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Time Series Analysis of Interest Rate in Nigeria: A Comparison of Arima and State Space Models

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Abstract This paper set out to analyse and forecast the monthly commercial banks interest rate data on time deposits in Nigeria for a period of 2005-2015. The main objective of this study is to propose an appropriate time series forecasting model for the interest rate data. The data which was obtained from the Central Bank of Nigeria (CBN) was analysed using Autoregressive Integrated Moving Average (ARIMA) procedure, Intervention Autoregressive Integrated Moving Average (Intervention ARIMA) procedure and State Space Modelling approach. As an illustration, the three approaches were compared for modelling and forecasting the interest rate data. Evidence showed Intervention ARIMA model to be more adequate than ARIMA (without intervention) model and State Space Model to be also more adequate than Intervention ARIMA model for the data set (interest rate in Nigeria) under consideration.

Keywords Interest rate, Forecasting, ARIMA, State Space

1. Introduction

In the recently years, more attention has been drawn to analyzing and forecasting Interest rates. This is particularly because interest rate is a key financial variable that affects decisions of consumers, businesses, financial institutions, professional investors and policymakers. Changes in interest rates have important implications for the economy's business cycle and are crucial to understanding financial development and changes in economic policy of Nigeria. Interest rates have fundamental implications for the economy, by either impacting on the cost of capital or influencing the availability of credit, by increasing savings, it is known to determine the level of investment in an economy. The importance of interest rate depends on its equilibrating influence on supply and demand in the financial sector [6] and [25]. Interest rates affect consumer spending. The higher the rate, the higher their loans will cost them, and the less they will be able to buy on credit. Interest rates are used by central banks as a means to control inflation. Movements in rates of interest either due to change in money supply or change in demand for money will affect the determination of national and financial institutional (Banks) income.

Time-series analysis and forecasts of interest rates can therefore provide valuable information to financial market participants and policymakers.

Forecasts of interest rates can also help to reduce interest rate risk faced by individuals and firms. Analysis and forecast of interest rates is very useful to central bank of Nigeria (CBN) in assessing the overall impact of its policy changes and taking appropriate corrective action, if necessary.

To achieve the desired level of interest rate, the Central Bank of Nigeria (CBN) adopts various monetary policy tools, key among which is the Monetary Policy Rate (MPR). This rate is the rate at which the Central Bank Nigeria (CBN) is willing to rediscount first class bills of exchange before maturity [26]. He further opined that by changing this rate the CBN is able to influence market cost of funds. If the CBN increases MPR, banks' lending rates are expected to increase with it, showing a positive relationship. Historically, the interest rate regime in Nigeria has been very stochastic as it varies from month to month and year to year. The central bank of Nigeria kept its benchmark interest rate at 11 percent on January 26th, 2016 as widely expected following an unexpected cut by 200bps at its November 2015 meeting in order to boost growth. The bank also held the cash reserve ratio for commercial banks at 20 percent. Interest Rates in Nigeria averaged 10.03 percent from 2007 until 2016, reaching an all-time high of 13 percent in November of 2014 and a record low of 6 percent in July of 2009. Interest Rates in Nigeria is reported by the Central Bank of Nigeria.

Several researchers have worked on interest rates data. [1], examined the implications of interest rate for savings and investment in Nigeria using Pearson's correlation coefficient and regression analysis. Evidence from their work showed that interest rate was a poor determinant of savings and investment, indicating that bank loans were mostly not used for productive purposes. [22], studied the relationship

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between interest rate and economic growth in Nigeria. The study employed cointegration and error correction modeling techniques and revealed that interest rate has significant effect on economic growth. [20], on his own studied Interest Rate Targeting: A Monetary Tool for Economic Growth inNigeria? Stakeholders'Approach. The study showed that there was a significant interest rate impact on economy growth in Nigeria. [23], also observed that interest rate can have a substantial influence on the rate and pattern of economic growth by influencing the volume and disposition of savings as well as the volume and productivity of investment. [27], forecasted short-term interest rates using univeriate models: Random walk, ARIMA, ARMA-GARCH and ARIMA-EGARCH and the results show that the interest time series have volatility clustering effect and hence GARCH based models are more appropriate to forecast than the other models. [31], investigated whether there was a linkage of interest rates between the united states, West Germany, and Switzerland during the period of flexible exchange rate, (1974-1984). It was shown that there was strong linkage exist during the second period, but during the first period there was no or only a weekly pronounced linkage.

Since authors have used many models and methods of analysing time series data (interest rates) such as ARIMA, ARIMA-GARCH, ARIMA-EGARCH, I(d) statistical models amongst others, the main objective of this study is to propose an appropriate time series forecasting model for the monthly interest rate data in Nigeria using ARIMA, ARIMA Intervention and State Space Models respectively. For this purpose, the study will help to fill the research gap as many researchers seem to have not researched on commercial banks interest rate in Nigeria using ARIMA and State Space models. It will expose researchers and other users of the work to an important field of time series that does not require stationarity (differencing) of time series data before analysis (State Space Modelling technique). This study will confirm if State Space Modelling is more adequate than Box and Jenkins ARIMA Modelling as argued by [12]. This study will also expose the current trend/pattern and level of commercial banks interest rate in Nigeria to researchers, investors, government and users of the work. Finally, it will make recommendations that could enable the government to make and implement policies and programs that will always favour the economic situation of Nigeria at any given time.

2. Research Methodology

This paper focuses on the analysis of monthly commercial banks interest rate on time deposits in Nigeria for a period of 2005-2015. The data analysed in this paper were obtained from Central Bank of Nigeria statistical bulletin of 2015. The major statistical tools used in this study is time series analysis using Autoregressive Integrated Moving Average (ARIMA), Intervention Autoregressive Integrated Moving Average (Intervention ARIMA) and State Space Modelling approaches

2.1. Box-Jenkins (ARIMA) Process

The general ARIMA (p,d,q) process can be written in the general form:

$$\left(1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B^p\right)(1-B)^d X_t = \left(1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q\right)\varepsilon_t \quad (2.1)$$

This process of analysis has three major stages. They are: Model identification, Model estimation and Model diagnostic checking stages.

Assuming for the series that there is no seasonal variation, the objective of the model identification stage is to determine values of d, p and q in the ARIMA (p,d,q) model. The level of differencing (d) is estimated by considering the autocorrelation plots. When the autocorrelations die out quickly, the appropriate value of d has been found. The autoregressive order (p) is determined from the partial autocorrelations of the appropriately differenced series. If the partial autocorrelations cut off after a few lags, the last lag with a large value would be the estimated value of p. If the partial autocorrelations do not cut off, you either have a moving average model (p=0) or an ARIMA model with positive p and q. And the moving average order (q) is found from the autocorrelations of the appropriately differenced series. If the autocorrelation function cut off after a few lags, the last lag with a large value would be the estimated value of q. If the autocorrelations do not cut off, you either have an autoregressive model (q=0) or an ARIMA model with a positive p and q. By considering the patterns of the autocorrelations and the partial autocorrelations, we can guess a reasonable model for the data.

By studying the two autocorrelation plots, you estimate these values.

Having achieved stationary and obtaining the specified model, we proceed to estimate the parameters of the complete model. This is done in this paper by maximum likelihood estimation method.

Once a model has been fitted, the final step is the diagnostic checking of the model. The checking is carried out by studying the autocorrelation plots of the residuals to see if further structure (large correlation values) can be found. If all the autocorrelations and partial autocorrelations are not significant, the model is considered adequate and forecasts are generated. If some of the autocorrelations are large, model is re-estimated. This process of checking the residuals and adjusting the values of p and q continues until the resulting residuals contain no additional structure. Once a suitable model is selected, the fitted model may be used to generate forecasts.

2.2. Intervention ARIMA Model

This is a special kind of ARIMA model with input series. It is also called an interrupted time series model. In an intervention model, the input series is an indicator variable that contains discrete values that flag the occurrence of an event affecting the response series. This event is an intervention in or an interruption of the normal evolution of the response time series, which, in the absence of the intervention, is usually assumed to be a pure ARIMA process. Intervention models can be used both to model and forecast the response series and also to analyze the impact of the intervention. Intervention analysis, introduced by [3] provides a framework for assessing the effect of an intervention on a time series under study. Given the model $Y_t = M_t + N_t$ where M_t is the change in the mean, and N_t is modeled as some ARIMA model where there is no intervention. The Time Series Y_t, $t < T$ is called the pre-intervention data.

Table 1. The intervention transfer function

Types of impact	Transfer function	Intervention variable
Abrupt, permanent	ω	I_t

For more details on other transfer functions see [3]

Usually, there are two major forms that characterize intervention or impact assessments. These are observed by the duration and nature of the impacts. Some interventions could give temporary or permanent effects with respect to the duration. The nature of impacts can also be seen as abrupt or gradual processes. Sudden and constant changes (abrupt permanent) are normally attributed to step functions; sudden and instantaneous changes (abrupt temporary) are modeled with pulse function; gradual and permanent effects are mainly modeled with step function with first-order decay rate; gradual and decaying changes (pulse decay) can also be modeled with pulse function with first-order decay rate.

The abrupt onset and permanent duration effects are popularly called a simple step function. Step functions are mainly used to model permanent changes in the response series Y_t. A step function with a first-order decay rate may be written as:

$$Y_t = \frac{\omega_0}{(1-\delta_1 L)} I_{t-b} + N_t \tag{2.2}$$

If after fitting the model in (2.2) the denominator reduces to unity, the model will then be called a simple step function with a zero-order decay, where $f(I_t) = S_t^{(T)} = \omega_0 I_{t-b}$. Also, if there is no time delays (b=0), then $f(I_t) = S_t^{(T)} = \omega_0 I_t$, and the full model will now be of the form;

$$Y = \omega_0 I_t + N_t \tag{2.3}$$

Two parts of the overall model have to be estimated – the basic ARIMA model for the series and the intervention effect. These effects can be estimated using the following steps: determine the ARIMA model for the series using the data before the intervention point. Use that ARIMA model to forecast values for the period after the intervention. Calculate the differences between actual values after the intervention and the forecasted values. Examine the differences in step 3 to determine a model for the intervention effect. Since statistical packages are available, we can use all of the data to estimate the overall model that combines ARIMA for the series and the intervention model.

2.3. State Space Modelling Approach

[12] argue that the Box-Jenkins approach is fundamentally problematic since real series are never stationary especially in economic and social fields, however much differencing is done to make it stationary. The authors argue that rather than using Box-Jenkins (ARIMA), it is better to use state space methods, as stationarity of the series is not required.

State space model (SSM) refers to a class of probabilistic graphical model that describes the probabilistic dependence between the latent state variable and the observed measurement [14]. The state or the measurement can be either continuous or discrete. The most well studied SSM is the Kalman filter, which defines an optimal algorithm for inferring linear Gaussian systems. The main purpose of SSM time series analysis is to infer the relevant properties of unobserved series of vectors μ_t's from a knowledge of the observations y_t's. Other purposes include estimation of parameters and forecasting.

The simplest model for a univariate time series (Y_t : t = 1, 2, . . .) is the so-called random walk plus noise model (or local level model), defined by

$$\mu_{t+1} = \mu_t + e_t \quad e_t \sim NID(0, \sigma_e^2) \tag{2.4}$$

$$y_t = \mu_t + \in_t \quad \in_t \sim NID(0, \sigma_\in^2) \tag{2.5}$$

For t = 1, . . ., n, where μ_t is the unobserved level at time t, e_t is the observation disturbance at time t, and ε_t is what we call the level disturbance at time t. In the literature on state space models, the observation disturbances ε_t and e_t are also referred to as the irregular component. The two disturbances are all assumed to be mutually independent and normally distributed with zero mean and variances σ^2_e and σ^2_ε respectively. (2.4) is called the state equation, while (2.5) is called the observation or measurement equation. When the state disturbances are fixed on $e_t = 0$ for t = 1, . . ., n, the local level model reduces to a *deterministic model*: in this case the level does not vary over time. On the other hand, when the level is allowed to vary over time, it is treated as a stochastic process which will be used in this research work since interest rate in Nigeria varies over time.

The local level State Space Model is used for the analysis as it is the most appropriate state space model for time series data that is not stationary and showing no clear trend or seasonal variation. Indeed, SSMs can be used for modelling nonstationary time series. On the contrary, the usual ARMA models require a preliminary transformation of the data to achieve stationarity if not stationary.

In forecasting with state space models, we replace the unknown elements of the system matrices or vectors by their estimates. At the first step we determined the state vector. The choice of state vector is based on canonical correlation analysis as proposed by [14]. After identifying the state vector, the state space model is estimated by approximate maximum likelihood. After the parameters are estimated forecasts are produced from the fitted state space model using kalman filtering technique.

Local level model is the most appropriate state space model for time series data that is not stationary and showing no clear trend or seasonal variation.

The stationarity of the interest rate series in state space approach has was tested using ADF test.

State Space Representation of Univariate Time-series Models (ARIMA)

Most univariate (linear) models such as regression, ARIMA, ANOVA and so on can be expressed in form of state space model.

As a simple example of a system that can be written in state space form, consider a pth order autoregressive process ($AR_{(p)}$).

$$y_{t+1} = \phi_1 y_t + \phi_2 y_{t-1} + \phi_3 y_{t-2} + \ldots + \phi_p y_{t-p+1} + \epsilon_{t+1},$$

$$\epsilon_t \sim NID(0, \sigma_\epsilon^2) \qquad (2.6)$$

Note that (2.7) (which is AR order p) can equivalently be written as:

$$\begin{pmatrix} y_{t+1} \\ y_t \\ . \\ . \\ . \\ y_{t-p+2} \end{pmatrix} = \begin{pmatrix} \phi_1 & \phi_2 & \cdots & \phi_{p-1} & \phi_p \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ . & . & \cdots & . & . \\ . & . & \cdots & . & . \\ . & . & \cdots & . & . \\ 0 & 0 & \cdots & 1 & 0 \end{pmatrix} \begin{pmatrix} y_t \\ y_{t-1} \\ . \\ . \\ . \\ y_{t-p+1} \end{pmatrix} + \begin{pmatrix} \epsilon_{t+1} \\ 0 \\ . \\ . \\ . \\ 0 \end{pmatrix} \qquad (2.7)$$

The first row of (2.7) simply reproduces (2.6) and other rows assert the identity y_{t-j} for j = 0, 1, …, p-2 with

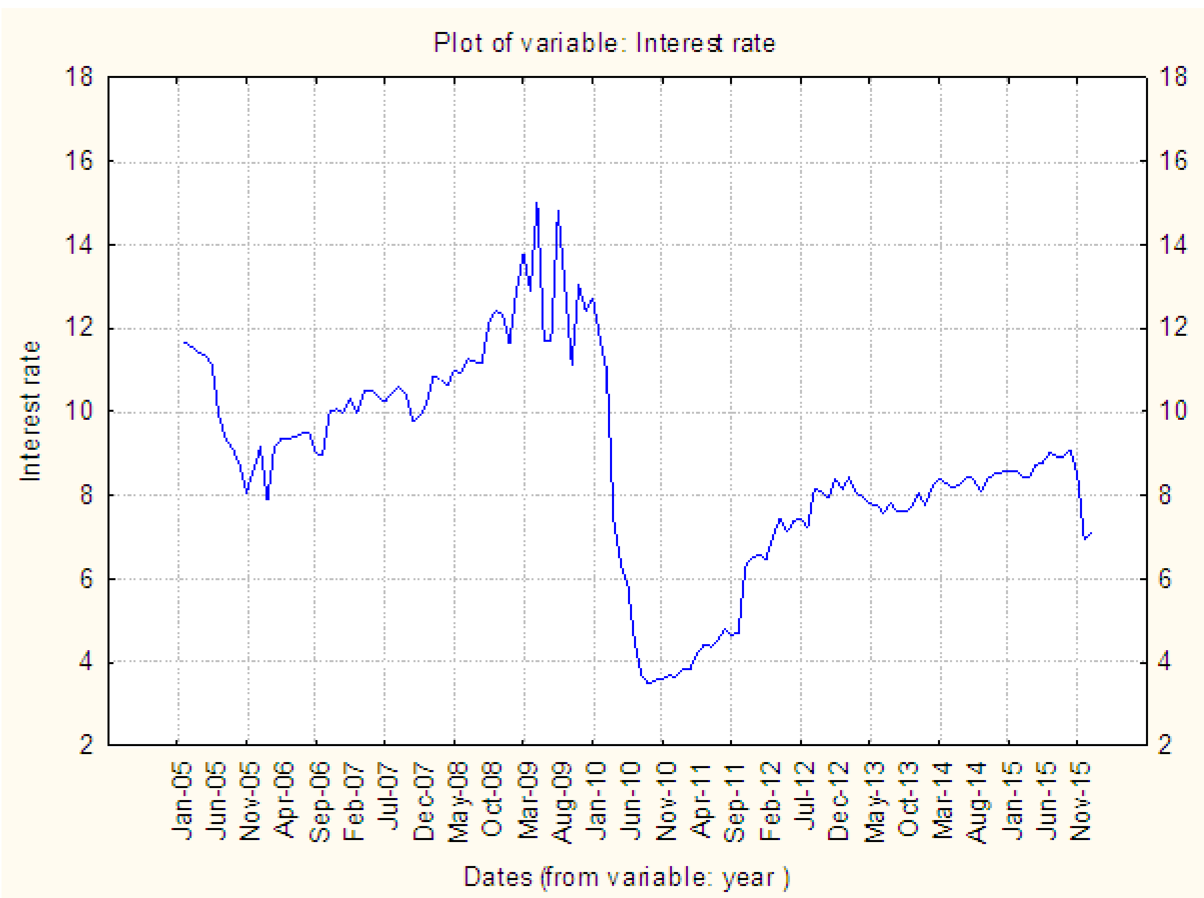

Figure 1. Time Plot of the Original interest rate data (2005-2015)

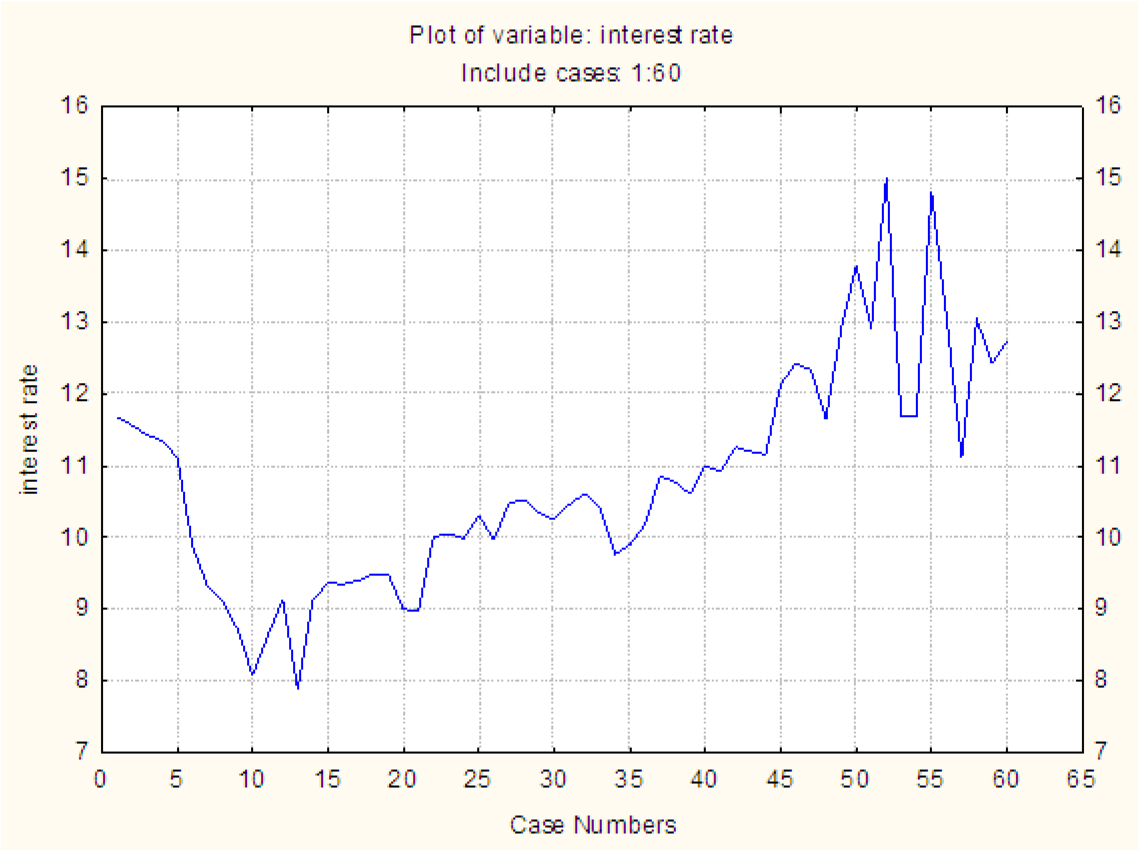

Figure 2. Time Plot of the Pre-Intervention series of the interest rate (1-60 data points)

$$\mu_t = (y_t y_{t-1} \dots y_{t-p+1})^I ,$$

$$\mu_{t+1} = (y_{t+1} y_t \dots y_{t-p+2})^I , \quad (2.8)$$

$\mathbf{e}_t = (\varepsilon_{t+1}\, 0 \dots 0)^I$ and (2.9)

$$\mathbf{T} = \begin{pmatrix} \phi_1 & \phi_2 & --- & \phi_{p-1} & \phi_p \\ 1 & 0 & --- & 0 & 0 \\ 0 & 1 & --- & 0 & 0 \\ . & . & --- & . & . \\ . & . & --- & . & . \\ . & . & --- & . & . \\ 0 & 0 & --- & 1 & 0 \end{pmatrix} \quad (2.10)$$

The eigen values of T can be shown to satisfy

$$\lambda^p - \phi_1\lambda^{p-1} - \phi_2\lambda^{p-2} - \dots - \phi_{p-1}\lambda - \phi_p = 0 \quad (2.11)$$

Thus stability of a p^{th} – order autoregression requires that any value λ satisfying (2.11) lies inside the unit circle [28].

2.4. Model Selection Criterion

The estimated models are compared based on the predictive power using the three forecasting accuracy measures: Akaike information criterion (AIC), Root mean square error (RMSE) and Visual comparison of 2015 forecasted values.

$$AIC = \frac{1}{n}[-2n \log l_d + 2(q+w)] \quad (2.12)$$

Where n is the number of observations in the time series, $\log L_d$ is the value of the log-likelihood function which is maximized in state space modeling, q is the number of diffuse initial value in the state and w is the total number disturbance variances estimated in the analysis.

$$RMSE = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(e_i^2)} \quad (2.13)$$

Where t is the number of forecast and e is the error.

When comparing different models using AIC and RMSE the smaller values denote better fitting models than larger ones.

3. Results and Discussions

Figure 1 is the time plot of the monthly interest rate data for the period of 2005-2015.

The Figure 1 shows that the series is not stationary. It can also be observed that there is a sudden downward jump in the series after point 60 (January 2010). This suggests that there could be an intervention at that point. To substantiate this claim, we proceed with modelling of the pre-intervention series section.

Time Plot of the pre-intervention series (2005-2010) is shown in Figure 2.

Figure 2 showed evidence of trend suggesting that the data are non-stationary. It is therefore necessary to difference the series.

Plot of the differenced series centers around zero as no particular trend is identifiable.

The decision to consider only the first difference of the series is based on the descriptive statistics in Table 2.

Comparing the descriptive statistics for various orders of differencing, we can observe that the first difference has the least standard deviation than other differences. We therefore conclude that stationarity was achieved at first difference.

To identify an ARIMA (p, d, q) process for the interest rate data, we examine the ACF and PACF plots as shown in figures 4 and 5 respectively.

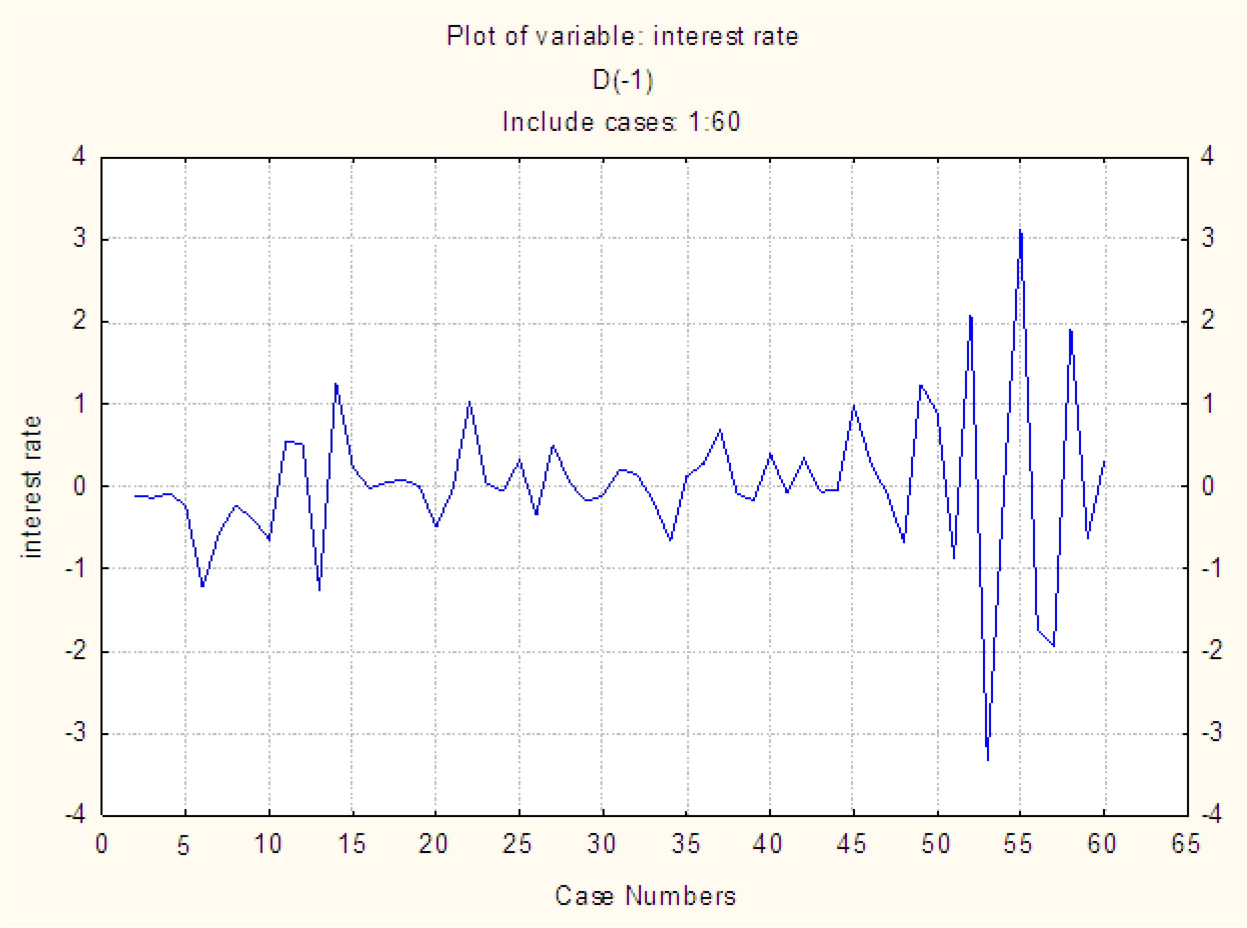

Figure 3. Plot of the first difference of the pre-intervention series

Table 2. Descriptive statistics showing different degrees of differencing the interest rate data, its corresponding means and standard deviations

	Mean	Std. Dv.	Min.	Max.	First-Case	Last-Case	N
Interest rate	10.7813	1.5313	7.8800	15.0100	1.0000	60.0000	60.0000
Interest rate: D(1)	0.0180	0.9310	-3.3300	3.1200	2.0000	60.0000	59.0000
Interest rate: D(2)	0.0072	1.5342	-5.4200	3.8700	3.0000	60.0000	58.0000
Interest rate: D(3)	0.0167	2.6801	-8.3700	8.7600	4.0000	60.0000	57.0000

Suggesting first order differencing (D=1)

Were D(1), D(2) and D(3) represents first order differencing, second order differencing and third order differencing respectively.

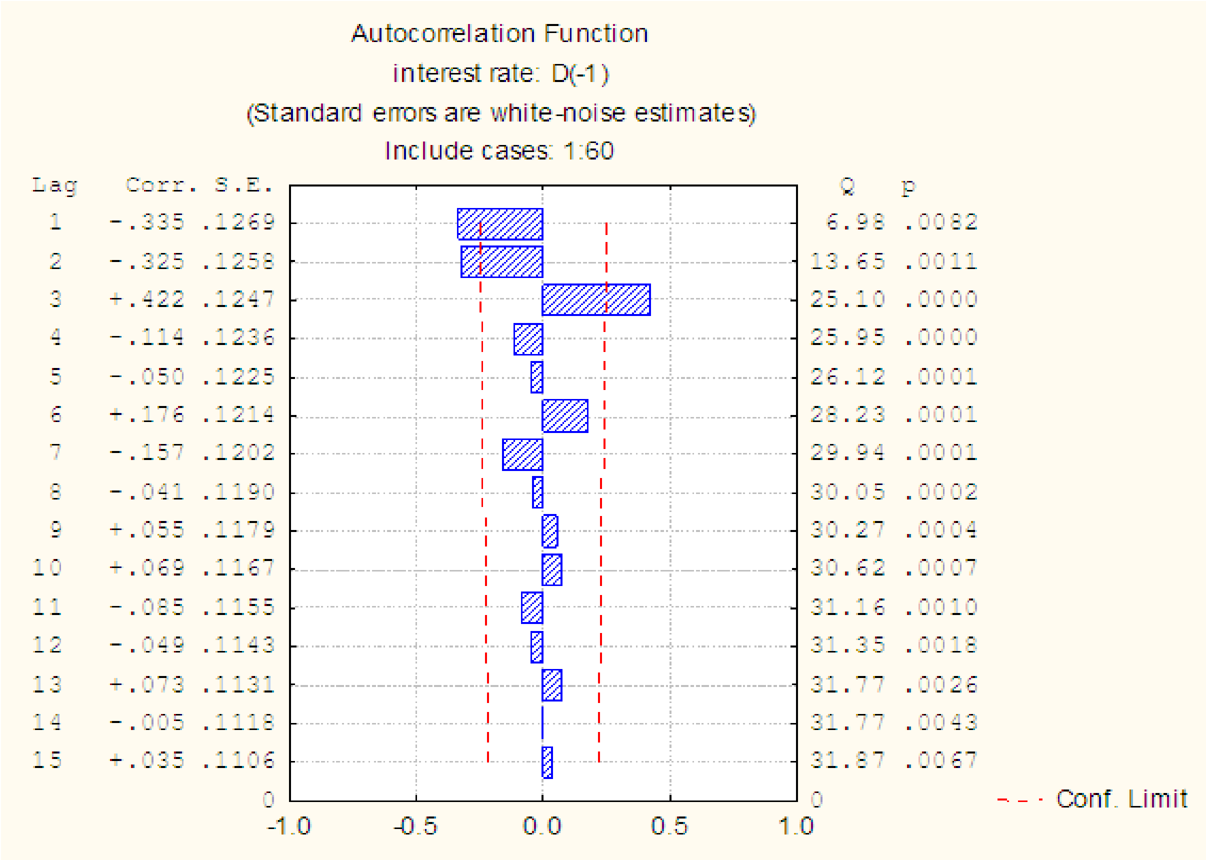

Figure 4. ACF plot of the first difference of the pre-intervention series

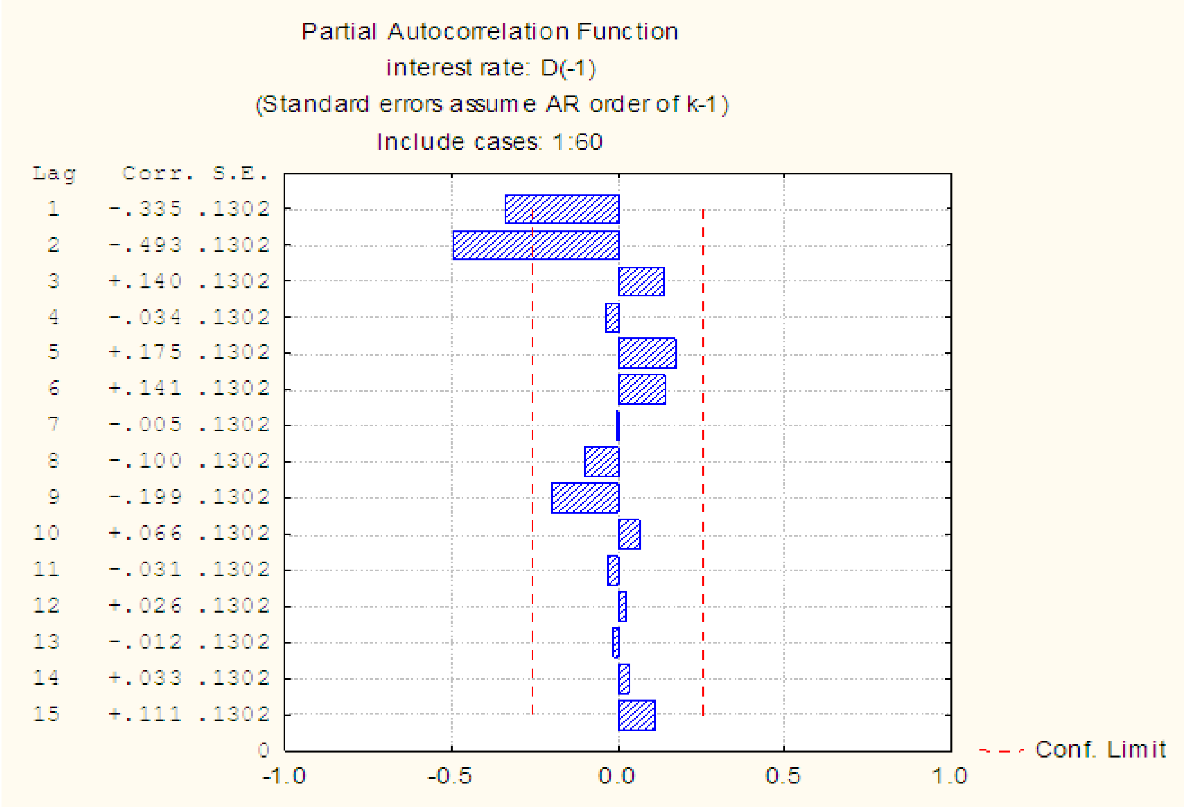

Figure 5. PACF plot of the first difference of the pre-intervention series

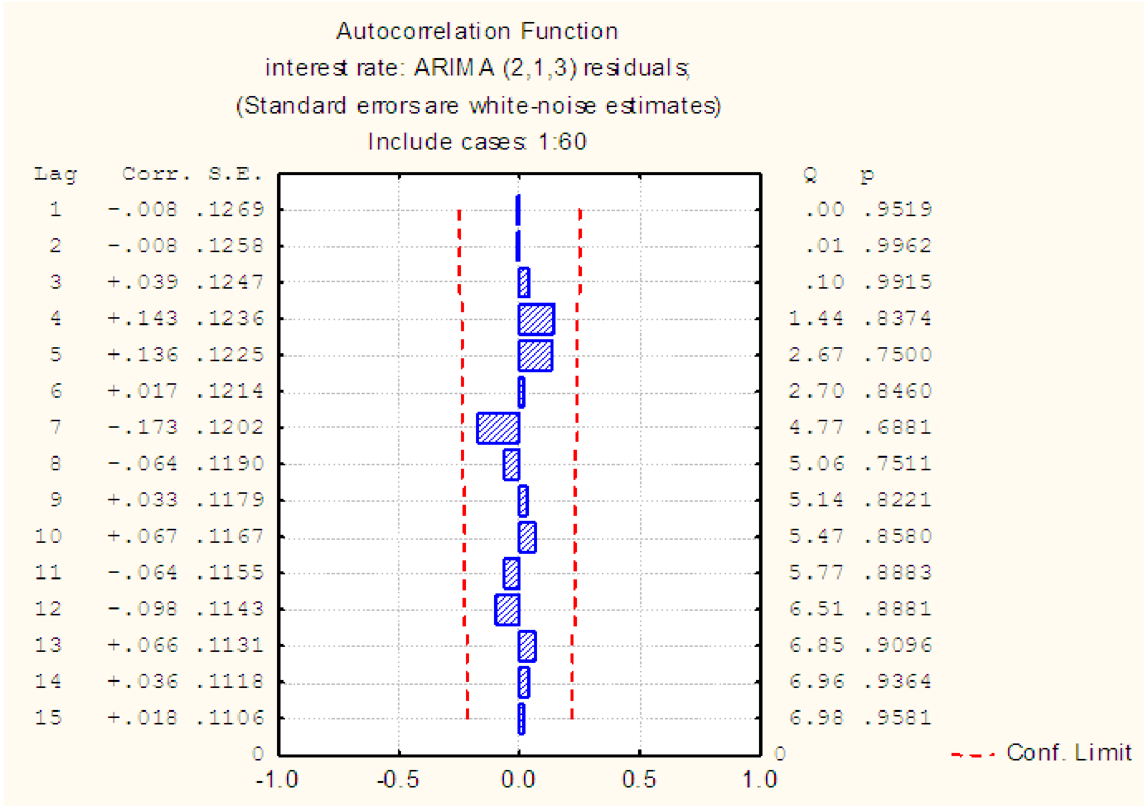

Figure 6. ACF plot of the pre-intervention residual series

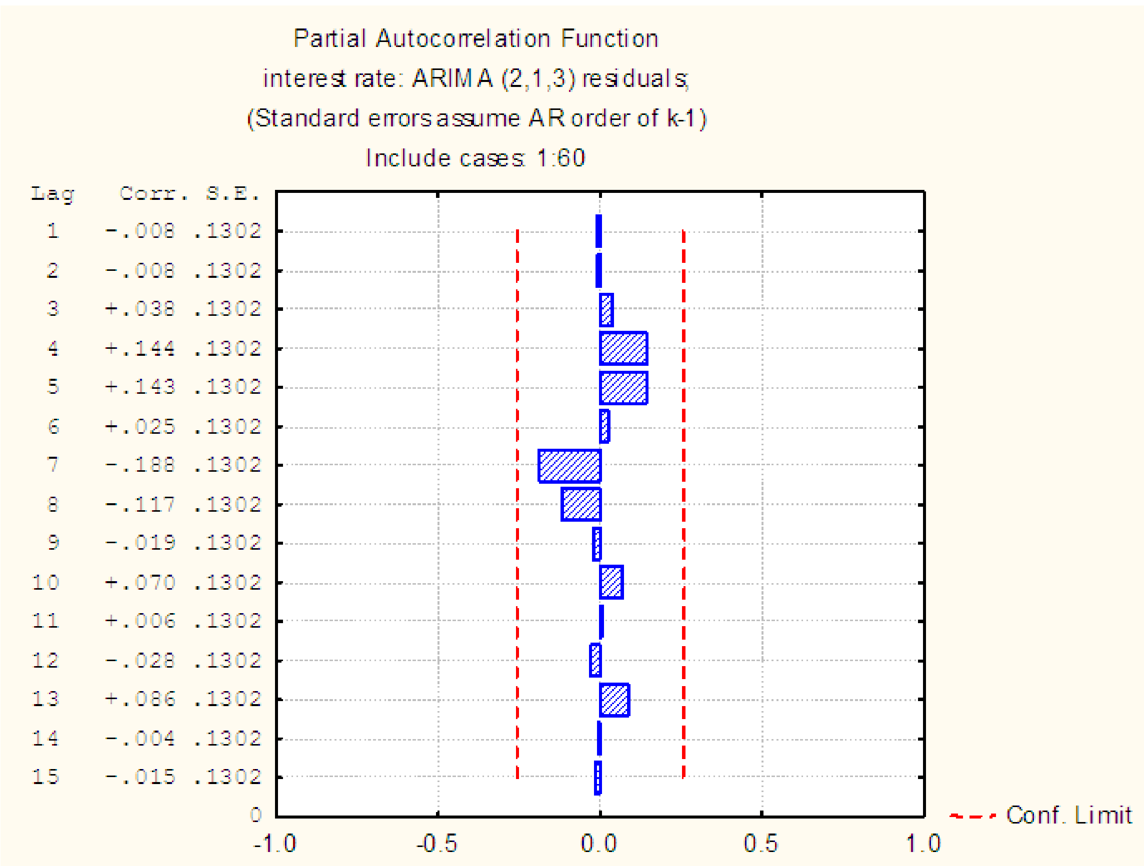

Figure 7. PACF Plot of the pre-intervention residual series

Table 3. The Estimates of the parameters of Intervention Model

	Param.	Asympt.-Std.Err.	Asympt-t(125)	p	Lower-95% Conf.	Upper-95% Conf.	Interv.-Case No.	Interv.-Type
P(1)	0.2707	0.1850	1.4633	0.1459	-0.0954	0.6369		
P(2)	0.0085	0.1831	0.0465	0.9630	-0.3539	0.3709		
q(1)	0.3571	0.1604	2.2267	0.0278	0.0397	0.6745		
q(2)	0.0686	0.1623	0.4229	0.6731	-0.2525	0.3898		
q(3)	-0.5262	0.0734	-7.1704	0.0000	-0.6714	-0.3809		
ω(1)	2.3385	0.6456	3.6223	0.0004	1.0608	3.6162	60.0000	Abr/Perm.

Where P(1) and P(2) are the first and second Autoregressive orders respectively and q(1), q(2) and q(3) are the first, second and third Moving Average orders respectively.

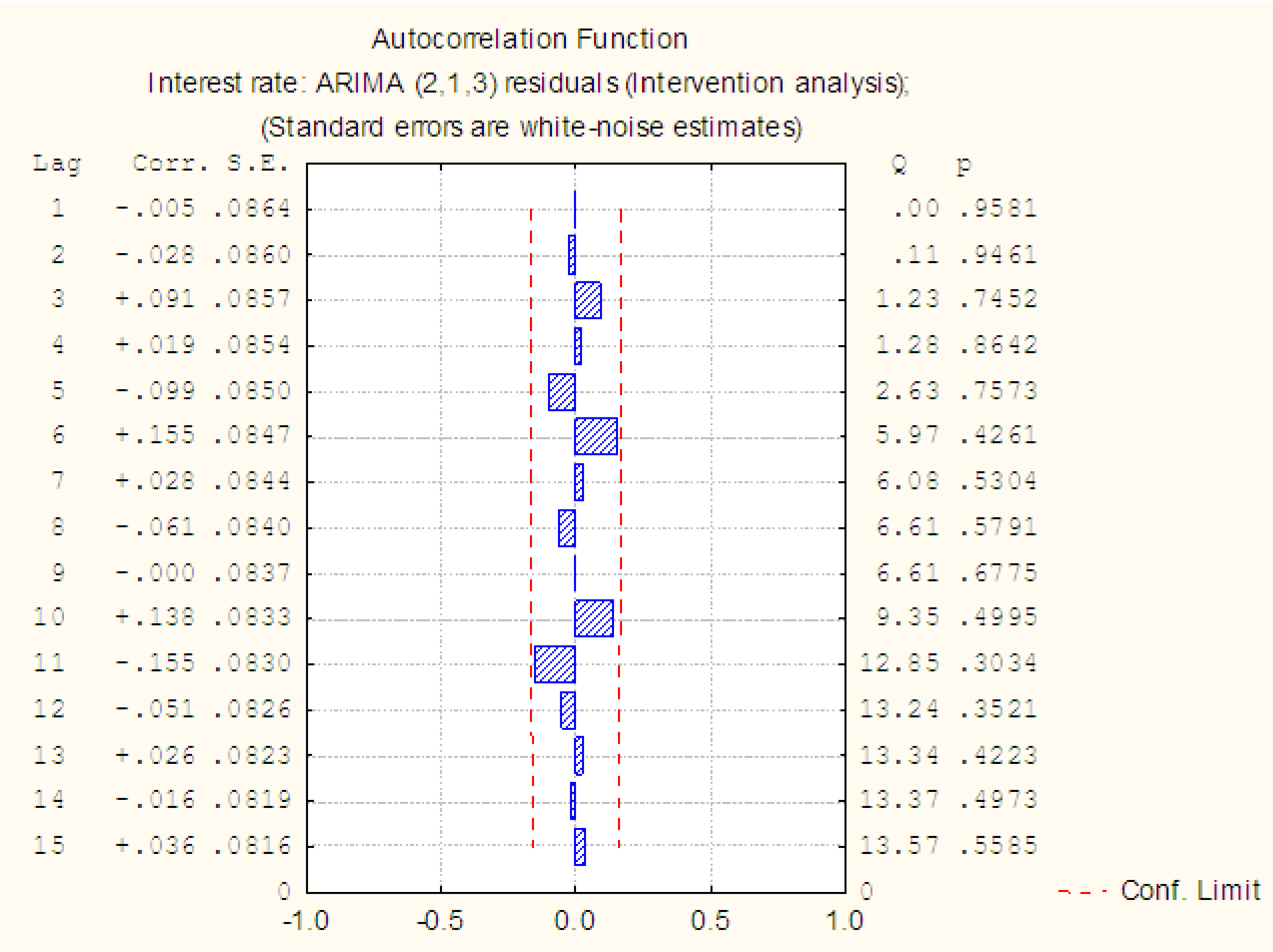

Figure 8. ACF Plot of the intervention residual

The ACF plot has a cut-off after lag 3 while the PACF plot has a significant cut off after lag 2. Hence, ARIMA (2, 1, 3) model is tentatively fit to the data.

Figure 6 and Figure 7 show no cut off indicating that the residual series is white noise.

The ACF and PACF of the residuals associated with the fitted model are shown in Figures 6 and 7 respectively.

The ARIMA (2, 1, 3) model of the pre-intervention interest rate series is now used to carry out the intervention analysis. The results of the estimated parameters, omega value and so on are displayed in Table 3

The Table 3 shows that the intervention is significant as the p-value of omega (0.0004) is less than the level of significance (α = 0.05). Hence, the intervention has an Abrumpt/Permanent change or effect to the interest rate data. Hence, the Intervention ARIMA (2, 1, 3) model is

$$y_t = x_{t-1} + 0.2707x_{t-1} - 0.2622x_{t-2} - 0.0085x_{t-3}$$
$$-0.3571e_{t-1} - 0.0686e_{t-2} + 0.5262e_{t-3} + 0.0004I_t + e_t \quad (3.1)$$

Figures 8 and 9 show ACF and PACF plots of the intervention residual respectively.

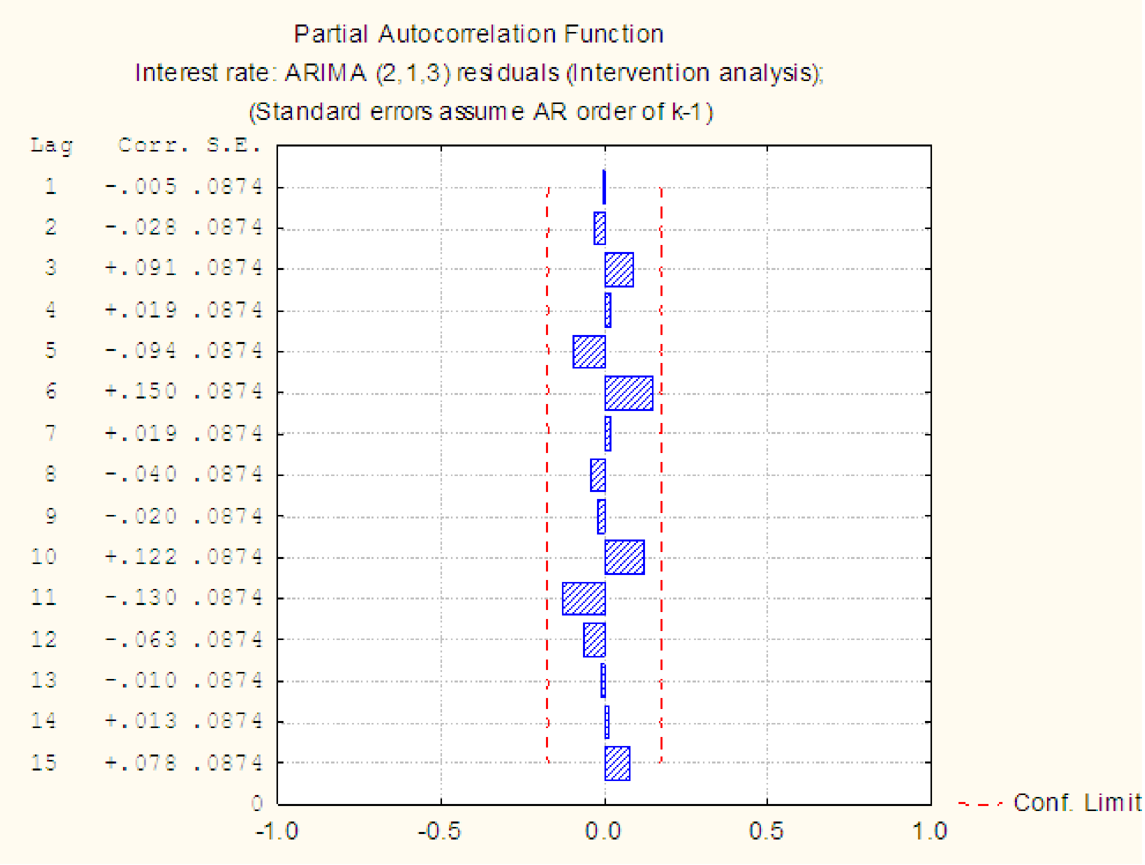

Figure 9. PACF Plot of the intervention residual

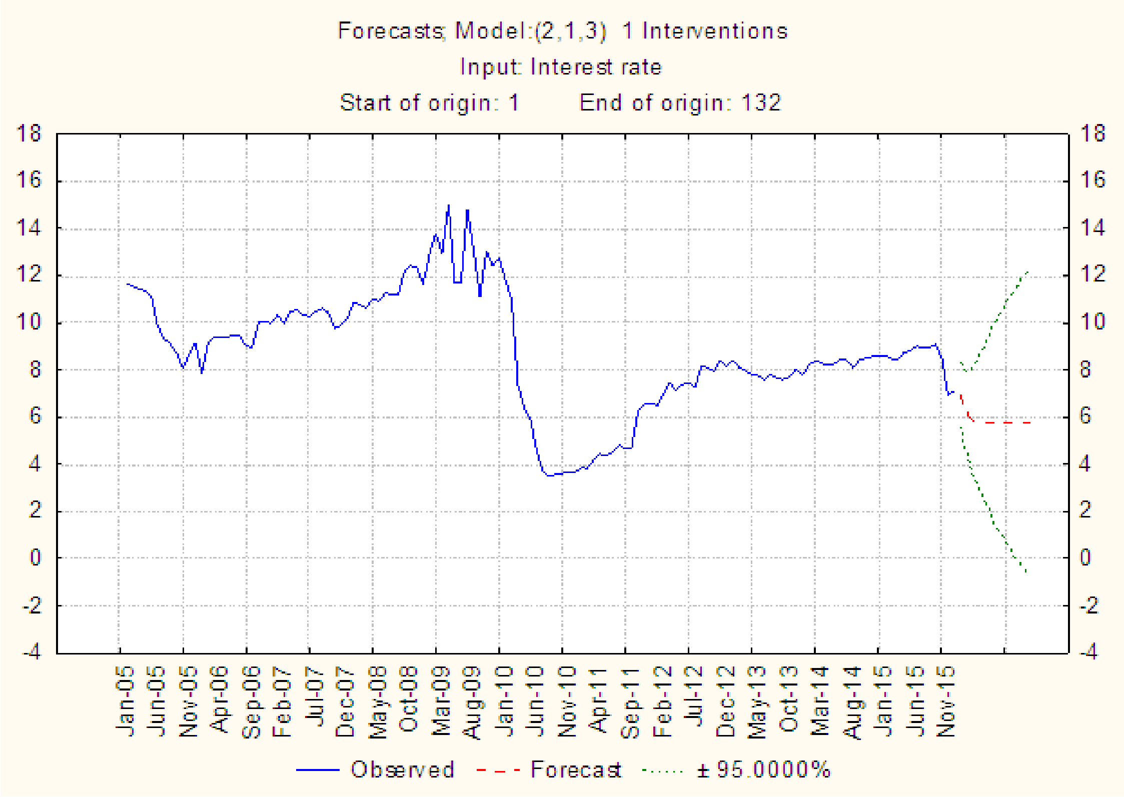

Figure 10. Time Plot of the interest rate series (2005-2015) and its forecast (2016)

Table 4. Parameters Estimates of the ARIMA (2, 1, 3) Model (without intervention)

	Param.	Asympt.-Std.Err.	Asympt-t(126)	p	Lower-95% Conf.	Upper-95% Conf.
P(1)	0.3096	0.1893	1.6354	0.1045	-0.0650	0.6842
P(2)	-1.1355	0.2477	-0.5470	0.5854	-0.6257	0.3547
q(1)	0.4284	0.1682	2.5477	0.0120	0.0956	0.7613
q(2)	-0.0931	0.2391	-0.3893	0.6977	-0.5663	0.3801
q(3)	-0.3999	0.0854	-4.6803	0.0000	-0.5689	-0.2308

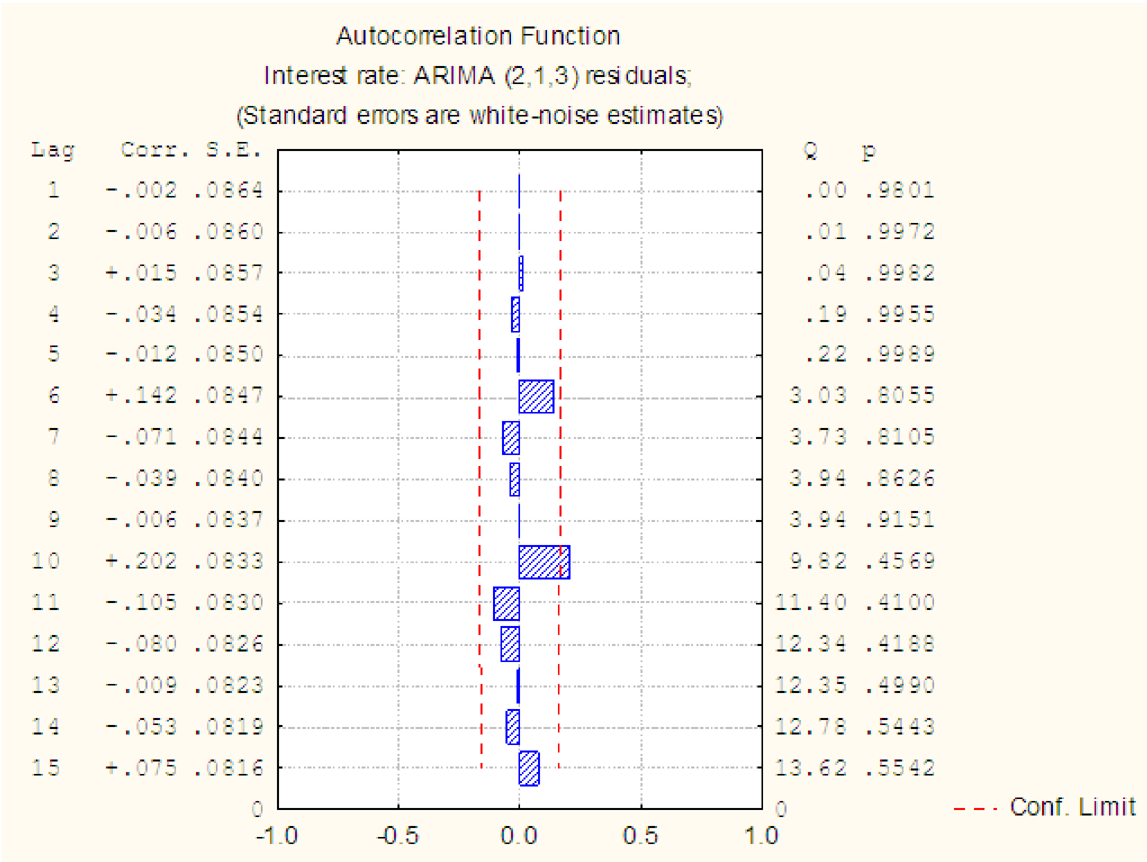

Figure 11. ACF Plot of the residual (without intervention)

The ACF and PACF plots of the intervention residual analysis as shown in Figures 8 and 9 confirm that the model is adequate as there is no significant cut-off at any point in both plots. Based on the fitted ARIMA model, the researcher made a one year forecast.

The graph of the interest rate values and its forecasted values is shown in Figure10.

Analysing the interest rate series without considering the intervention effect, the estimates of the parameters of the tentative ARIMA (2, 1, 3) process in table 4 are obtained.

Figures 11 and 12 show the ACF and PACF plots of the residual series without intervention.

State Space Model Analysis

The State Space analysis and residual diagnosis of the interest rate data was done using the filtered State and its residual respectively.

Estimates of parameters of the Local Level models (at all levels) were estimated by **R** using Mximum Likelihood estimation method and are given as:

Current estimate of the states (a) is 7.109642, the coefficient of $\mathbf{u}_t$ is 1, log-likelihood function ($logl_d$) is 0.5262395, the transition or state variance (σ^2_e) is 0.4720813, the observation variance (σ^2_ε) is 0.06037131, the initial level of the states ($\mathbf{u}_t$) is 11.67 and the initial state estimate of $\mathbf{u}_1$ is 11.200669.

Hence, the resulting equation for the State Space Model (local level) at level t = 1 becomes

$$\mu_{t+1} = 11.2007 + e_t$$

$$y_t = 11.2007 + \varepsilon_t \qquad (3.2)$$

Where the first equation of (3.2) is the state equation at level t = 1 and the second is the observation equation at the same level t = 1.

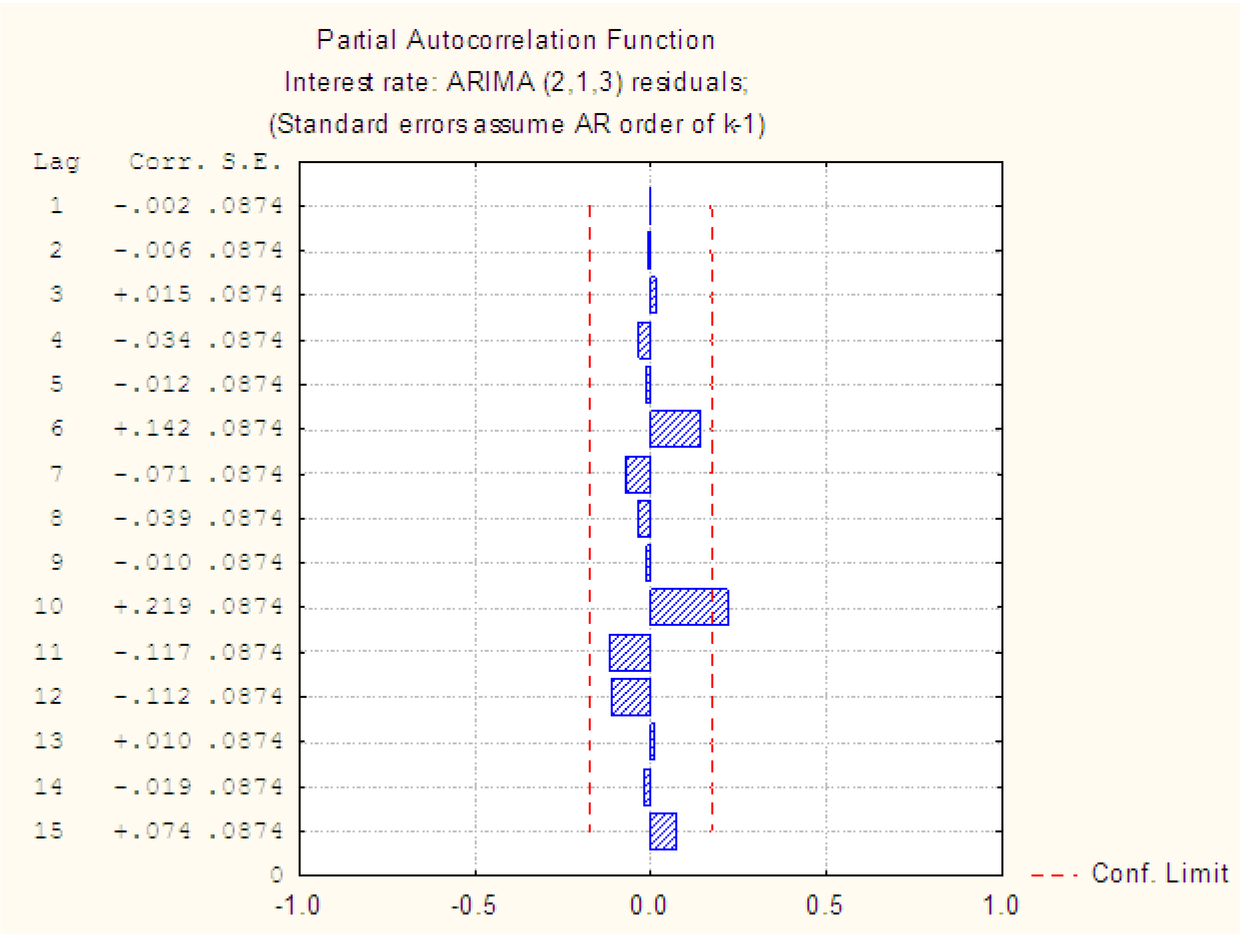

Figure 12. PACF Plot of the residual (without intervention)

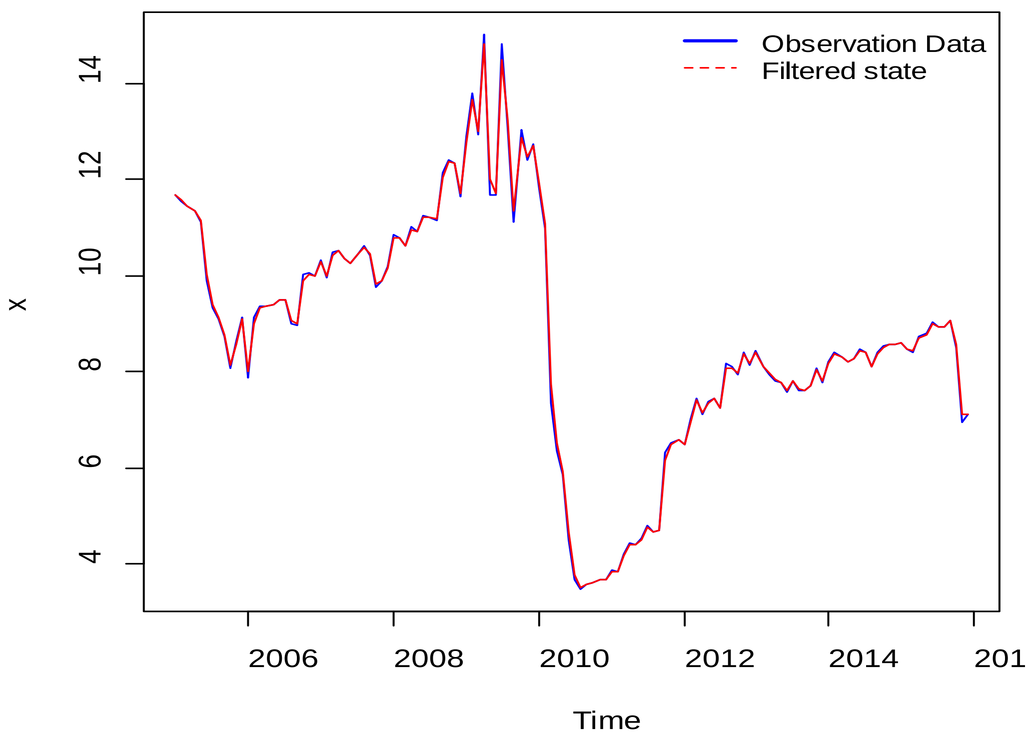

Figure 13. Plot of the Observed Data and Filtered State

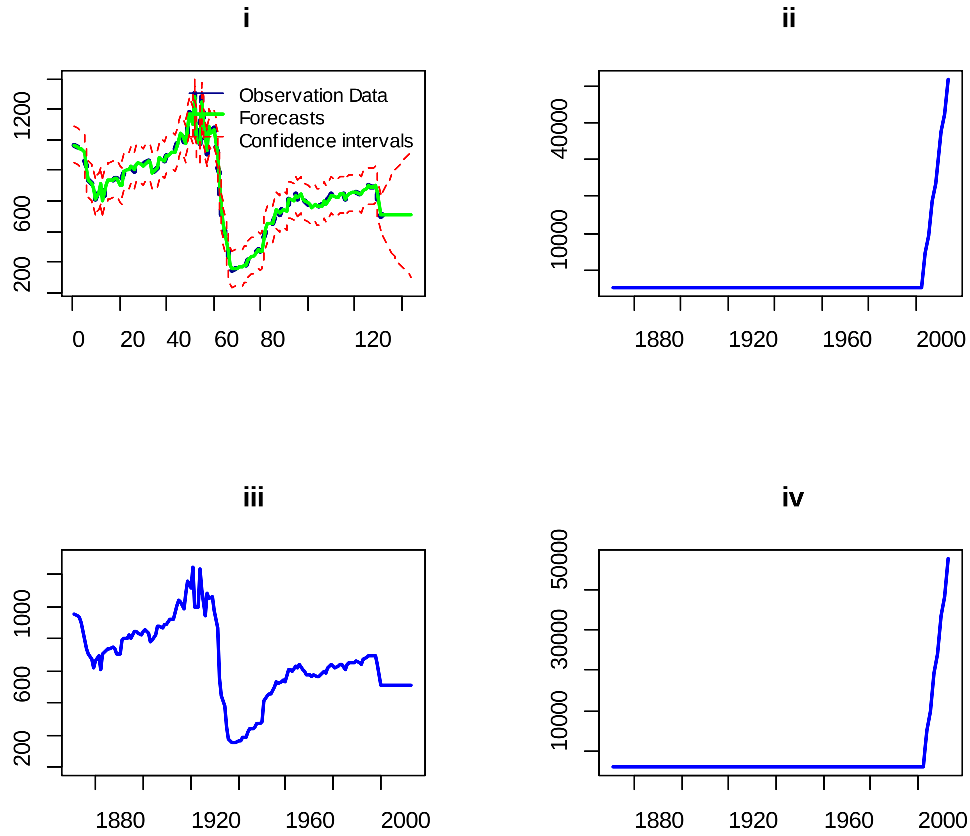

Figure 14. Plots of filtered States, its variance and Observation series, its variance

Stationarity Test on the Smoothed filtered States

stationarity Test using the Augumented Dickey Fuller test statistic = -2.68512, p-value = 0.02916 at 5% level of significant.

The Augumented Dicker-Fuller test shows that the filtered state is stationary as the corresponding p-value (0.02916) is less than the level of significant (0.05). This implies that there is no unit root at 95% level of confidence. Hence, the fitted State is stationary.

Figure 13 shows the plot of the observed data with its filtered state.

This (Figure 13) shows that the filtered state fits in very well to the actual data, meaning that there is no much difference between the observation and the filtered states.

Figure 14 shows the filtered state, its variance and the observation series and its variance.

Where Fig.14 (i) is filtered state a_t and its confidence intervals, Fig.14 (ii) is filtered state variance P_t, Fig.14 (iii) observation forecast errors $V_{t,}$ and Fig.14 (iv) observation forecast variance F_t. The most obvious feature of the four graphs is that P_t and F_t converge rapidly to constant value which confirms that the local level model has a steady state solution.

Comparison of the Estimated Intervention ARIMA (2, 1, 3), ARIMA (2, 1, 3) and the Local Level State Space Models.

From table 5, Akaike Information Criterion (AIC) for the State Space Model provides lower value as compared to the Intervention ARIMA (2, 1, 3) model and Intervention ARIMA (2, 1, 3) model provides lower value as compared to the ARIMA (2, 1, 3) model. The Root Mean Square Error (RMSE) also confirms the results (AIC). Further goodness of fit statistics, viz. Comparing the forecasted 2015 values on the basis of the identified models with the actual observations for assessing accuracy of the fitted models indicates that the State Space Model yields forecast values that are more closer to the actual value than that of ARIMA (2, 1, 3) and Intervention ARIMA (2, 1, 3) forecast values respectively.

Table 5. Goodness of fit statistics

Statistics	Model		
	ARIMA (2, 1, 3)	Intervention ARIMA (2, 1, 3)	State Space Model
AIC	285.11	281.79	-1.01
RMSE	1.53	1.16	0.01

ARIMA (2, 1, 3) models (with and without intervention) were also compared separately using their respective plots of ACF and PACF, and it is observed that the ACF and PACF of the residual analysis (without intervention) as shown in Figures 11 and 12 has a significant cut off at lag 10 of both plots. While the ACF and PACF of the residual intervention analysis as shown in Figures 8 and 9 shows that the intervention ARIMA (2, 1, 3) model is a better model than ARIMA (2, 1, 3) as there is no significant cut-off at any point in the both plots. Hence, there is need to test for the effect of intervention in any series that appears to have intervention. This must be done in order to get a dependable model that can be used for reliable forecast.

Thus, for the data set (interest rate in Nigeria) under consideration, State Space Modelling technique performs better than the Intervention ARIMA approach while the Intervention ARIMA approach performs better than ARIMA approach.

Finally, one year (2016) monthly forecast of the interest rate data using local level state space model was done.

4. Summary/Conclusions

Time series analysis of interest rate data (of Commercial Banks on Time Deposits in Nigeria) from the period of (2005-2015) was carried out in this study. A sudden downward jump in the series after point 60 (January 2010) was observed. This suspected to have been cursed by the Central Bank of Nigeria through their former governor Lamido Sanusi who said in January, 2010 that Nigeria will keep interest rate low so as to boost the economy even as the inflation outlook becomes more uncertain because of rising government spending. Intervention ARIMA (2, 1, 3) and ARIMA (2, 1, 3) models were estimated with the aid of *STATISTICA software* and it was confirmed that the intervention has an abrupt, permanent change to the interest rate data. State Space (local level) model was also estimated with the aid of *R software*. Comparison between the estimated ARIMA (2, 1, 3), intervention ARIMA (2, 1, 3) and state space models were made and the result confirmed state space model to be more adequate. Thus, for the data set (interest rate in Nigeria) under consideration, State Space Modelling technique performs better than the ARIMA approaches.

5. Recommendations

The researchers therefore recommend that the interest rate trend should often be properly monitored to know its level at any given time since it is a nebulous concept. Researchers should always go into modelling of interest rate data so as to monitor and control the effects that sudden changes in interest rate could cost to our economy. We also encourage researchers to go into State Space Modelling technique as it has been confirmed more adequate than ARIMA techniques in analysing especially time-series data (interest rate in Nigeria). Finally, we recommend that government (through CBN) should always amend our monetary policies or implement new ones that will always monitor the level of interest rate in Nigeria and set it in the way it will always favour the current economic situation of Nigeria at any given time.

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