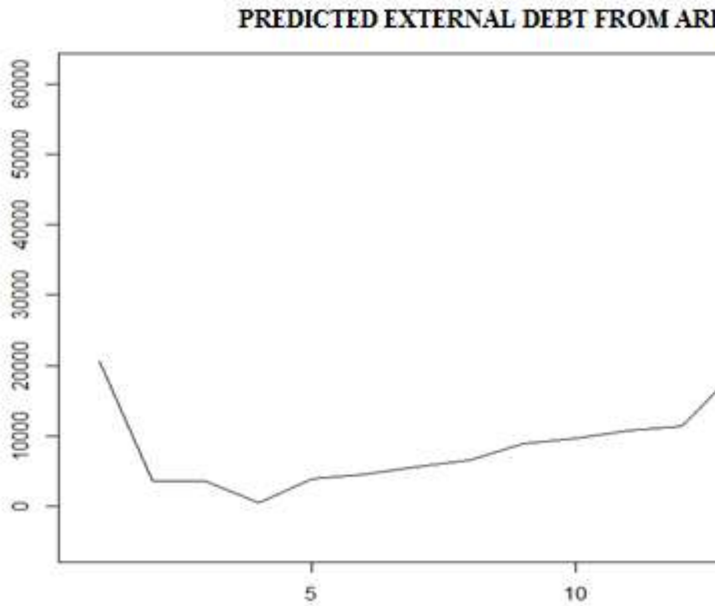
```
> fit=arima(EXTERNAL_DEBT,order=c(1,1,1))
> fit
Call:
arima(x = EXTERNAL_DEBT, order = c(1, 1, 1))
Coefficients:
         ar1      ma1
      0.6431  -0.3394
s.e.  0.5761   0.6651

sigma^2 estimated as 27656551:  log likelihood
> fit resid=residuals(fit)
                                     j-Box")

                                      0.3176

                                     it,h=5)

                                         Lo 9
                                     L6337.231
                                     L0374.029
                                      4812.216
                                      -377.899
                                     -5203.084
```




```
> plot(x,main="PREDICTED EXTERNAL DEBT FROM AR
```

Fig5: Forecast from ARIMA(1,1,1) produced via forward

Looking at the forecast above, one can observe that ARIM

k seems to be more optimistic about the future than ARIM

a (AIC) is higher than that of ARIMA(1,1,0) model. But t

```
#checking the Accuracy of the model:
```

```
> accuracy(forecast_EXTERNAL_DEBT)
                   ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 442.8088 5080.631 3021.166 -19.00798 71.62814 0.9345278 -0.2341826
```

Discussion of Results

From the analysis performed, one can infer from the results that ARIMA model has a high power of prediction/forecast. The plot of the forecast under ARIMA(0,2,0) which was produced by auto.arima function from R, showed a slight upward trend with time-varying forecast about the future, while that of ARIMA(1,1,0) and ARIMA(1,1,1) produced by forward stepwise approach which is strict adherence to the set down rules from ACF and PACF plots, showed a better linear trend. The blue shading indicates 80% confidence interval while the faint or ash shading indicates the 95% confidence interval. From the forecast from ARIMA(0,2,0) produced by auto.arima function from R software, it was observed that model with 2 differencing assumes a time-varying local trend. It's a Linear Exponential Smoothing model (LES) and not optimistic about the future as seen from the look of the forecast. This is in agreement with (Robert 2020) findings. The Akaike Information Criteria (AIC) of ARIMA(1,1,0) model = 284.03 is smaller than that of ARIMA(1,1,1) = 285.79 model and the smaller the AIC, the better. However, ARIMA(1,1,0) was chosen as the best fitted model. It was also evident from the research that the country's external debt has negative effects on economy growth.

Conclusion

The predicting power of ARIMA has been displayed in this study and the set down rules for choosing the best model itemized by practice. It therefore becomes imperative that researchers should appropriate them for better results. The country's external debt depicted a slight upward trend in the 5 years forecast.

Recommendations

Based on the findings and conclusion drawn above, the following recommendations were made. Scholars should know that there are no shortcuts in choosing ARIMA models but by forward stepwise approach. Government should perceive the dangers of borrowing and misappropriation of funds to the economy.

References

Adepoju, A.A., Salau A.S. and Obayelu, A.E. (2007). "The Effect of External Debt Management on Sustainable Economic Growth and Development: Lessons from Nigeria", MPRA Paper No. 2147.

Amassoma, D. (2011). "External Debt, Internal Debt and Economic Growth Bound in Nigeria Using a Causality Approach", *Current Research Journal of Social Sciences 3(4): 320-25, July.*

CBN (2019). "Bullion"; Publication of Central Bank of Nigeria vol 43 N0.1 January –March 2019.

DMO (2018), Nigerian External Debt Management 2019 publication. *Retrieved on 2nd September*, 2020 from https://dmo.gov.ng or www.indexmundi.com

Box, G. E. P., & Tiao, G. C. (1965). A change in level of nonstationary time series. Biometrika, 181-192.

Box, G. E. P., & Tiao, G. C. (1975). Intervention analysis with application to economic and environmental problems. *Journal of the American Statistical Association*, 70, 70-92.

Box, G. E. P., & Jenkins, G. M. (1976). Time-series analysis: Forecasting and control . San Francisco: Holden Hay.

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (1994). Time series analysis: Forecasting and control (3rd Ed.) Englewood Cliffs, NJ: Prentice-Hall, Inc.

Glass, G. V., Willson, V. L., & Gottman, J. M. (1975). Design and analysis of time series experiments, 80 . Boulder, CO: Colorado Associate University Press.

Karagol, E. (2002). The causality analysis of external debt service and G N P: *The case of Turkey. Central Bank Review*, Vol. 2, No.1.

Krugman, P.R (1988). "Financing Versus Forgiving a Debt Overhang". *Journal of Development Economics.* Vol 29, 253-268

Ljung, G. M., & Box, G. E. P. (1978). On a measure of lack of fit in time series models. Biometrika , 297-303.

Robert N (2020). Statistical forecasting notes on regression and time series analysis: Duke University USA. *Retrieved on 2nd September*, 2020 from

https://people.duke.edu/~rnau/411home.htm or https://people.duke.edu/~rnau/arimrule.htm