

Statistical Intervention Analysis of Nigerian Monthly Inflation

Ette Harrison Etuk

Department of Mathematics
Rivers State University, Port Harcourt
Email: etuk.ette@ust.edu.ng

ABSTRACT

Since 2016, Nigeria has been in economic recession. Coincidentally, its inflation rates have been rising too with time. The goal of government has been to maintain the inflation in a single digit range. From 2013 up to January 2016, this goal has been achieved according to the records of the Central Bank of Nigeria after which it has swung back to two digits until now. The index is rising on a monthly basis. It is known that recession could worsen inflation. This paper is an attempt to propose an intervention model to explain this relationship between the two variables: inflation and recession. Clearly the point of intervention is February 2016, the change in the mean level being observed to be statistically significant. The pre-intervention series is observed to be non-stationary and thereby differenced to make it stationary. The correlogram of this resultant series has a spike in the partial autocorrelation function at lag 3 and no spike at all in the autocorrelation function, suggesting an AR(3) model, which fitted is observed to be adequate, the residuals following a Gaussian distribution. The difference of the post-intervention observations and the AR(3) forecasts are analyzed for the intervention model. There is very close agreement between the observations and the intervention model forecasts. It is recommended that the Nigerian economy be upped with appropriate economic policies in order to ameliorate the inflation situation.

Keywords: ARIMA modelling, economic recession, intervention analysis, Nigerian Inflation

INTRODUCTION

The inflation of a country reflects the purchasing power of the country's currency, and the higher it is the less the purchasing power is. It has been the aim of the Nigerian Government to keep its inflation along single digits. Since 2013, by the records of the Central Bank of Nigeria (CBN) this has been realized until early 2016, precisely February 2016 when the inflation assumed a two-digit status and as time progresses it has grown worse. Time series analysis of inflation is a common engagement among scholars. Fannoh *et al.*, (2012) modelled Liberian monthly inflation as a SARIMA

$(0,1,0) \times (2,0,0)_{12}$ model. Nigerian inflation has been modelled as a SARIMA $(0,1,1) \times (0,1,1)_{12}$ model (Etuk *et al.*, 2012). Akuffo and Ampaw (2013) used a SARIMA $(1,1,2) \times (1,0,1)_{12}$ to model Ghanaian inflation. Akhter (2013) gave an ARIMA $(1,1,1) \times (1,0,1)_{12}$ fit to the inflation of Bangladesh. Gikungu *et al.*, (2015) fitted a SARIMA $(0,1,0) \times (0,0,1)_4$ model to Kenyan quarterly inflation series. Karlson (2016) observed that the SARIMA approach outdid the ARIMA and VECM approaches in the modelling of Ugandan monthly inflation. The scholar fitted a SARIMA $(1,1,0) \times (1,0,1)_{12}$ model. Mohamed and Etuk (2016) fitted a SARIMA $(1,1,0) \times (1,1,1)_{12}$ model to Sudanese inflation, to mention a few.

Nigerian inflation which is the subject of the write-up has been severally analysed as a time series. A few examples of publications on it are Etuk *et al.*, (2012), which has already been mentioned above, Doguwa and Alade (2013) and Otu *et al.*, (2014).

Economic recession in a country is a situation where activities in the economy have slowed down considerably. At this time, there is a reduction in the gross domestic product (GDP) of the country. There have been efforts to relate a country's inflation to its economic recession. Gokal and Hanif (2004) observed that a weak negative correlation between inflation and GDP growth. Moreover they noted that "the causality between the two variables ran one-way from GDP growth to inflation". This means that there is a causal relationship from recession to inflation. The same position has been corroborated by The Money Enigma (2017), intervention is done when an incident or event disrupts the normal flow of a time series. In this case it is speculated that Nigerian inflation has risen because of the prevalent economic recession. This disruption of the normal course of the time series is called intervention. Applying transfer function modelling an intervention model is developed to account for any change in the mean of the series.

Since its introduction by Box and Tiao (1975), who also applied it to model mean monthly levels of ozone in Los Angeles and monthly United States consumer price index, it has engaged the attention of researchers. For instance Mol *et al.*, (2005) used time series intervention analysis to study the impact of an intervention strategy in order to improve antimicrobial prescription in University Hospital Groningen. McLeod and Vingilis (2005, 2008) studied computational techniques in intervention modelling and analysed the effect of liquor bar closing time change on late-night

automobile mortalities. Gilmour *et al.* (2006) used intervention analysis to assess the impact of heroin shortage on the incidence heroin-related crimes. Shittu (2009) developed an intervention model for US Dollar/ Nigerian Naira exchange rates. Masukawa *et al.*, (2014) carried out a study to find out the effect of the introduction of rotavirus vaccine for acute diarrhoea on the rate hospital admission. This is to mention only a few.

Intervention analysis of Nigerian inflation has been done by Egbuna and Obikili (2013) and Okereke *et al.*, (2016) to mention a few. The former noticed a short-lived effect of currency restructuring in the country on food inflation. The latter observed that the policy called National Economic and Empowerment Strategy (NEEDS) had a temporary influence on inflation rates.

In this work application of intervention analysis is to ascertain the effect of economic recession on the level of inflation in Nigeria. The one-digit era from January 2013 to January 2016 is considered the pre-intervention period and the two-digit period from February to September 2016 is the post-intervention period.

In this work it is assumed that there is need for intervention to revert the series back to its one-digit level. The one-digit level shall be assumed to be the pre-intervention part of the data and the double-digit part the post-intervention part. The structure of this work is as follows: Section 1 is the introduction; Materials and Methods are discussed in Section2; Section 3 is concerned with the Results and Discussion and Section 4 concludes it.

MATERIALS AND METHOD

Data

The data for this work are the Nigerian monthly inflation rates from January 2013 to September 2016. The source is from the CBN website cenbank.org. The data may be accessed in the **Inflation subheading** of the **Statistics heading** of the website. The data are expressed as percentages.

ARIMA Modelling

Box and Jenkins (1976) defined *an autoregressive integrated moving average model of order p, d and q*, denoted by ARIMA(p, d, q) by

$$A(L)\nabla^d X_t = B(L)\varepsilon_t \quad (1)$$

Where $\{X_t\}$ is a time series, $\{\varepsilon_t\}$ is a white noise process, $A(L) = 1 - \alpha_1L - \alpha_2L^2 - \dots - \alpha_pL^p$, $B(L) = 1 + \beta_1L + \beta_2L^2 + \dots + \beta_qL^q$, $L^kX_t = X_{t-k}$ and $\nabla = 1 - L$. The α 's and β 's are constants such that the model is both stationary and invertible. $A(L)$ is the autoregressive (AR) operator and $B(L)$ is the moving average (MA) operator; L is the backshift operator as earlier defined and d is the order of differencing to achieve data stationarity. ∇X_t is the d^{th} difference of X_t .

If $d = 0$ model (1) is the *autoregressive moving average model of order p and q denoted by ARMA(p, q)*. Then the α 's represent the effects of the past p values of the series respectively and the β 's represent the effects of the past q random shocks respectively.

Model (1) may be written as

$$X_t = \frac{B(L)}{A(L)(1-L)^d} \varepsilon_t \quad (2)$$

Fitting of the model to real-life data involves model identification, model estimation and diagnostic checking. If the series shows evidence of non-stationarity, Box and Jenkins (1976) suggested that differencing to an appropriate order d could make the series stationary. The stationarity status of the series could be ascertained with the Augmented Dickey Fuller (ADF) test. The correlogram of the stationary series could help in model identification. The truncation point of the partial autocorrelation function, PACF, if any, estimates the autoregressive order and the truncation point of the autocorrelation function, ACF, if any, is an indication of q , the moving average (MA) order. The α 's and β 's could then be estimated, usually by either the least squares approach or the maximum likelihood approach. Diagnostic checking involves residual analysis to confirm model adequacy. Comparison of contending models could be done by the use of Akaike's information criterion (AIC).

Intervention Modelling

Box and Tiao (1975) pioneered the introduction and application of intervention models. A disruption of the normal flow of a time series by some event is what is called intervention. After the incident the series changes accordingly. It is the aim of the intervention analysis to find out whether the intervention has an effect on the series and to estimate this effect. Let the pre-intervention data be modelled by model (2). An overall intervention model is given by

$$Y_t = Z_t I_t + \frac{B(L)}{A(L)(1-L)^d} \varepsilon_t \quad (3)$$

Where Y_t is the inflation at time t and $I_t = 0, t < T$ and $I_t \geq T$ where T is the point of intervention. If after the intervention point there is a change in level first gradually to a more or less constant level the appropriate intervention model is given by

$$Z_t = \frac{c(1)(1-c(2)^{t-T+1})}{(1-c(2))} \quad (4)$$

Where $c(1)$ and $c(2)$ are constants to be estimated (Box and Tiao, 1975), (The Pennsylvania State University, 2016).

Computer Software

The computer package used is the Eviews 7. It adopts the least squares procedure for model estimation.

RESULTS AND DISCUSSION

The time plot of the data in Figure 1 shows two parts of the data, the one-digit part which has no trend, which covers from January 2013 to January 2016 and then a two-digit part with a positive trend up to September 2016. The first part is regarded as the pre-intervention part and the second the post-intervention part. This follows the desire of government to keep inflation within the single-digit range. The pre-intervention part, which involves 37 values, has a mean of 8.5578 and a standard deviation of 0.594885. The post-intervention part, which involves 8 values, has a mean of 15.3150 and standard deviation of 2.4178. Comparison of the two means using the Student's t-test shows that their difference is statistically significant ($p < 0.0005$). This means that the intervention effect of economic recession is significant. It is noteworthy that in this work the intervention point is therefore $T=38$; that is in February 2016.

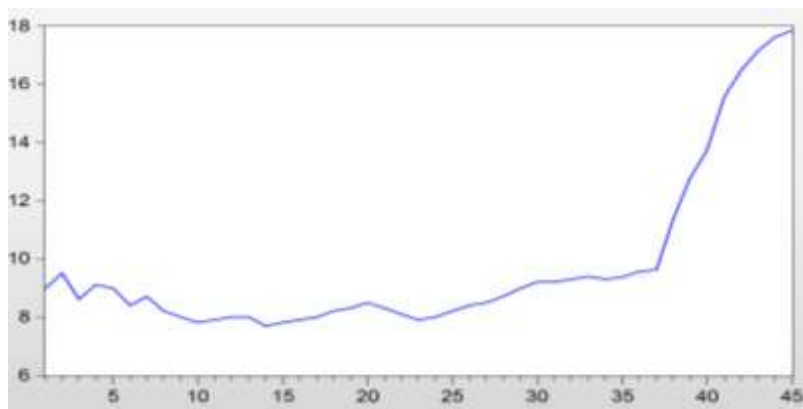


Figure 1: Nigerian Inflation Series

The pre-intervention data plot in Figure 2 reveals an initial negative trend before a positive trend. The ADF test of Table 1 shows this series to be non-stationary. First differencing of the series produces a series with an overall horizontal trend (See Figure 3). It is shown in Table 2 to be stationary. Its correlogram in Figure 4 shows a significant spike on the partial autocorrelation function at lag 3, suggesting an autoregressive model of order 3.

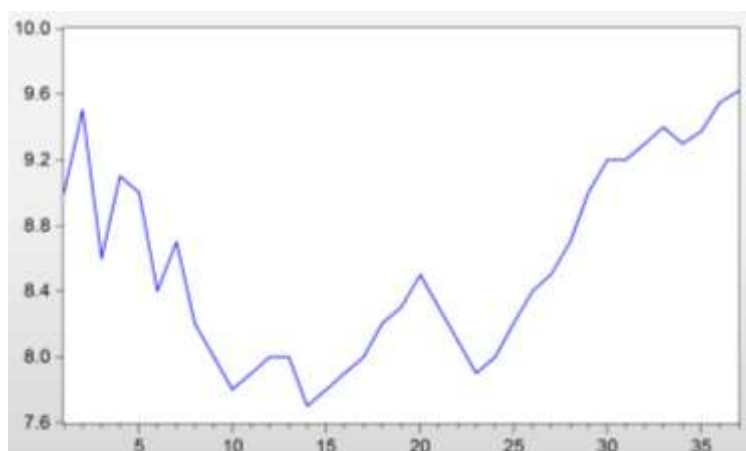


Figure 2: Pre-intervention Data

Table 1: The ADF Test on the Pre-intervention Data

	t-Statistic	Prob*
Augmented Dickey-Fuller test statistic	-0.948745	0.7607
Test critical values		
1% level	-3.626784	
5% level	-2.945842	
10% level	-2.611531	

*MacKinnon (1996) one-sided p-values

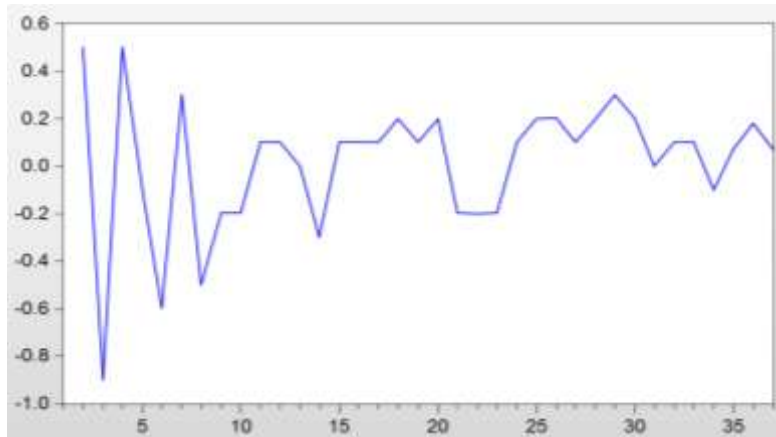


Figure 3: Difference of the Pre-intervention Data

Table 2: The ADF Test on differences of Pre-intervention Data

	t-Statistic	Prob*
Augmented Dickey-Fuller test statistic	-8.058610	0.0000
Test critical values		
1% level	-3.632900	
5% level	-2.948404	
10% level	-2.612874	

*MacKinnon(1996)

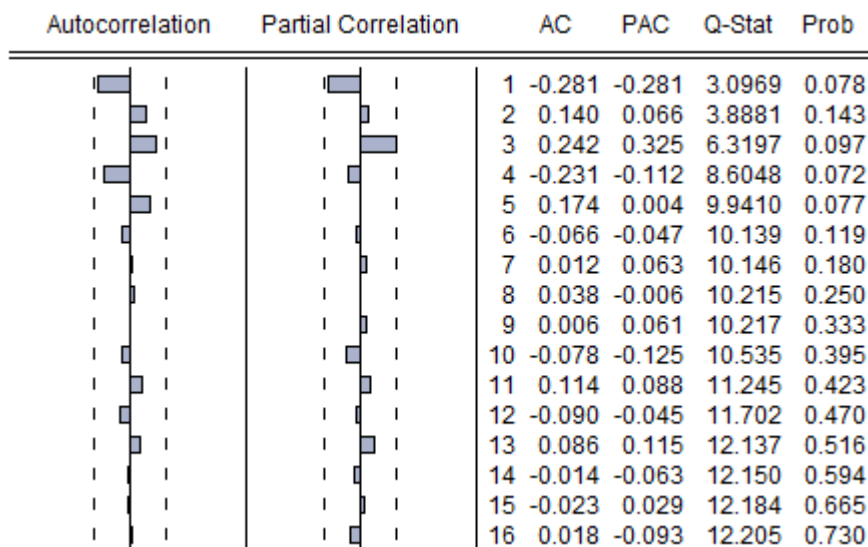


Figure 4: Correlogram of the Difference of the Pre-intervention Data

Table 3: Estimation of the Full-Order Pre-intervention ARIMA(3,1,0) Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.033519	0.159600	0.210017	0.8351
AR(2)	0.158937	0.136926	1.160751	0.2549
AR(3)	0.288323	0.131093	2.199372	0.0357
Akaike info criterion(AIC)	-0.247055			
Inverted AR Roots	.75	-0.36-.50i	-0.36+.50i	

The initial fitted (full order) model as estimated in Table 3

$$W_t = 0.0335W_{t-1} + 0.1589W_{t-2} + 0.2883W_{t-3} + \varepsilon_t \quad (5)$$

Where W_t is the ∇X_t the first difference of the pre-intervention series X_t . However with the lags 1 and 2 coefficients not statistically significant, they were dropped from the model. This led to the fitting of subset order model (6) below.

Therefore as estimated in Table 4

$$W_t = 0.2465W_{t-3} + \varepsilon_t \quad (6)$$

Clearly model (6) is the better model in terms of having a lower AIC.

This is equivalent to

$$X_t = \frac{\varepsilon_t}{(1-.2465L)(1-L)} \quad (7)$$

Table 4: Estimation of the Subset-Order Pre-intervention ARIMA(3,1,0) Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(3)	0.246545	0.122244	2.016826	0.0522
Akaike info criterion (AIC)	-0.324156			
Inverted AR Roots	.63	-.31+.54i	-.31-.54i	

Forecasts of the intervention data (i.e. from February 2016 to September 2016) based on model (6) are respectively 9.64, 9.68, 9.70, 9.70, 9.71, 9.71, 9.71 and 9.71. This pre-intervention model (6) is adequate since its residuals are normally distributed (See Figure 5).

Modelling the differences between these and their corresponding observed data produces the model estimated in Table 5 as

$$Z_t = 1.760139 \frac{(1-0.845748^{t-37})}{(1-0.845748)}, t \geq 38 \quad (8)$$

A combination of (7) and (8) yields the overall intervention model as

$$Y_t = \frac{\varepsilon_t}{(1-.2465L)(1-L)} + 1.760139(1-.845748^{t-37})/(1-.845748) \quad (9)$$

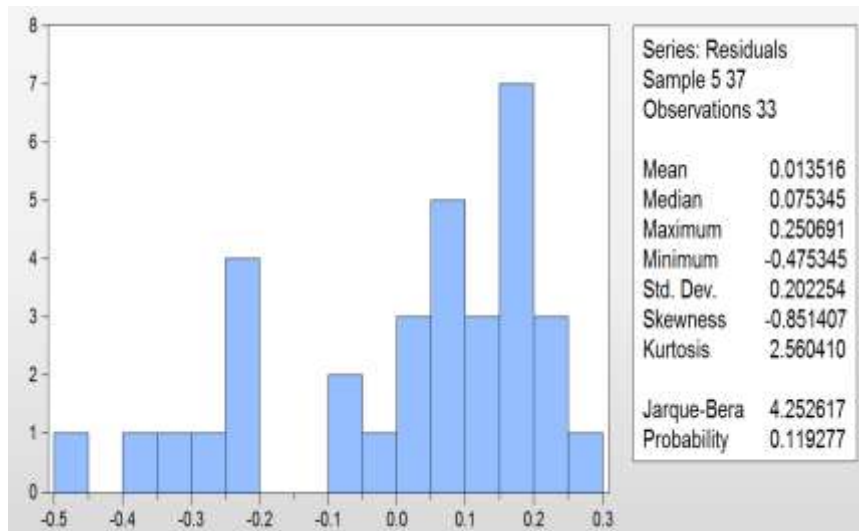


Figure 5: Histogram of the Residuals of the Subset-Order Pre-intervention ARIMA(3,1,0) Model

Table 5: Estimation of the Intervention Model

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.760139	0.101509	17.33972	0.0000
C(2)	0.845748	0.023695	35.69283	0.0000

Where $t > 37$. From table 5, the estimated transfer function (8) is statistically significant since the p-values of the estimates of $c(1)$ and $c(2)$ are both less than 0.05. This is an indication of the adequacy of the intervention model. The model forecasts agree closely with the observations for the post-intervention period as may be seen in Figure 6. For the overall series there is a fairly close agreement between observed data and the intervention forecasts (See Figure 7).

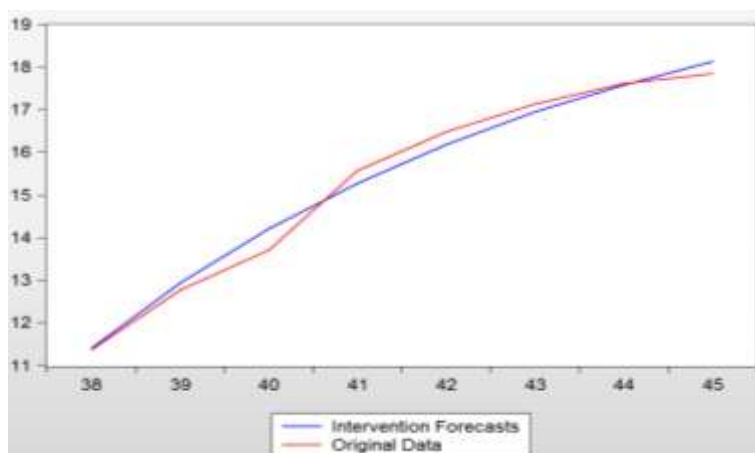


Figure 6: Post-Intervention original data and forecasts

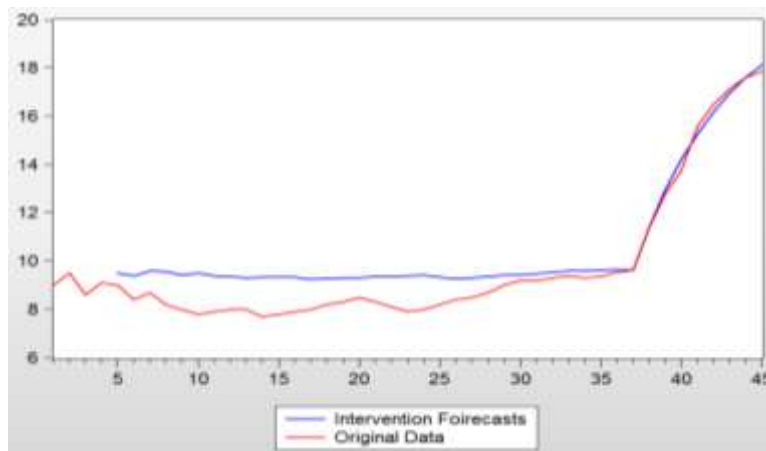


Figure 7: Original Data and Intervention Forecasts

CONCLUSION

It may be concluded that economic recession has a significant on Nigerian inflation. Model (9) is an intervention model to explain and possibly manage this situation. It is therefore recommended that the Nigerian government should embark on adequate economic policies to pull it out recession. This might improve the inflation rates.

REFERENCES

- Akhter. T. (2013). Short term forecasting of inflation in Bangladesh with Seasonal ARIMA process. Online at <https://mpra.ub.uni-muechen.de/43729/MPRA> paper no. 43729, posted 15 January 2013 20:04 UTC.
- Akuffo, B. and Ampaw, E. M. (2013). An Autoregressive Integrated Moving Average (ARIMA) Model for Ghana's nflation. *Mathematical Theory and Modeling*, 3(3): 10 – 26.
- Box, G. E. P. and Jenkins, G. M. (1976). *Time Series Analysis, Forecasting and Control*. San Francisco: Holden-Day.
- Box, G. E. P. and Tiao, G. C. (1975). Intervention Analysis with Applications to Economic and Environmental Problems, *Journal of American Statistical Association*, 70(349): 70 – 79.
- Doguwa, S. I. and Alade, S. O. (2013). Short-term Inflation Forecasting Models for Nigeria. *CBN Journal of Applied Statistics*, 4(2): 1 – 29.
- Egbuna, N. E. and Obikili, N. (2013). The Introduction of Higher Banknotes and the Price level in Nigeria: An Empirical Investigation. *International Journal of Economics and Finance*, 5(1): 105-111.

- Etuk, E. H., Uchendu, B. and Victor-Edema, U. A. (2012). Forecasting Nigerian Inflation by a Seasonal Model. *Canadian Journal of Pure and Applied Sciences*, 6(3): 2179 – 2185.
- Fannoh, R., Orwa, G. O. and Mung'atu, J. K. (2012). Modelling the inflation Rates in Liberia SARIMA Approach. *International Journal of Science and Research (IJSR)*, 3(6): 1360 - 1367.
- Gikungu, S. W., Waitutu, A. G. and Kihoro, J. M. (2015). Forecasting inflation rate in Kenya using SARIMA model. *American Journal of Theoretical and Applied Statistics*, 4(1): 15 – 18.
- Gilmour, S., Degenhardt, L., Hall, W. and Day, C. (2006). Using intervention time series analyses to assess the effects of imperfectly identifiable natural events: a general method and example. *BMC Medical Research Methodology*, 6(16): doi:10.1186/1471-2288-6-16. <http://www.biomedcentral.com/1471-2288/6/16>
- Gokai, V. and Hanif, S. (2004). Relationship Between Inflation and Economic Growth. http://www.rbf.gov.fj/docs/2004_04_wp.pdf
- Karlson, N. (2016). Forecasting of the Inflation Rates in Uganda: A comparison of ARIMA, SARMA and VECM Models. Masters in Applied Statistics Thesis, Orebro University School of Business, Orebro University. <http://www.diva-portal.org/smash/get/diva2:912462/FULLTEXT02.pdf>.
- McLeod, A. I. and Vingilis (2005). Power Computations for Intervention Analysis. *Technometrics*, 47(2): 174 – 181.
- McLeod, A. I. and Vingilis, E. R. (2008). Power computations in time series analyses for traffic safety interventions. *Accident Analysis and Prevention*, 40: 1244 – 1248.
- Masukawa, M. L. T., Moriwaki, A. M., Uchimura, N. S., Souza, E. M. and Uchimura, T. T. (2014). Intervention analysis of introduction of rotavirus vaccine on hospital admissions rates due to acute diarrhea. *Cadernos de Saude Publica*, 30(10): 1 – 11.
- Mohamed, T. M. and Etuk, E. H. (2016). Modelling the Inflation Rate in Sudan by a Seasonal ARIMA Model, *Euro-Asian Journal of Economics and Finance*, 4(3): 81 – 92.
- Mol, P. G. M., Wieringa, J. E., NannaPanday, P. V., Gans, R. O. B., Degener, J. E., Laseur, M. and Haaijer-Ruskamp, F. M. (2005). Improving compliance with hospital antibiotic guidelines: a time-series intervention analysis. *Journal of Antimicrobial Chemotherapy*, 55: 550 - 557.

- Okereke, O. E., Ire, K. I. and Omekara, C. O. (2016). The Impact of NEEDS on Inflation Rate in Nigeria: An Intervention Analysis. *International Journal of African and Asian Studies*, 22: 46-54.
- Otu, O. A., Osuji, G. A., Juge, O., Ifeyinwa, M. H. and Iheagwara, A. I. (2014). Application of Sarima Models in Modelling and Forecasting Nigeria's Inflation Rates. *American Journal of Applied Mathematics and Statistics*, 2(1): 16 – 28.
- Shittu, O. I. (2009). Modelling Exchange Rate in Nigeria in the Presence of Financial and Political Instability: An Intervention Analysis Approach. *Middle Eastern Finance and Economics*, 5: 117 – 122.
- The Money Enigma (2017). Will inflation Rise or Fall in the Next Recession <http://www.themoneyenigma.com/will-inflation-rise-or-fall-in-the-next-recession/>
- The Pennsylvania State University (2016). Welcome to STAT 510! Applied Time Series Analysis Lecture Notes. Lesson 10: Intervention Analysis. Department of Statistics Online Program. www.onlinecourses.science.psu.edu/stat510/ accessed 9th November 2016.

Reference to this paper should be made as follows: Etuk, E. H. (2017), Statistical Intervention Analysis of Nigerian Monthly Inflation. *Intl J. of Management Studies, Business & Entrepreneurship Research*, Vol. 2, No. 4, 2017, Pp 174-185
