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The Impact of NEEDS on Inflation Rate in Nigeria: An Intervention Analysis

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Abstract
This paper examined the effect of NEEDS on inflation in Nigeria using intervention Analysis. The data used for this study were secondary data on inflation rates which were collected from the Central bank of Nigeria Bulletin, 2012 for the period 2003 to 2013. Our results revealed that NEEDS has abrupt temporary effect on inflation. We therefore recommended that more efforts be made to ensure continuous implementation of policies needed to combat inflation.
Keywords: Inflation, Autoregressive process of order one, transformation, differencing, Intervention model.

1.0 Introduction

Inflation is a term used to describe the persistent increase in the level of consumer prices or persistent decrease in the purchasing power of money. A situation where the demand for goods and services exceed their supply often gives rise to inflation. The negative effects of inflation cannot be overemphasized. Fixed income earners suffer most when prices of commodities rise as they cannot buy as much as they could buy when the prices of goods were relatively cheaper (Aidoo, 2010). Inflation also affects savings, efficient allocation of resources and economic growth (Osuala *et al*. 2013).

Inflation targeting is one of the monetary policies adopted by the central bank of Nigeria(CBN) to control inflation in Nigeria (O'Cornell,2008, Ihezuchukwu, 2008, Migap, 2011, Tolupe and Ajilore, 2013). Authors for example Onyeiwu (2012), and Onye *et al*. (2012) have illustrated through empirical research the efficacy of the monetary policy in controlling inflation. However, Nigeria is described as facing the challenge of instability in its monetary policy (Onye *et al.*, 2012).

The National Economic and Empowerment Strategy was introduced in Nigeria during president Olusegun Obasanjo regime for the purpose of addressing economic problems facing Nigeria. One of the key policy thrusts of NEEDS is to adopt policies to raise domestic savings, reduce the inflation rate and sustain a rapid broad based GDP growth rate outside of the oil sector that is consistent with poverty reduction (National Planning Commission, 2004). An effective way of achieving these goals is to adopt measures that reduce the inflation rates in Nigeria (Soludo, 2009)

A lot of studies involving inflation rates have been done since the inception of NEEDS. For example, Otu *et al.* (2013) analyzed Nigeria inflation rates using Box Jenkins methodology. Their findings revealed a decreasing pattern of inflation rates in the first quarter of 2014 and a turning point in the beginning of second quarter of 2014. They affirmed that inflation rates in Nigeria were seasonal over the period 201 to 2013. As a result, they fitted ARIMA$(1,1,1)(0,0,1)_{12}$ model to the data. In their own research, Olajide *et al.* (2012) found inflation rates for the period 1961-2010, to be a non stationary time series which became stationary after first order differencing. Their study considered ARIMA (1,1,1) to be the most appropriate model for the inflation rates during the period under review.

Despite the rich literature on inflation, no research work has addressed the impact of special interventions on inflation rates. Therefore, the purpose of this study is to perform an ARIMA intervention analysis of inflation rates in Nigeria from 2003 to 2013 using NEEDS policy as an intervention.

2.0 Methodology

The data used in this study, are secondary data on inflation rates in Nigeria over the period January 2003 to December 2013. The data can be retrieved from the website www.cenbank.org. In analyzing the data, we employ intervention analysis. This method of analyzing is aimed at fitting a time series model to time series data influenced by an intervention. An intervention model is generally given by

$$X_t = N_t + f(I_t) \tag{2.1}$$

Where X_t= observed value of the time series at time t
$f(I_t)$ is the intervention function and N_t is the ARIMA noise model

In fitting an intervention model to time series data we first determine the point of intervention on the series. Next we fit an ARIMA model to the pre intervention series based on Box Jenkins approach. Stationarity is a basic requirement for the application of Box Jenkins methodology. The mean function and variance function of a stationary time series are constant over time. It then follows that a time series is non stationary if at least one of its mean and variance depends on time. Through differencing, a stationary time series with time varying mean can be converted into a stationary time series when the time series has stochastic trend. The mth order difference of the time series takes the form

$$\nabla^m X_t = X_t - X_{t-m} \quad (2.2)$$

For seasonal differences, we have

$$\nabla^S X_t = X_t - X_{t-S} \quad (2.3)$$

Where S is the seasonal length. The seasonal length for monthly data is S = 12.
The order of differencing can be determined by visual inspection of the time series plot, Continuous inspection of the time series plot of the differenced series and plot of the ACF after each stage of differencing until there is evidence of stationarity.

Stationary time series are expected to have constant variance over time. When the variance is not stable, an appropriate transformation can be applied to stabilize the variance. A formal procedure for determining what transformation to apply to a time series was introduced by Akpanta and Iwueze (2009). This method requires the estimation of the regression model of the annual standard deviation on the annual means. The regression model given for k no of years is

$$\log_e \hat{\sigma}_i = \hat{\alpha} + \hat{\beta} \log_e \overline{X}_i \quad (2.4)$$

Various values of $\hat{\beta}$ and their corresponding transformation are shown in Table 2.1.

Table 2.1: Various values of $\hat{\beta}$ and their corresponding Transformations

S/NO	1	2	3	4	5	6	7
$\hat{\beta}$	0	0.5	1	1.5	2	3	-1
Transformation	None	$\sqrt{X_t}$	$\log_e X_t$	$\frac{1}{\sqrt{X_t}}$	$\frac{1}{X_t}$	$\frac{1}{X_t^2}$	X_t^2

Source: Akpanta and Iwueze (2009)

The ARIMA (p,d,q) model is a well known class of time series models which can be fitted using the Box-Jenkins approach. This model has the following representation

$$\phi(\mathrm{B})(1-\mathrm{B})^d X_t = \theta(\mathrm{B})e_t \quad (2.5)$$

In the model (2.5), B is the backshift operator such that $\mathrm{B}^m X_t = X_{t-m}$, $\phi(\mathrm{B}) = (1-\phi_1\mathrm{B} - \phi_2\mathrm{B}^2 - ..\phi_p\mathrm{B}^p)$ and $\theta(\mathrm{B}) = (1-\theta_1\mathrm{B} - \theta_2\mathrm{B}^2 - ..\phi_q\mathrm{B}^q)$ are polynomials of degrees p and q respectively, d is the order of non seasonal(regular) differencing and e_t is a white noise process.

The autocorrelation function and partial autocorrelation function play important roles in the identification of the ARIMA (p,d,q) model. To fit a time series model to a time series data we need to estimate the parameter(s) of the model. This can be done by method of moments, method of non linear least squares and method of maximum likelihood.(Aidoo,2010). Programs for estimation of parameters of such models are available in the statistical package MINITAB. If the fitted model is adequate, the plots of the associated residual ACF and PACF are expected to have the properties of a white noise process.

Intervention Functions

The step and pulse functions are the two commonly used functions for investigating the effects of interventions on the mean functions of time series.(Cryer and Chan,2008)
Let t be the time an intervention takes place in a given time series. For a step function, we have

$$S_t^{(T)} = \begin{cases} 1, \text{ if } t > T \\ 0, \text{ otherwise} \end{cases} \quad (2.6)$$

Obviously, the step function assumes the value 0 during the intervention period and 1 throughout the post intervention period.
Again, the pulse function is given by

$$P_t^{(T)} = S_t^{(T)} - S_{t-1}^{(T)} = \begin{cases} 1, \text{ if } t = T \\ 0, \text{ otherwise} \end{cases} \quad (2.7)$$

It shall be noted that P_t^T is the indicator or dummy variable assuming the values 1 when there is an intervention in the series and zero otherwise. More details on the functional forms of step and pulse functions as well as their graphical representations are given by Cryer and Chan (2008) among others. Available statistical software for estimation of Intervention models include Statistica and R. Accordingly, R is used in this study.

Intervention analysis requires that the point of occurrence of the event (intervention) is known and specific functional form be specified for the effect that the event has on the time series (Glamour et al. 2006).

3.0 Results and Discussion

In this section the intervention time series analysis is performed on inflation rates in Nigeria, for the period under consideration. Figure 4.1 shows time plot of the series.

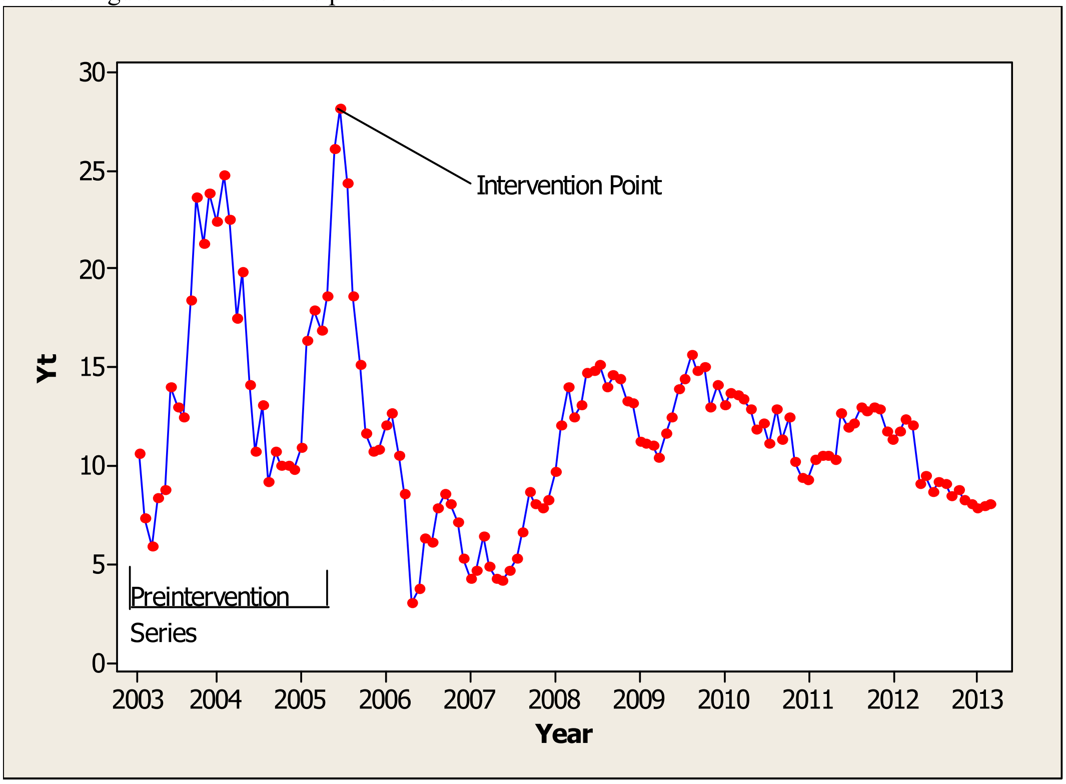


Figure 3.1: Time plot of Nigeria Monthly Inflation Rate

There appears to be structural breaks in the time series as shown in Figure 3.1. Notably, the largest inflation rate occurred in August, 2005. This has been chosen as the intervention point in this study because of the because of the behavior of the series after this point. Visual inspection of Figure 3.1 indicates that the concerned series may have no constant variance. In what follows, we seek a variance stabilizing transformation for the series.

3.1 Choice of appropriate transformation for the inflation rate data

The annual means and annual standard deviation of the series are shown in Table 3.1

Table 3.1: Natural logs of annual means and annual standard deviations

Year	$\overline{X}_i$	$\hat{\sigma}_i$	$\ln \overline{X}_i$	$\ln \hat{\sigma}_i$
2003	13.93	6.38	2.63404	1.85317
2004	15.38	5.73	2.73307	1.74572
2005	17.84	5.87	2.88144	1.76985
2006	8.375	3.124	2.12525	1.13911
2007	5.417	1.293	1.68954	0.25697
2008	11.525	2.894	2.44452	1.06264
2009	12.592	1.489	2.53306	0.39810
2010	13.758	1.077	2.62162	0.07418
2011	10.85	1.12	2.38417	0.11333
2012	12.242	0.538	2.50487	-0.61990
2013	8.517	0.552	2.14206	-0.59421

The estimates of the parameters of the fitted regression model as well as their corresponding standard errors are contained in Table 3.2

Table 3.2: Estimates of the parameters based on the Regression of the natural log of annual standard deviation on natural log of annual mean

Parameter	Estimate	Standard Error
α	-2.351	1.983
β	1.2385	0.8103

R Squared= 20.6%, R-Squared Adjusted=11.8%

From Table 3.2, we have $\hat{\beta}$ = 1.24 which lies between 1 and 1.5 but closer to one (1) indicating that a natural logarithmic transformation might be suitable for the data. We then examine the suitability of the logarithm transformation by testing the hypothesis

Ho: $\beta = 1$ (i.e logarithmic appropriate transformation is appropriate) against the alternative Ha: $\beta \neq 1$ (i.e logarithmic appropriate transformation is not appropriate). When the calculated t-value (0.296) is compared with the tabulated value (2.26) at $\alpha = 0.05$ level of significance and 9 degrees of freedom, the null hypothesis is not rejected indicating that the logarithmic transformation may be the appropriate transformation.

This transformation is then applied to the original data and subsequent analysis is based on the transformed data. It can easily be verified using the procedure for determining the appropriate transformation that log inflation rates no longer require transformation.

3.2 Modeling the pre-intervention series

Here, we fit an ARIMA model to the pre-intervention series (i.e the observed values of the time series before August, 2005) with the help of plots of the ACF and PACF shown in Figures 3.2 and 3.3 respectively.

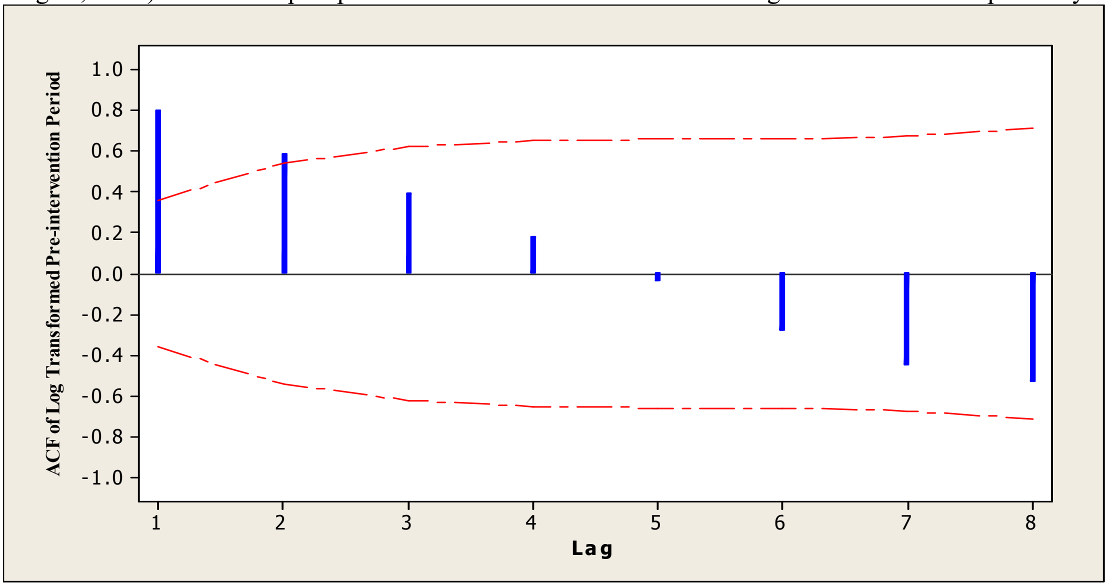


Fig. 3.2: ACF of Log Transformed Pre-Intervention series

The ACF of the pre-intervention series is characterized by an exponential decay.

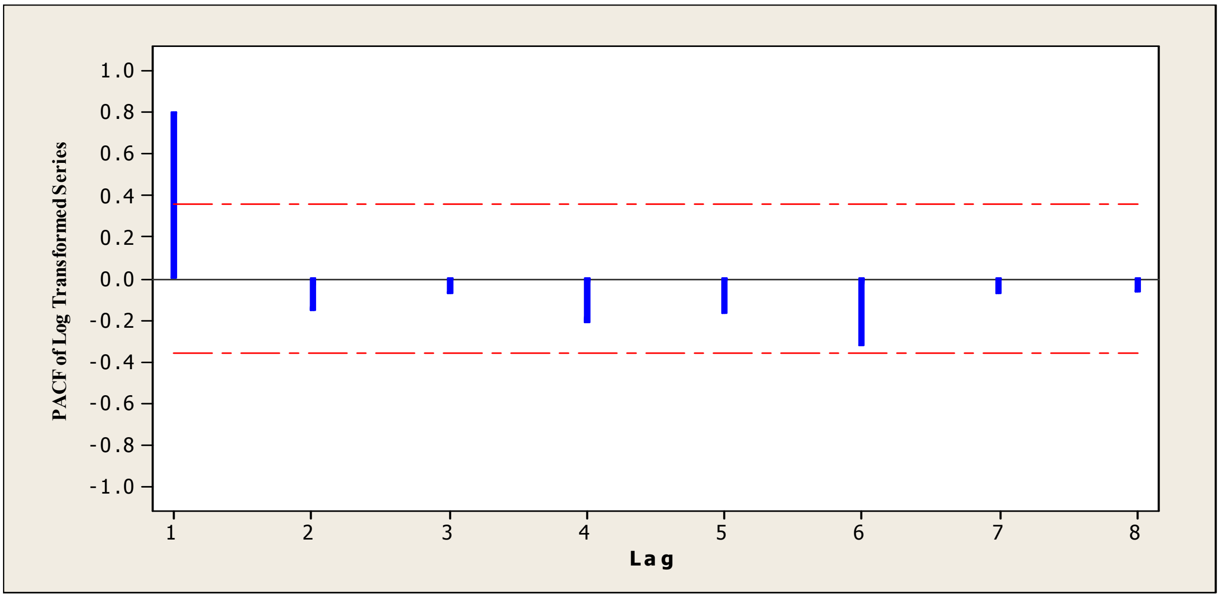


Figure 3.3 : PACF of the Transformed Pre-Intervention Series

It can be deduced from Figure 3.3 that there is a cut off after lag 1 in the PACF of the pre-intervention series, indicating that the pre-intervention series may have been generated by the first order autoregressive model (AR (1) model).

3.3 Estimation of parameters of log transformed pre-intervention series

The parameters of the fitted ARIMA (1,0,0) model to the pre-intervention series is shown in Table 4.7 below

Table 3.3: Final estimates of parameters of the pre-intervention model

Model	Coefficient	Standard Error	P
AR(1)	0.9864	0.0152	0.000

The time plot of the residuals of the pre-intervention series is shown in Figure 3.4. We can observe that the time plot of the residuals clearly shows that the residuals appear to be randomly scattered. This suggests that the residuals are purely random. To substantiate this claim, we plot the ACF and PACF of the residuals. The ACF of the residual series shown in Figure 3.5 has no significant autocorrelation coefficient. The PACF of the residuals in Figure 3.6 has no spike. From the foregoing, it is evident that the residuals constitute a white noise process. This confirms the suitability of the fitted AR (1) model.

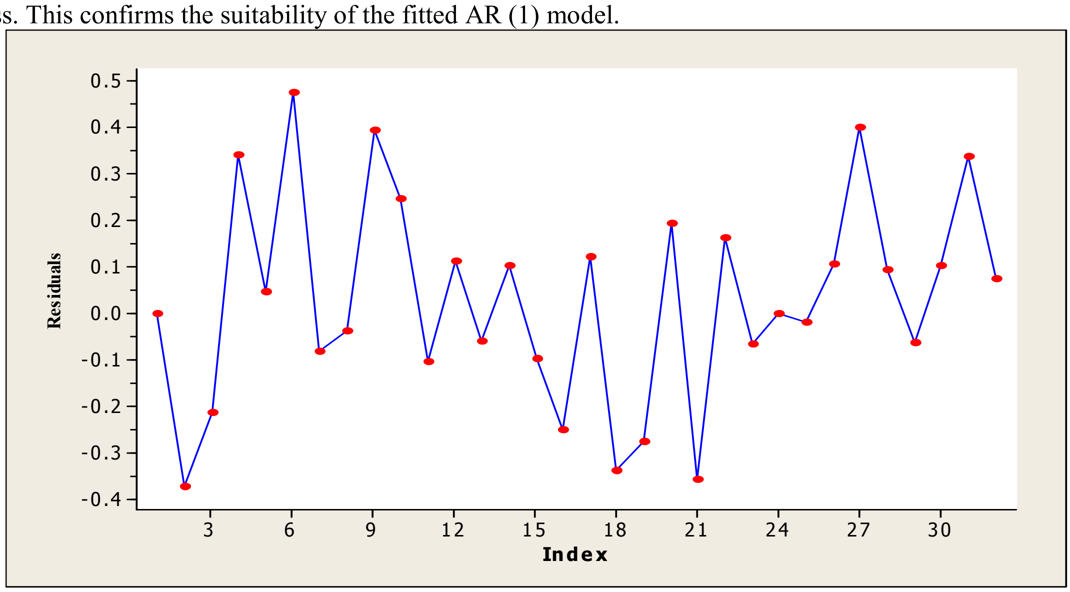


Figure 3.4: Time plot of the residuals of the pre-intervention model

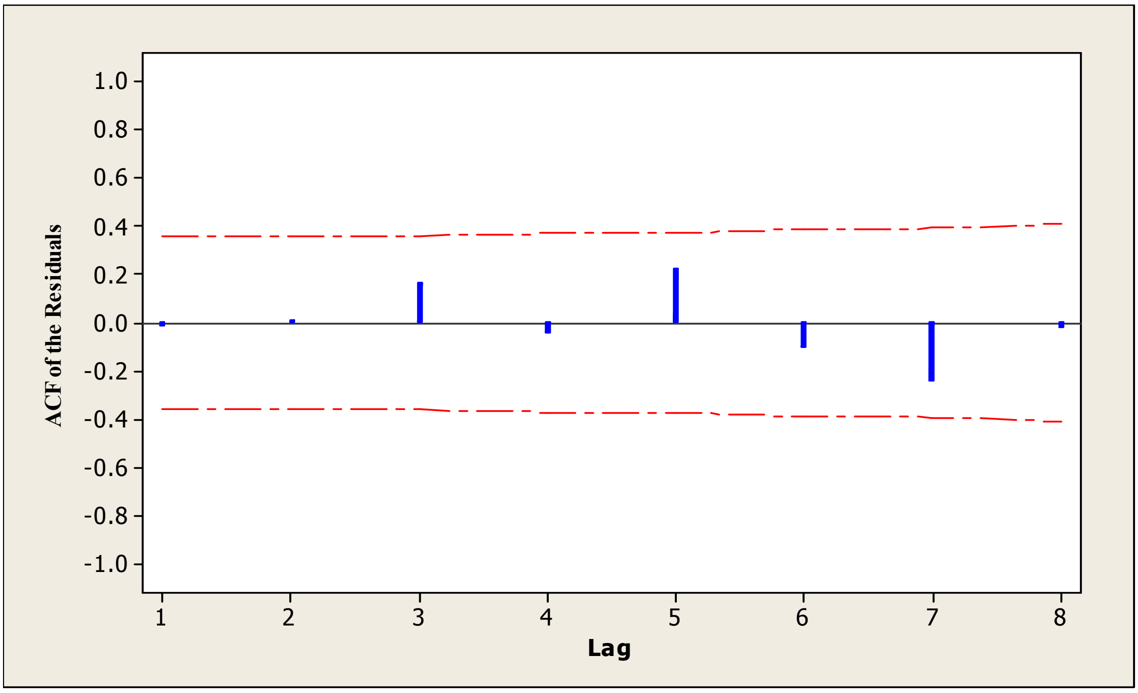


Figure 3.5: ACF of Residuals of the fitted ARIMA (1,0,0) Model

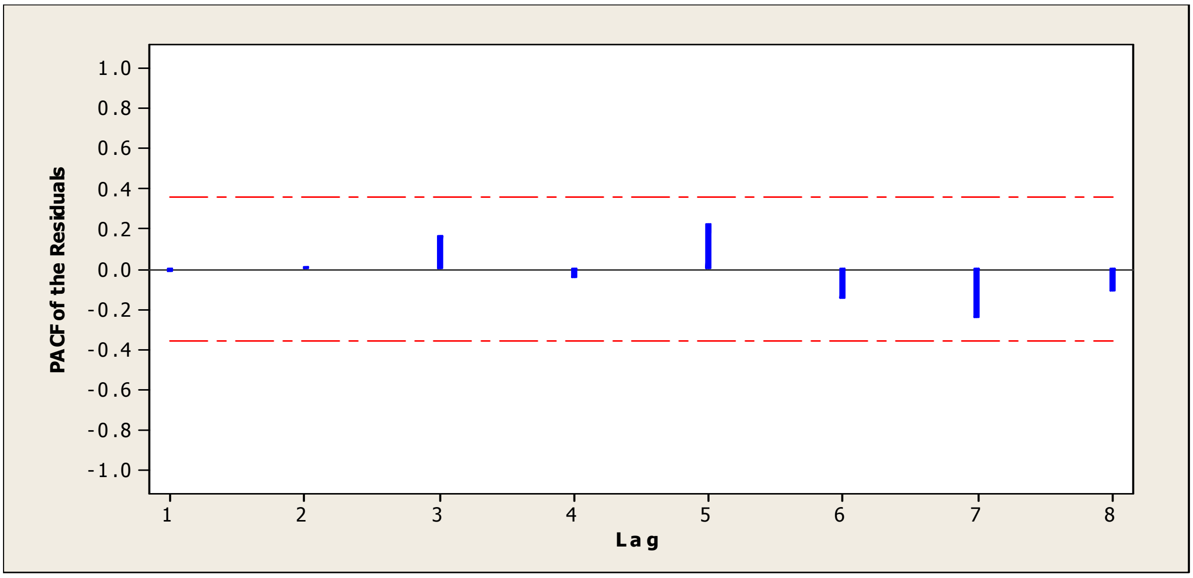


Figure 3.6 : PACF of Residuals of the fitted ARIMA (1,0,0) model

3.4 Estimation of full intervention model

In this Section, the R software package is used to estimate the parameters of the full intervention model for the Nigeria inflation rates data. The parameter estimates are shown in table 4.10

Table 3.4 Parameters estimates of the full intervention model

	Parameter Estimate	Asympt. Std.Err.	p	Lower 95% Conf	Upper 95% Conf	Interv. Case No.
AR(1)	0.986	0.0153	0.000	0.956	1.017	
Omega (ω)	4.521	1.978	0.024	0.608	8.435	32
Delta (δ)	0.508	0.262	0.055	-0.011	1.027	32

Table 3.4 reports the parameter estimates of the full intervention model. The estimate of the parameter for the AR(1) model is significantly differ from zero since its associated P-value of 0.000 is less than 0.05. It also conforms to the bounds of stationarity since it lies between -1 and 1.

Using the information in Table 3.4 and the dummy variable I_t, we obtain the full intervention model

$$X_t = \frac{4.521}{1-0.508B} I_t + 0.986 X_{t-1} \tag{3.1}$$

Since the P-value (0.024) corresponding to the parameter estimate of ω (4.521) is less than 0.05, we conclude that ω is significantly different from zero at 5% level of significance. At 5% level of significance, the estimate of δ (0.508) is not significantly different from zero because the corresponding P-value of 0.055 exceeds 0.05.

3.5 Diagnostic check for the full intervention model.

Using Figure 3.7 and the associated p-value of 0.036, we can conclude that the residuals are normally distributed at 1% significance level.

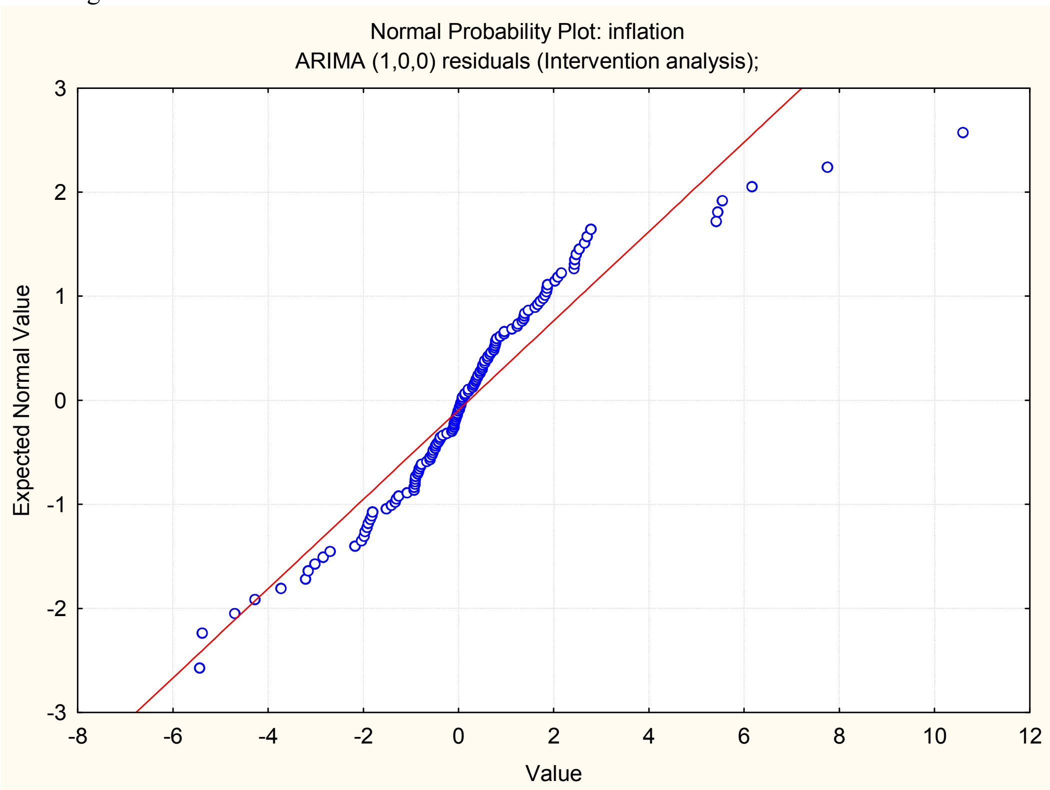
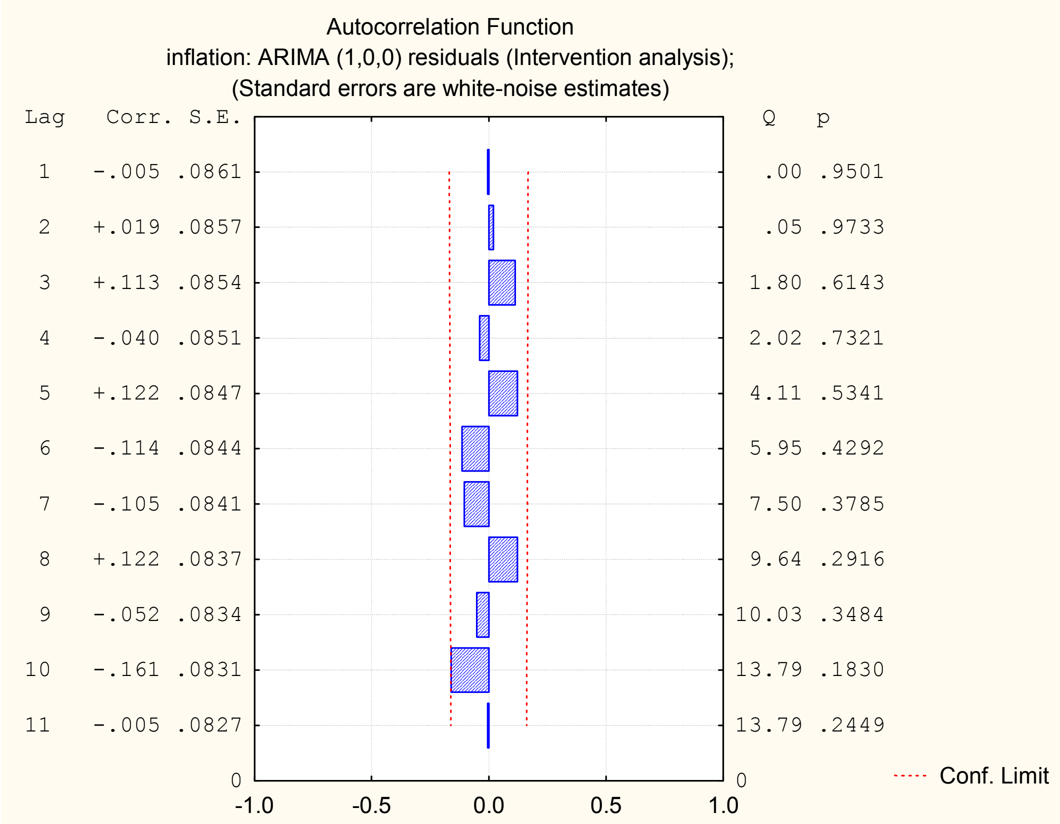


Figure 3.7: Normal probability plot of the residuals from AR (1) intervention model

It is also clear from Figure 3.8 that there is no cut off in the ACF of the residuals from the full intervention model. This confirms the adequacy of the fitted intervention model.



6.0 Conclusion

The purpose of the study was to investigate the impact of NEEDS on inflation rates in Nigeria using the intervention analysis. Our findings showed that the inflation rates in Nigeria over the period 2003 to 2013 have none constant variance and required logarithmic transformation to achieve variance stationarity. Following the patterns exhibited by the autocorrelation function and partial autocorrelation function of the pre-intervention series, AR (1) model was tentatively fitted to the pre intervention series. Careful examination of the residual from the fitted model confirmed the adequacy of the fitted model. Using the R package an intervention model involving a first order decay rate was fitted to the data. Based on the model, we observed that the NEEDS has significant negative effect on inflation rates in Nigeria. However, the already established effect of the NEEDS is temporary. Hence, there is an abrupt temporary effect of NEEDS on inflation in Nigeria.

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