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ETS - ARIMA Intervention Modelling of Bangladesh Taka/Nigerian Naira Exchange Rates

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Abstract: In real-world scenarios, numerous external events disrupt many time series, causing fluctuations in the series' mean level. When modeling such series using the traditional ARIMA model, this can result in distortions in the model's parameter estimations, the structure of the fitted model, and future value projections. Any unusual values in the series that might have arisen as a result of the special event could be adjusted using the Box-Tiao intervention modeling technique. This study investigates time series intervention modelling based on ETS and ARIMA models aimed at studying the response of the comparative value of the Bangladesh Taka to the Nigerian Naira due to the 2016 economic recession. The dataset for this study is the daily exchange rate of Bangladesh Taka to Nigerian Naira from January to December 2016. The BDT/NGN2016 exchange rates have been considered, with a step intervention being the introduction of the economic recession in June 2016. Results revealed an initial impact of 0.5217. The intervention caused a 68.49% depreciation in the value of the Naira exchanged with the Bangladesh Taka in the exchange rate market, with a decay rate of 0.6. The intervention effect was persistent, with a long-run effect of 1.2862. Hence, the intervention had a gradual start and a permanent effect.

Keywords: ETS Model, ARIMA, Intervention Modelling, Bangladesh Taka/Nigerian Naira

1. Introduction

Time series models have advantages over other statistical models in certain situations. They can be easily used for forecasting purposes because historical sequence of observations is readily available from published secondary sources and these successive observations are statistically dependent. Thus, time series modelling is concerned with techniques for analyzing such dependencies. In many situations, collection of information on explanatory variables affecting the study variables may be impossible and hence availability of long series data on explanatory variables a problematic. In such situations, the time series models are a boon for forecasters. In time series modelling, decomposition models are among the oldest approaches to time series analysis.

Albeit, a number of theoretical weaknesses from a statistical point of view. These were followed by the crudest form of forecasting methods called the moving averages method. As an improvement over this method which had equal weights, the exponential smoothing methods came into being which gave more weights to recent observation (Holt [20], Brown [7], Winters [36], Makridakis *et al* [27]). Later, they were found to be particular cases of the statistically sound models by Box-Jenkins [3-5], the Autoregressive Integrated Moving Averages (ARIMA) models used in modelling and forecasting. In practice, many time series are being interrupted by lots of external events which leads to change in the mean level of the series and modelling such series is problematic. Thus, requires an appropriate technique. However, the forecasting ability of the ARIMA model may be influenced when the patterns of the time series under study are affected by an external occurrence known as "intervention," such as the implementation of new policies, strikes, global epidemics, economic downturns, etc. Nevertheless, by using an appropriate approach devised by Box and Tiao [6], the Intervention model, this can be improved.

Over the years, intervention modeling has traditionally depended primarily on ARIMA models. Like in the case of Deutsch and Alt [9], who examined the Effect of Massachusetts' Gun Control Law on Gun – related Crimes in the City of Boston. Sharma and Khare [33], used intervention analysis model to study the impact of the intervention introduced by the Indian Government to control the pollution caused by the vehicular exhaust emissions. Girard [19], applied the ARIMA model with intervention in order to analyze the epidemiological situation of whooping – cough in England and Wales for the period of 1940 – 1990. Nelson [31], uses an ARIMA intervention analysis to estimate the impact of the Bankruptcy Act of 1978. Lai and Lu [25], uses intervention model to look at the impact of the September 11, 2001 terrorist attack on air transport passenger demand in the USA. Min [28], applied intervention analysis to assess whether two events, the 9 – 21 Earthquake in 1999 and the Severe Acute Respiratory Syndrome (SASS) outbreak in 2003, had a temporary or long – term impact on the inbound tourism demand from Japan. Lam *et al* [26], used a time series intervention ARIMA model to measure the intervention effects and the asymptotic change in the simulation results of the business process reengineering that is based on the activity model analysis. Jarrett and Kyper [24], examined the impact of world financial crisis (WFC) on the Chinee Stock Price. Darkwah et al [8], uses intervention time series analysis to assess the nature and impact of the establishment and operations of community policing in communities in Ghana. Mrinmoy *et al* [30], assessed the impact of Bt – Cotton variety on Cotton Yield in Indian. With step intervention, being the introduction of Bt – Cotton variety in 2002.

Yang [37], used ARIMA with intervention model analyzed the impact of new product releases on revenue. Etuk and Amadi [10], analyzed the effect of the exit of Great Britain from European Union on GBP/USD exchange rate. Etuk and Eleki [12], modelled the daily Yuan – Naira Exchange Rates using ARIMA intervention analysis. Etuk *et al* [14], use the intervention analysis approach on the daily exchange rate of Yen/Naira. Etuk and Udoudo [18], uses intervention model to explain the impact of economic recession on the daily Indian Rupee and Nigerian Naira exchange rate. Etuk and Ntagu [17], examined modelling of the intervention of daily Swiss Franc (CHF) and Nigerian Naira (NGN) exchange rates, which spanned 18th May 2016 to 16th November 2016. Etuk and Chukwukelo [11], modelled daily Moroccan Dirham (MAD) and Nigerian Naira (NGN) using intervention analysis. Shittu and Inyang [34], modelled Nigerian monthly crude oil prices using ARIMA-Intervention model with a view to comparing the result with that of the intervention model using lag operator. Etuk and George [13], proposed an intervention model for the exchange rate of Malaysian Ringitt (MYR) and the Liberian Dollar (LRD). Etuk *et al* [16], fitted an autoregressive integrated moving average intervention model to daily Brazilian Real (BRL)/Nigerian Naira (NGN) exchange rates. Etuk *et al* [15], investigated the impact of declaration of cooperation (DoC) on the Nigerian crude oil production. Moffat and Inyang [29], investigated the impact of the Nigerian government amnesty programme (GAP) on her crude oil production. Inyang *et al* [22], studied the effect of global oil politics on the Nigerian oil price using the Box – Tiao approach. Results revealed that the December 2016 intervention by the Organization of Petroleum Exporting Countries had a significant and abrupt impact on the Nigerian oil price after its introduction, with an associated increment of 33.72%.

Intervention modelling combined with the exponential smoothing methods has rarely been attempted. Thus far, Inyang *et al* [21], studied Time Series Intervention Modelling Based on ESM and ARIMA Models: Daily Pakistan Rupee/Nigerian Naira Exchange Rate. Jaganathan [23], used ARIMA Linear Transfer Function and Exponential Smoothing (ES) with intervention models to model pandemic data in the context of forecasting demand to explain its impact and build accurate predictive models. Seong and Lee [32], proposed a method of intervention analysis based on exponential smoothing models through an innovational state – space model. Two applications were analyzed: the 9/11 effect on US airlines and the COVID – 19 effects on the current population of Seoul, Korea. Trapero *et al* [35], investigated the accuracy of judgmental forecasting at SKU level in the presence of promotions, based on weekly data from a manufacturing company using simple model based on a transfer function combined with Single Exponential Smoothing (SES).

This study considered intervention modelling with ARIMA models as been overused, therefore extend intervention modelling with ETS models aimed at examining the response of the comparative value of Bangladesh Taka to Nigerian Naira in face of 2016 economic recessions.

2. Data Presentation and Methodology

2.1. Data Description

The data used in this study are the daily Bangladesh Taka/Nigerian Naira (BDT/NGN) exchange rates spanning from January - December 2016, were obtained from the central Bank of Nigeria Website. The dataset was divided into observations belonging to pre-intervention (Jan. 1 – June 20, 2020) and post-intervention periods (June 21 – Dec., 2020). The statistical package used for the analysis of this work is the R language (R-4.1.2-win & R-4.1.3-win).

2.2. Model Specification

The Box-Jenkins ARIMA model has been known as the most widely used technique for modelling and forecasting [3-5], denoted by ARIMA (p,d,q). But when the time series is affected by external events, the forecasting power of ARIMA model may fail. Thus, Box-Tiao [6], proposed the ARIMA-Intervention analysis given by

$$X_t = V(L) + W_t \quad (1)$$

Where $V(L)$ is the transfer function component and W_t is noise component

2.2.1. Intervention Model with ARIMA

$$X_t = \frac{\omega(L)L^b}{\delta(L)} I_t + \frac{B(L)}{A(L)} \epsilon_t \quad (2)$$

Since $V(L) = \frac{\omega(L)L^b}{\delta(L)} I_t$ and $W_t = \frac{B(L)}{A(L)} \epsilon_t$

Where:

$A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_p L^p$ and $B(L) = 1 + \beta_1 L + \beta_2 L^2 + \cdots + \beta_q L^q$

$\delta(B) = 1 - \delta_1 L - \cdots - \delta_r L^r$ and $\omega(L) = \omega_0 - \omega_1 L - \cdots - \omega_s L^s$

X_t is the BDT/NGN exchange rates at time t, b =delay parameter, ω =impact parameter, δ =slope parameter, $\alpha =$ Non-seasonal autoregressive parameter, $\beta =$Non-seasonal moving average parameter, $\epsilon_t =$White noise.

W_t is a Box – Jenkins ARIMA(p,d,q) model which represents the baseline daily

Bangladesh Taka /Nigerian exchange rate in pre – intervention period.

$I_t = S^T{}_t$, the indicator variable. Mathematically, they are written as

$$S^T{}_t = \begin{cases} 1, t \geq T \\ 0, t < T \end{cases} \quad (3)$$

$S^T{}_t$ is called the step function.

Hence, (2) becomes

$$X_t = \frac{\omega(L)}{\delta(L)} S^T{}_{t-b} + \frac{B(L)}{A(L)} \epsilon_t \quad (4)$$

2.2.2. Intervention Model with ETS

The underlying model is given by

$$Y_t = \frac{\omega(L)}{\delta(L)} S^T{}_{t-b} + ETS(M, N, N) \quad (5)$$

The form in (5) is similar to the intervention model with ARIMA models in (2). And with a persistent change of intervention effect with ETS with multiplicative error, no trend, no seasonal component.

2.2.3. Intervention Effect

The impact of an intervention is numerically assessed by two values: the initial impact given by ω_0 and then, the long run term effect, given by

$$\frac{\omega(1)}{\delta(1)} = \frac{\omega}{1-\delta} \quad (6)$$

Then, the percentage change is given by

$$[1 - Exp(\omega)] \times 100\% \quad (7)$$

Where ω is the impact parameter and δ the growth rate.

2.2.4. Unit Root Test

As a prerequisite for any further analysis in time series modeling, it is pertinent to formally diagnose the characteristics of the series that are used in the study.

The Augmented Dickey-Fuller (ADF) test is based on the regression equation

$$X_t = \phi X_{t-1} + \sum_{j=1}^{p-1} X_j \Delta X_{t-j} + \epsilon_t \quad (8)$$

Where X_t is the series being tested and p is the number of lagged differenced terms included to capture any autocorrelation.

Hypothesis:

$H_0: \beta = 0$ (series contains a unit root)

Against

$$H_1: \beta \neq 0$$

Test statistics are:

$$T_\rho = \frac{\hat{\phi}-1}{S.E(\hat{\phi})} \sim t_\propto(n) \quad (9)$$

If the null hypothesis is rejected, we conclude that the series contains no unit root.

2.2.5. Model Validation

Diagnostic test is an important step in time series model building and this consist of scrutinizing a variety of diagnostics to determine whether the selected model is healthy and hence ready to forecast. We consider here;

(i). Plot of the Residual ACF

Once an appropriate ARIMA model is fitted, one can examine the goodness of fit by means of plotting the ACF of the residuals of the fitted model. If most of the sample autocorrelations coefficients of the residuals are within the bound of $\pm \frac{2}{\sqrt{T}}$, where T is the series length then the residuals are white noise indicating that the model is a good fit.

(ii). Akaike Information Criterion (AIC)

The AIC [1], is formulated as

$$\text{AIC} = M_T \left[1 + \frac{2P}{T-P}\right] \quad (10)$$

Where:

$M_T =$ Index related to production error (known as residual sum of squares)

$p =$ No of parameters in the model, T= No. of data points.

(iii). Bayesian Information Criterion (BIC)

The BIC is a criterion for model selection among a finite set of models. Given any two or more estimated models, the model with the lowest value BIC is the one to be preferred. It is given by:

$$\text{BIC} = n ln \hat{\sigma}_e^2 + k ln(n) \quad (11)$$

Where $\hat{\sigma}_e^2$ is the estimated error variance defined by

$$\hat{\sigma}_e^2 = \frac{1}{T} \sum_i^T (x_i - \bar{x})^2$$

$x =$ Observed data, $T =$Number of observations, $k =$ Number of free parameters to be estimated.

(iv). Ljung Box Test

The Ljung Box Test is a way to test for the absence of serial autocorrelation, up to lag k.

To run the Ljung Box test, you must calculate the statistic Q. Given a series X_t of length ς:

$$Q(m) = \varsigma(\varsigma + 2) \sum_{j=1}^{\aleph} \frac{r_j^2}{\varsigma - j} \tag{12}$$

Where: r_j = accumulated sample autocorrelations, $\aleph$ = the time lag.

Hypothesis:

H_0: (residuals do not show any autocorrelation)

Against

H_1: (H_0 is false)

2.2.6. Measuring Forecast Error

The forecasting errors represented by MAE and RMSE, which are Mean Absolute Error and Root Mean Squared Error respectively, are chosen as the performance metric.

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |e_t| \tag{13}$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} e^2{}_t} \tag{14}$$

Where e_t is residual at time t and T is the total number of the time period. If a method fits the past time series data very good, MAE is near zero, whereas if a method fits the past time series data poorly, MAE is large. Therefore, when two or more forecasting methods are compared, the one with the minimum MAE is selected as most accurate. RMSE is the square root of MSE.

3. Results Presentation and Discussions

3.1. Time Plot

The time plot showing the daily Bangladesh Taka to Nigerian Naira exchange rate from January to December 2016 is given in Figure A1 in Appendix I. The graph of the series shows an upward trend which was marked on Tuesday 21, June 2016 as point of intervention with value 2.5999NGN and keep increasing. From the plot, we can observe the lowest exchange rate of 2.5248NGN on Thursday 2, June 2016 while the highest exchange rate of 4.446NGN was witnessed on Monday 22, August 2016. The average exchange rate in 2016 is 3.2799NGN.

3.2. Intervention Modelling

ARIMA-intervention model in equation (4) and ETS-intervention model in equation (5) are used to model the exchange rate dataset. The suspected point where the intervention took place on the exchange rate dataset were labelled by indicator functions as:

$$S_t{}^T = \begin{cases} 1, t \geq June\ 21, 2016 \\ 0, t < June\ 21, 2016 \end{cases} \tag{15}$$

Where: T= June 21, 2016 and $S_t{}^T$ is the Step function type.

3.3. Pre–Intervention Modelling

Data on daily Bangladesh Taka to Nigerian Naira exchange rate from January 01, 2016 to June 20, 2016 is used for pre-intervention ARIMA model fitting and data during June 21, 2016 – December 31, 2016 have been used to know the intervention component form.

Pre-intervention time plot shown in Figure A2, the graph of the series exhibits the characteristics of a non-stationary (confirmed by the unit root test in Table 1). The inability of both the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the series to die out completely at high lags further confirmed that the series is not stationary, Figure A4 and A5 respectively.

Table 1. *Unit Root Test at Level (Pre-Series).*

Test	Augmented Dickey-Fuller
Data	BDT/NG2016 (Pre-Series)
Dickey-Fuller	-2.397
Lag order	5
P-value	0.4105
Alternative hypothesis	Stationary

Table 2. *Unit Root Test at First Difference (Pre-Series).*

Test	Augmented Dickey-Fuller
Data	BDT/NG2016
Dickey-Fuller	-8.3302
Lag order	5
P-value	0.01
Alternative hypothesis	Stationary

To attain stationarity, the series is differenced once. The graph of the differenced series in figure A6 indicates that the series is stationary. A unit root test at first difference further confirmed that the series is stationary, since the p-value of the Augmented Dickey-Fuller Test is less than the alpha level (that is, p-value=0.01 < 0.05), Table 2. On the basis of their correlogram in Figure A7 and A8, ARIMA(1,1,1) model is fitted with their statistics summarized in Table 3. Adequacy of ARIMA(1,1,1) model is not in doubt since virtually all its residual correlations are non-significant (i.e. the coefficients of both the ACF and PACF of the residuals are within significance bounds of ± 0.1525, Figure A9) and with the least BIC and AIC values of -1425.975 and -1435.4 respectively, Table 4. Hence, the model is statistically significant, appropriate and adequate for the dataset, Table 5.

Table 3. *Parameters of the Estimated Models (Pre-Series).*

ARIMA(p,d,q) Model		Estimate	Std. Error	z value	Prob. Value
(1,1,0)	AR1	0.381749	0.070386	-5.4237	5.839e-08 ***
(0,1,1)	MA1	-0.716511	0.076018	-9.4255	2.2e-16 ***
(1,1,1)	AR1	0.253974	0.094750	2.6805	0.007352 **

ARIMA(p,d,q) Model		Estimate	Std. Error	z value	Prob. Value
	MA1	-0.841825	0.050728	-16.5950	2.2e-16 ***
(0,1,2)	MA1	-0.614438	0.070439	-8.7230	2e-16 ***
	MA2	-0.160586	0.067632	-2.3744	0.01758 *
(2,1,0)	AR1	-0.453320	0.075021	-6.0426	1.516e-09 ***
	AR2	-0.184900	0.074791	-2.4722	0.01343 *

Table 4. *Model Evaluation (Pre-Series).*

Model	BIC	AIC
ARIMA(1,1,0)	-1404.997	-1411.28
ARIMA(0,1,1)	-1424.556	-1430.839
ARIMA(1,1,1)	-1425.975	-1435.4
ARIMA(0,1,2)	-1424.805	-1434.23
ARIMA(2,1,0)	-1405.856	-1415.281

Table 5. *Ljung-Box Test for ARIMA(1,1,1) Model (Pre-Series).*

ARIMA(1,1,1)
Q* = 5.5212, df = 8, p-value = 0.7007
Model df:2. Total lags used:10

Table 6. *Forecasts with ARIMA(1,1,1) Model.*

DATE	Actual value (POSTIS)	Forecast	|Residuals|
2016/06/21	2.5999	2.535135	0.9648
2016/06/22	3.6107	2.534585	1.0761
2016/06/23	3.6073	2.534446	1.0729
2016/06/24	3.595	2.534410	1.0606
2016/06/25	3.5946	2.534401	1.0602

3.4. ARIMA-Intervention Model

The forecasted values from ARIMA(1,1,1) model was very close to the actual value of Post-series when compared, Table 6. The forecasting is done to first five post-intervention observations in order to compute the impulse response function. From the impulse response function in Figure A10, it can be inferred that b=1 i.e., though the intervention has occurred in June 21, 2016 but its effect was felt after a delay of one period (June 22, 2016).

Table 7. *Parameter Estimation for the Full Intervention Model.*

Parameter	Estamte	Std.Error	Z-value	P-value
AR(1)	-0.227131	0.104135	-2.1811	0.02917 *
MA(1)	-0.266075	0.101034	-2.6335	0.00845 **
ω	0.521690	0.033923	15.3788	< 2e-16 ***
δ	0.594366	0.027934	21.2777	< 2e-16 ***
b	1			

Table 8. *Ljung-Box Test for the Full Intervention Models.*

ARIMA(1,1,1)-INTERVENTION
Q* = 3.8377, df = 6, p-value = 0.6986
Model df: 4., Total lags used: 10

The parameter ω with value 0.5217 was significant with p-value of 0.0000, Table 7. The positive sign of the intervention parameter indicates that there was an increment in the exchange rate. That is, the Bangladesh Taka appreciated over the Nigerian naira in the exchange rate market on Tuesday 21 June, 2016 at 1BDT=2.5999NGN compared to period before the intervention occurred.

The estimates show that the external event cause a 68.49% $[-68.49\% = \{1 - \exp(0.5217)\} \times 100\%]$ fall in the value of the Naira against Bangladesh Taka in exchange rate market.

The ARIMA-Intervention model is represented mathematically as

$$Y_t = \frac{0.5217}{1-0.5944B} S_{t-1}{}^T + \frac{(1-.2661)}{(1+0.2271B)} \varepsilon_t \tag{16}$$

The model in (16) was found to be statistically significant and adequate for the dataset when diagnosed (see the residual of fitted model in Figure A11 and Table 8). And this was confirmed by the plot of the fitted ARIMA-Intervention model with the actual values in Figure A12, since the fitted values mimic the actual values.

3.5. ETS-Intervention Model

Since no trend and no seasonality is found in the BDT/NGN-2016 series. Then, Simple Exponential Smoothing model with multiplicative error is tentatively specified. The model is labeled ETS(M,N,N), the abbreviation indicating multiplicative error, No trend and No seasonal components.

Table 9. *Estimated Parameters for* $ETS(M,N,N) + Intervention\ Type$.

Parameters	α	l	ω	δ
Estimates	0.3421	2.5355	-0.3090*	0.60
Standard Errors	0.0275	0.0991	0.0482	

The ETS(M,N,N) model with intervention component are estimated in Table 9. The smoothing constant α, controls the flexibility of the level and is estimated as $\alpha = 0.3421$, implies that the level updates. Corresponding intervention parameters are $\omega = -0.3090$ and $\delta = 0.60$ with a delay of one period after the intervention. The estimates are all significant at 5% level. The impact parameter implies a negative change, that is, the 2016 global economic recession cause a fall in the value of the Nigerian Naira in exchange with the Bangladesh Taka (1 BDT=2.5999NGN) compared to period before and after the intervention took place.

The ETS-Intervention model is represented mathematically as

$$Y_{t_{2016}} = \frac{-0.3090}{1-0.60B} \mathrm{B}S_t{}^T + ETS(M,N,N) \tag{17}$$

The model in (17) was found to be statistically significant and adequate for the data, Figure A15. And this was confirmed by the plot of the fitted ETS(M,N,N)-Intervention model with the actual values in Figure A16, since the fitted values mimic the actual values.

4. Conclusion

Comparing the two models, it's evident that ARIMA–

Intervention model show a better fit than the ESM–Intervention model, since the estimated error variance, AIC and forecast accuracy measures, MAE and RMSE of ARIMA(1,1,1)–Intervention model are smaller than those of the ESM(M,N,N)–Intervention model, Table A1 of Appendix II. A plot of the fitted ARIMA(1,1,1)-Intervention model with the actual values showed that the fitted values mimic the actual values, which further confirmed that the arrived model is adequate for the series, Figure A12. Hence, forecasting the future values of BDT/NGN using the ARIMA(1,1,1)–Intervention model, the forecasted values were very close to the actual values when compared, Table A2.

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Conflict of Interest

The authors declare no conflict of interest.

Appendix

Appendix I: Plots of BDT/NGN 2016 Exchange Rates

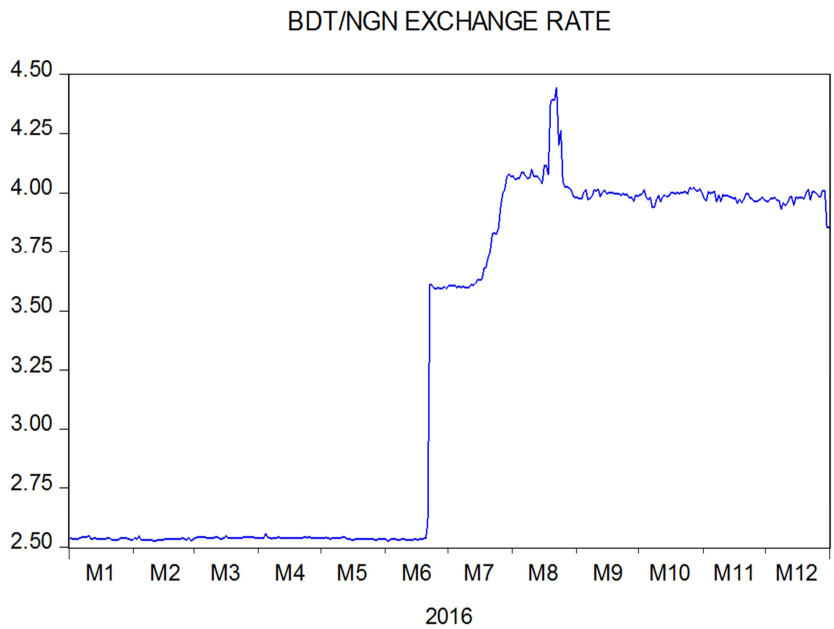

Figure A1. *Time Series Plot of BDT/NGN2016 Exchange Rate (ER).*

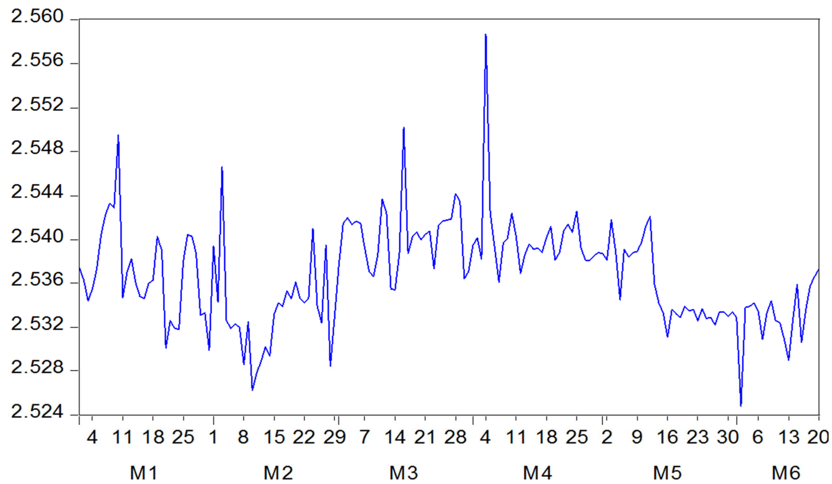

Figure A2. *Time Series Plot of BDT/NGN2016 ER (Pre-series).*

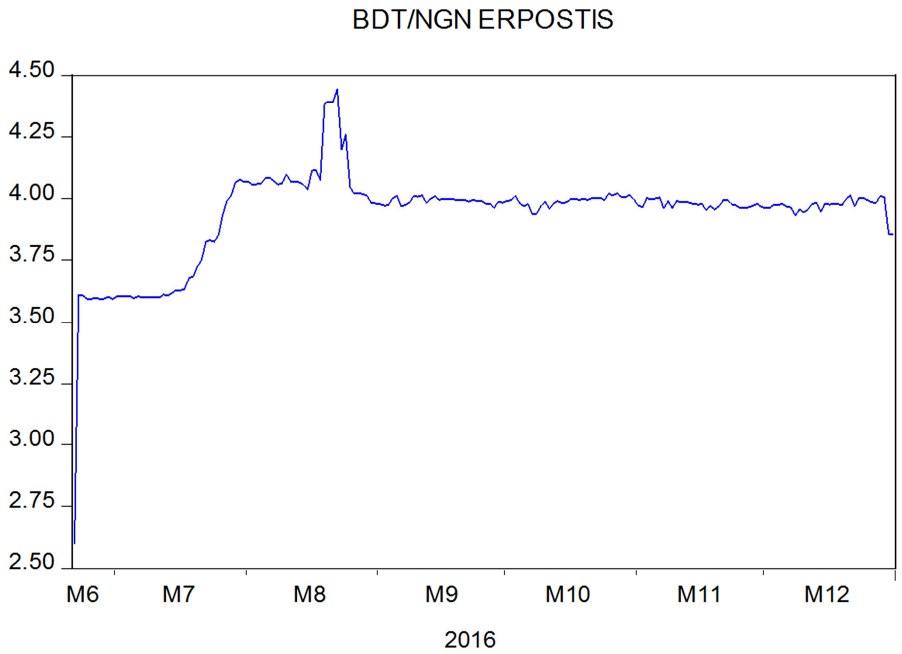

Figure A3. *Time Series Plot of BDT/NGN2016 ER (Post-series).*

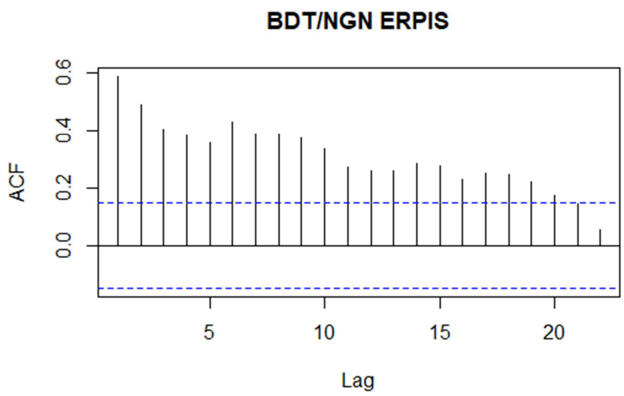

Figure A4. *ACF of BDT/NGN2016 ER (Pre-series).*

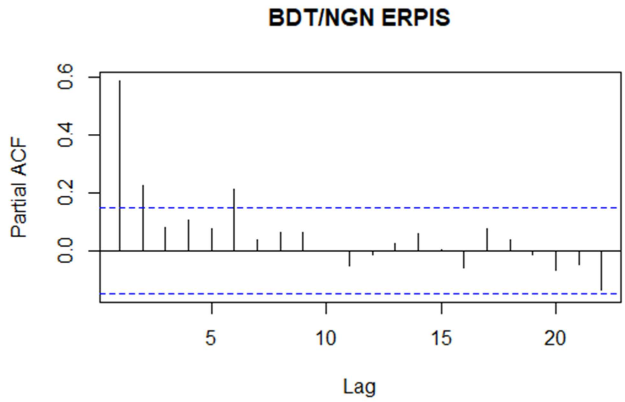

Figure A5. *PACF of BDT/NGN2016 ER (Pre-series).*

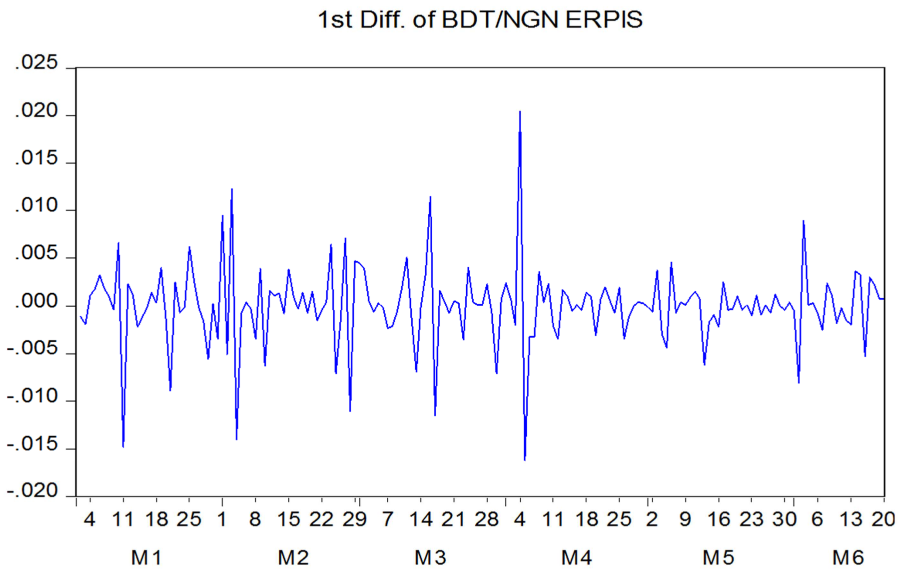

Figure A6. *First Difference of BDT/NGN2016 ER (Pre-series).*

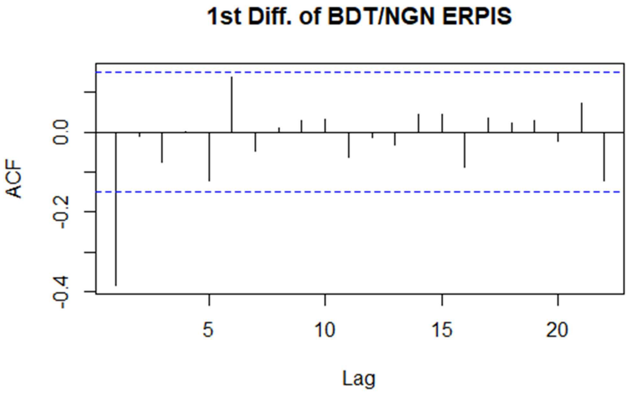

Figure A7. ACF of First Difference of BDT/NGN2016 ER (Pre-series).

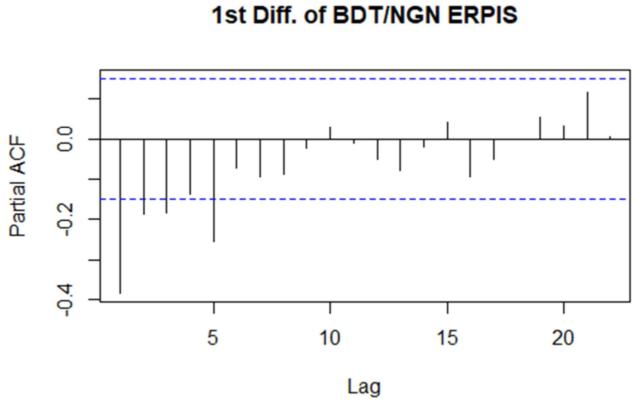

Figure A8. PACF of First Difference of BDT/NGN2016 ER (Pre-series).

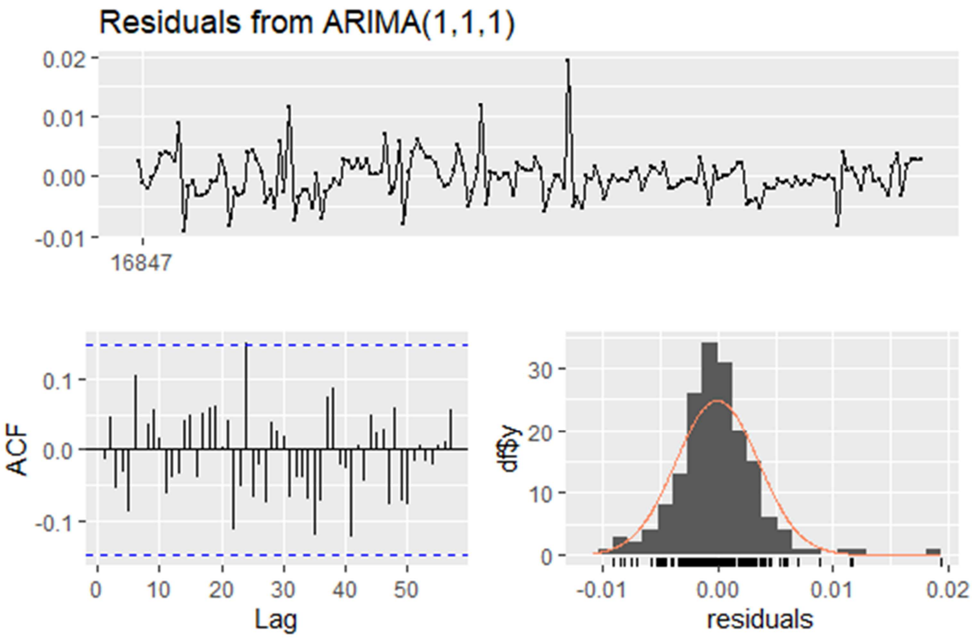

Figure A9. Residuals of ARIMA(1,1,1) Model (Pre-series).

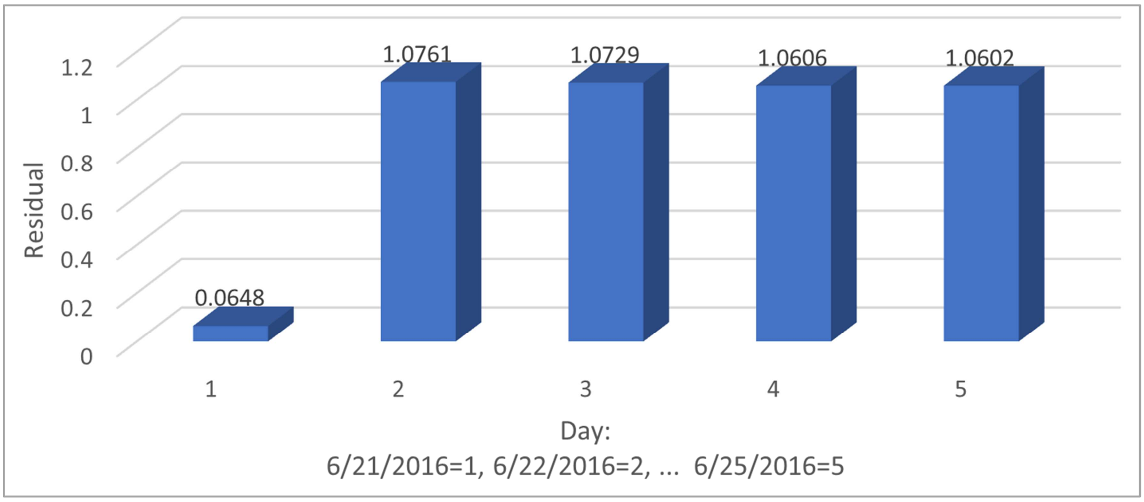

Figure A10. Impulse Response Function.

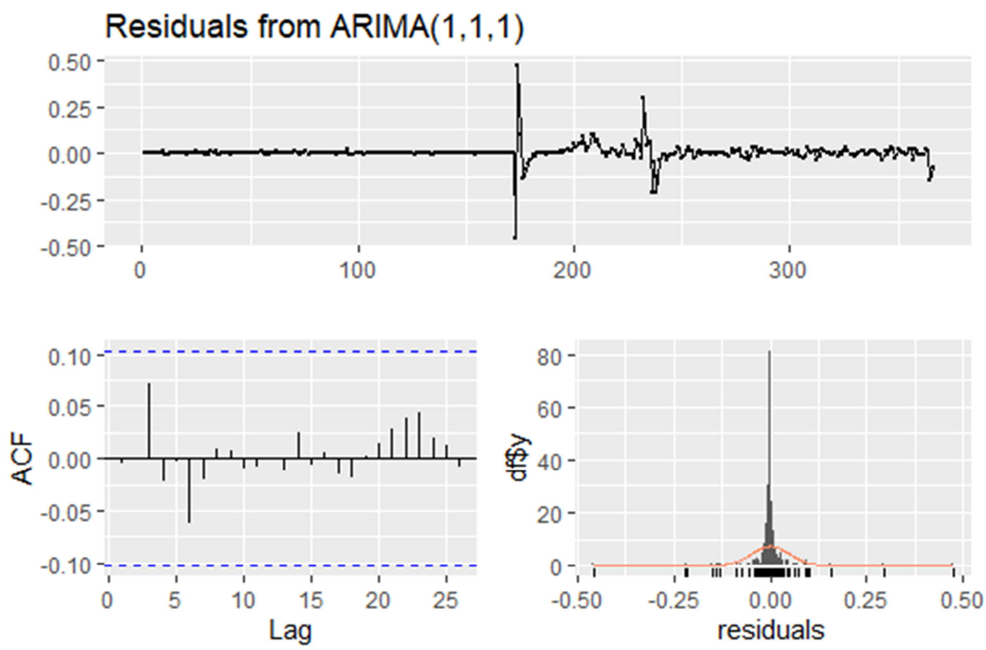

Figure A11. *Residuals for ARIMA-INTERVENTION Model.*

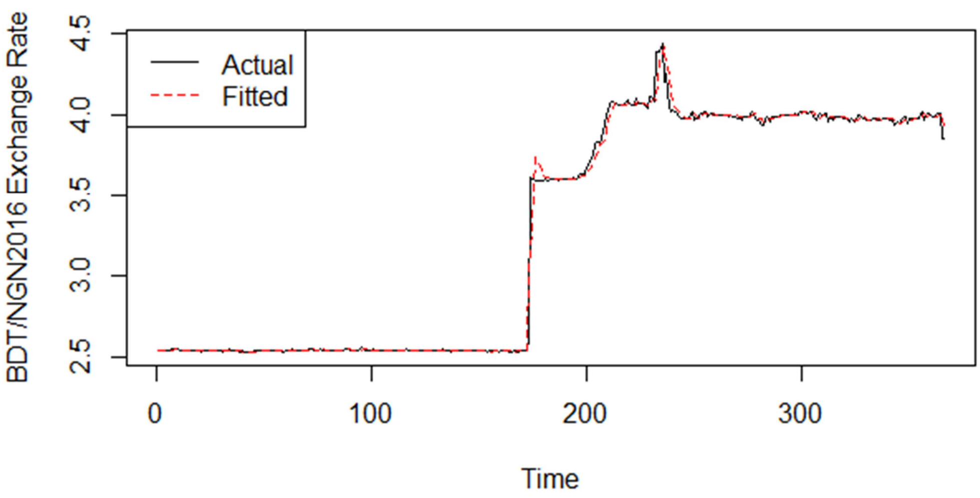

Figure A12. *Fitted ARIMA-INTERVENTION Model.*

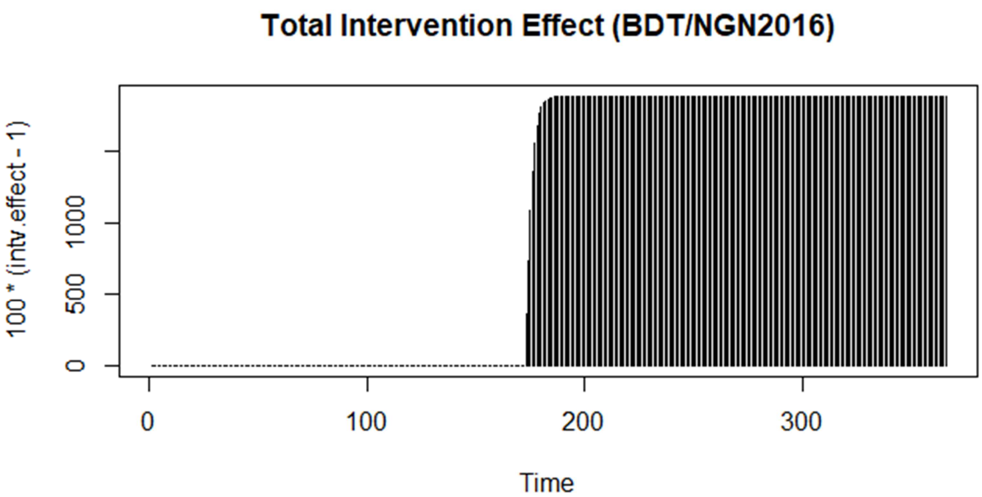

Figure A13. *Total Intervention Effect.*

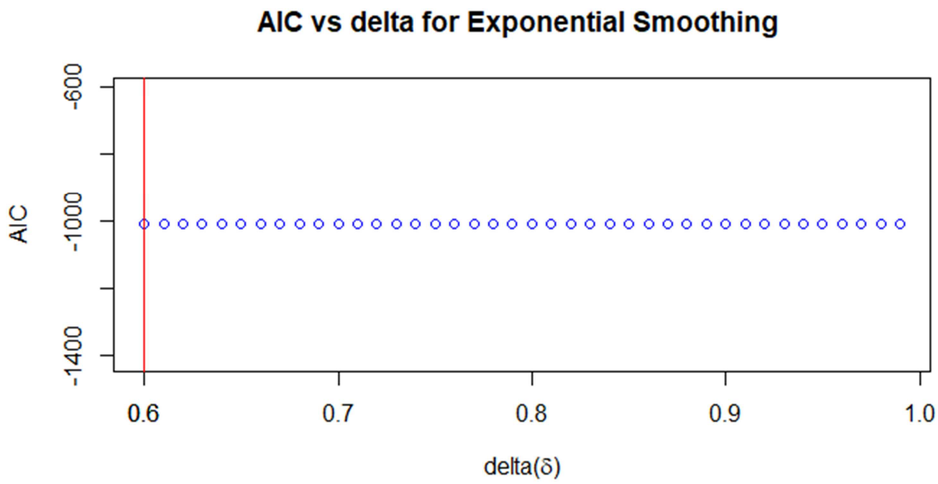

Figure A14. *AIC vs Delta for ETS(M,N,N) Model.*

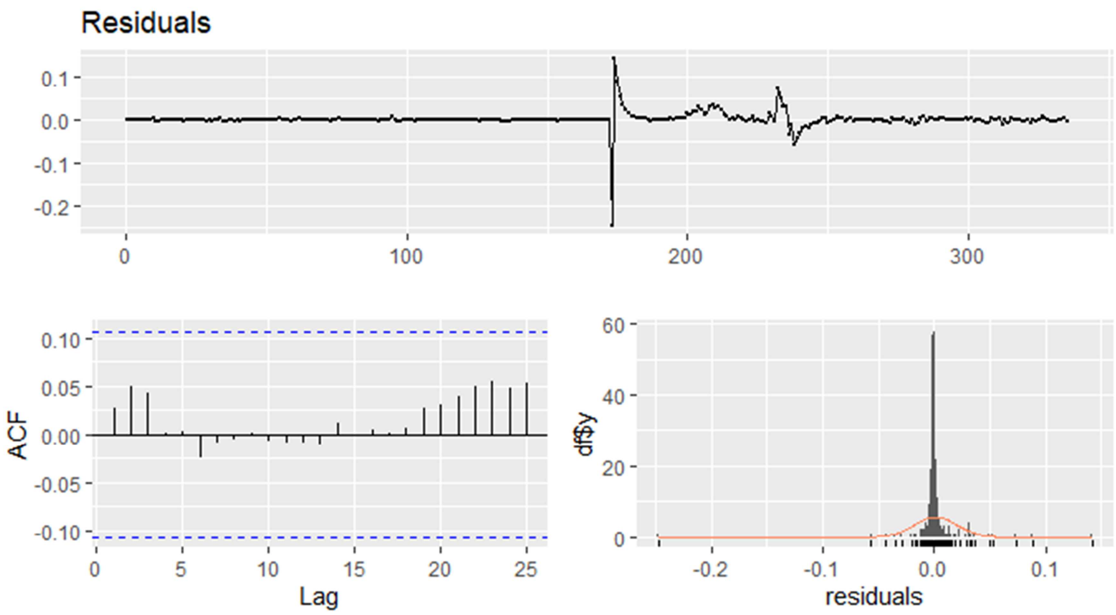

Figure A15. *Residuals for ETS(M,N,N) Model.*

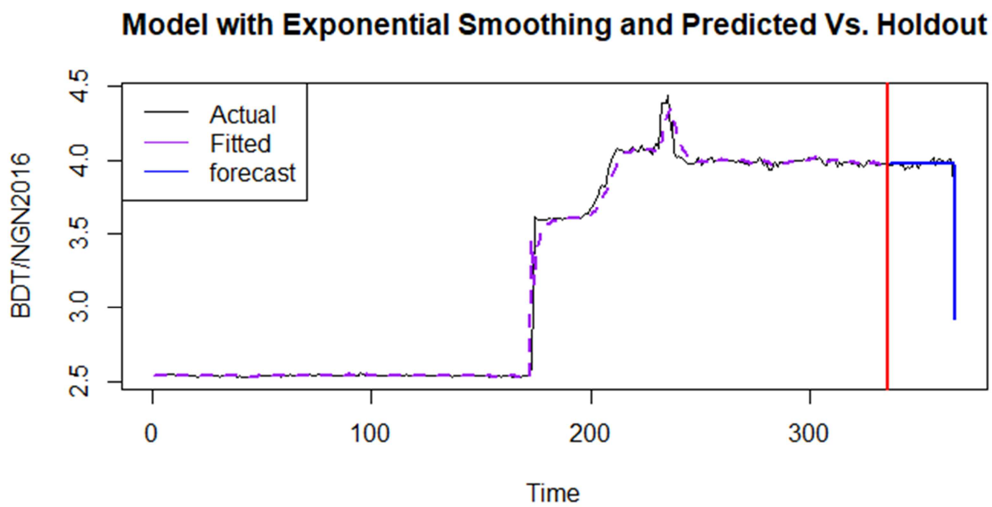

Figure A16. *Fitted ETS(M,N,N)-INTERVENTION Model.*

Appendix II: Model Comparison and Forecasts Generation

Table A1. *Model Evaluation for the Two Techniques.*

Model +Intervention Type	$\hat{\sigma}^2$	AIC	MAE	RMSE
$ARIMA(1,1,1)+\frac{\omega(B)B^b}{1-\delta(B)}S_t^{\,T}$	0.002324	-1167.443	0.0164956	0.0481434
$ETS(M,N,N)+\frac{\omega(B)B^b}{1-\delta(B)}S_t^{\,T}$	0.0003686	-926.8225	0.05	0.171

Table A2. *Forecasting with ARIMA(1,1,1)-INTERVENTION Model.*

S/N	DATE	ACTUAL VALUE	FORECAST	95% PREDICTION INTERVAL	
				LOWER	UPPER
336	1-Dec-2016	3.9639	3.967276	3.835495	4.100857
337	2-Dec-2016	3.9637	3.967157	3.778499	4.159525
338	3-Dec-2016	3.9774	3.967093	3.734181	4.205688
339	4-Dec-2016	3.9769	3.967059	3.696704	4.245101
340	5-Dec-2016	3.9782	3.967040	3.663738	4.280054
341	6-Dec-2016	3.9671	3.967031	3.634037	4.311768
342	7-Dec-2016	3.9659	3.967025	3.606838	4.340994

References

[1] Akaike, H. (1974). A New Look at the Statistical Model Identification. I. E. E. E. Transactions of Automatic Control, AC, 19, 716–723.

[2] BGT/NGN (2016). https://www.exchangerates.org.uk/BGT-NGN-spot-exchange-rates-history-2016.html

[3] Box, G. and Jenkins, G. (1970). Time Series Analysis: Forecasting and Control. Holden – Day, San Francisco.

[4] Box, G. E. P. and Jenkins, G. M. (1976). Time Series Analysis: Forecasting and Control, Revised Edition, San Francisco: Holden Day.

[5] Box, G. E. P., Reinsel, G. C., and Jenkins, G. M. (1994). Time Series Analysis: Forecasting and Control. 3rd Ed. Prentice – Hall, England Cliffs, N. J.

[6] Box, G. E. P. and Tiao, G. C. (1975). Intervention Analysis with Application to Economic and Environmental Problems. Journal of American Statistical Association, Vol,. 70, No. 349. Pp. 70-79.

[7] Brown, R. G. (1959). Statistical Forecasting for Inventory Control. McGraw-Hill, New York.

[8] Darkwah, K. F., Okyere, G. A., and Boakye, A. (2012). Intervention Analysis of serious Crimes in the Eastern Region of Ghana. International Journal of Business and Social Research (IJBSR), Vol. 2, No. 7, December 2012.

[9] Deutsch, S. J. and Alt, F. B. (1977). The Effect of Massachusetts' Gun Control Law on Gun –related Crimes in the City of Boston. Evaluation Quarterly, Vol. 1, No. 4, pp. 543–568, November 1977.

[10] Etuk, E. H. and Amadi, E. H. (2016). Intervention Analysis of Daily GBP – USA Exchange Rates Occassioned by BREXIT. International Journal of Management, Accounting and Economics, 3(12), 797–805.

[11] Etuk, E. H. and Chukwukelo, V. N. (2018). Intervention Analysis of Daily Moroccan Dirham/Nigerian Naira Exchange Rates. International Journal of Management Studies, Business & Entrepreneurship Research. Vol. 3, No. 1, March 2018.

[12] Etuk, H. E. and Eleki, A. G. (2016). Intervention Analysis of Daily Yuan – Naira Exchange Rates. CARD International Journal of Science and Advanced Innovative Research (IJSAIR), Vol. 1, No. 3, December 2016.

[13] Etuk, E. H. and George, D. S. (2020). Interrupted Time Series Modelling of Daily Malaysian Ringitt MYR/Liberian Dollar LRD Exchange Rates. International Journal of Science and Advance Innovative Research, Vol. 5, No. 2, June 2020.

[14] Etuk, E. H., Dimkpa, M., Sibeate, P., and Onyeka, N. G. (2017). Intervention Analysis of Daily Yen/Naira Exchange Rates. Management and Administrative Sciences Review, Vol. 6, Issue 1., January 2017.

[15] Etuk, E. H., Inyang, E. J. and Udoudo, U. P. (2022). Impact of Declaration of Cooperation on the Nigerian Crude Oil Production. International Journal of Statistics and Applied Mathematics 2022; 7(2): 165–169.

[16] Etuk, E. H., Onyeka, G. N., and Leesie, L. (2021). An Autoregressive Integrated Moving Average Intervention Model of 2016 Brazilian Real and Nigerian Naira Exchange Rates. Journal of Basic and Applied Research International, 27 (9): 1–7, 2021.

[17] Etuk, E. H. and Ntagu, O. K. (2018). Modelling of the Intervention of Daily Swiss Franc (CHF)/Nigerain Naira (NGN) Exchange Rates. International Journal of Science and Advanced Innovative Research, Vol. 3, No. 1, March 2018.

[18] Etuk, E. H. and Udoudo, U. P. (2018). Intervention Analysis of Daily Indian Rupee/Nigerian Naira Exchange Rates. Noble International Journal of Business and Management Research. Vol. 02, No. 06, pp: 47–52, 2018.

[19] Girard, D. Z. (2000). Intervention Time Series Analysis of Pertussis Vaccination in England and Wales. Health Policy, 54, 13–25.

[20] Holt, C. C. (1957). Forecasting Trends and Seasonals by Exponentially Weighted Averages. O. N. R. Memorandum 52/1957, Camegies Instute of Technology.

[21] Inyang, E. J., Etuk, E. H., Nafo, N. M., and Da-Wariboko, Y. A. Time Series Intervention Modelling Based on ESM and ARIMA Models: Daily Pakistan Rupee/Nigerian Naira Exchange Rate. Asian Journal of Probability and Statistics, Vol. 25, No. 3, pp. 1-17, 2023; Article no. AJPAS.106693. ISSN: 2582-0230. DOI: 10.9734/AJPAS/2023/v25i3560

[22] Inyang, E. J., Nsien, E. F., Clement, E. P., and Danjeh, A. G. (2022). Statistical Investigation of the impact of global oil politics: An Interrupted Time Series Approach. JP Journal of Mathematical Sciences, Vol. 32, Iss 1& 2, pp. 1–13.

[23] Jaganathan, S. (2021). Modeling and Predicting Demand During Pandemics Using Time Series Models. https://www.linkedin.com/pulse/modelling-predicting-demand-during-pandemics-using-time-series-jaganathan.

[24] Jarrett, J. E. and Kyper, E. (2011). ARIMA Modelling with Intervention to Forecast and Analyze Chinese Stock Prices. Int. j. eng. bus. Manag., Vol. 3, 53–58.

[25] Lai, S. L. and Lu, W. L. (2005). Impact Analysis of September 11 on Air Travel Demand in the USA. Journal of Air Transport Management, 11(6), 455–458.

[26] Lam, C. Y., Ip, W. H., and Lau, C. W. (2009). A Business Process Activity Model and Performance Measuremen Using a Time Series ARIMA Intervention Analysis. Expert Systems with Aplications, 36, 925–932.

[27] Makridakis, S., Wheelwright, S. C., and Hyndman, R. J. (1998). Forecasting Methods and Applications, 3rd Edition, John Wiley, New York.

[28] Min, J. C. H. (2008). Forecasting Japanese Tourism Demad in Taiwan using an Intervention Analysis. International Journal of Culture, Tourism and Hospital Research, Vol. 2, Iss 3, pp. 197–216.

[29] Moffat, I. U. and Inyang, E. J. (2022). Impact Assessment of Gap on Nigerian Crude Oil Production: A Box-Tiao Intervention Approach. Asian Journal of Probability and Statistics, 17(2), 52–60. https://doi.org/10.9734/ajpas/2022/v17i230419

[30] Mrinmoy, R., Ramasubramanian, V., Amrender, K. and Anil, R. (2014). Application of Time Series Intervention Modelling for Modelling and Forcasting Cotton Yield. Statistics and Applications. Vol. 12, No. 1& 2, pp. 61–70.

[31] Nelson, J. P. (2000). Consumer Bankruptcies and the Bankruptcy Reform Act: A Time – Series Intervention Analysi, 1960 – 1997. Journal of Financial Services Research, 17:2, 181–200, 2000.

[32] Seong, B. and Lee, K. (2020). Intervention Analysis Based on Exponential Smoothing Methods: Application to 9/11 and COVID–19 Effects. Economic Modelling, https://doi.org/10.1016/j.econmod.2020.11.014.

[33] Sharma, P. and Khare, M. (1999). Application of Intervention Analysis for Assessing the Effectiveness of CO Pollution Control Legislation in India. Transportation Research Part D 4 (1999), 427–432.

[34] Shittu, O. I. and Inyang, E. J. (2019). Statistical Assessment of Government's Interventions on Nigerian Crude Oil Prices. A Publication of Professional Statisticians Society of Nigeria, Proceedings of 3rd International Conference. 2019; 3: 519-524.

[35] Trapero, J. R., Pedregal, D. J., Fildes, R., and Kourentzes, N. (2013). Analysis of Judgmental Adjustments in the Presence of Promotions. International Journal of Forecasting, 29(2), 234–243.

[36] Winters, P. R. (1960). Forecasting Sales by Exponentially Weighted Averages. Management Sciences, 6, 324–342.

[37] Yang, L. (2014). Pricing Virtual Goods: Using Intervention Analysis and Products' Usage Data. A Thesis Presented to the University of Waterloo in Fulfillment of the Thesis Requirement of the Degree of Master of Applied Science in Management Sciences, 2014.