Available online www.jsaer.com

***Journal of Scientific and Engineering Research*, 2017, 4(3):59-65**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Box-Tiao Intervention Modelling of Monthly EUR-NGN Exchange Rates due to Nigerian Economic Recession

Ette Harrison Etuk[1]*, Uyodhu Amekauma Victor-Edema[2]

[1]Department of Mathematics, Rivers State University of Science and Technology, Port Harcourt, Nigeria
[2]Department of Mathematics/Statistics, Ignatius Ajuru Universty of Education, Port Harcourt, Nigeria

Abstract The time-plot of monthly amount of Nigerian Naira (NGN) per European Euro (EUR) from 2004 to 2016 reveals a series with a slight positive trend up to May 2016. From June 2016 forward there was an abrupt astronomical rise till the end of the year. This rise is attributed to the current economic recession bedevilling the Nigerian nation and it calls for intervention. The point of intervention is therefore June 2016. The pre-intervention exchange rate series is non-stationary and therefore subjected to differencing. The first difference is adjudged stationary by the Augmented Dickey Fuller Test. Based on the correlogram, an ARMA(11,11) is fitted to the first difference. That is, an ARIMA(11,1,11) model is fitted to the pre-intervention exchange rates. Forecasts are obtained for the post-intervention period on the basis of this model. The differences between these forecasts and the corresponding post-intervention observations are modelled to obtain the intervention model. The intervention model forecast is superimposed with the original data. Intervention may therefore be based on the derived model.

Keywords Euro, Naira, exchange rates, intervention model

Introduction

Examination of the trend of monthly European Euro (EUR)-Nigerian Naira (NGN) exchange rate from 2004 to 2016 shows a series with an overall slight trend and an astronomical increase from June to December 2016. Definitely this is a case of intervention with June 2016 as the intervention point.

Earlier studies of the euro-naira exchange rates, to mention a few, include monthly from 2004 to 2011 [1] and daily from December 8, 2012 to March 30, 2013 [2]. He fitted a SARIMA$(0,1,1)x(1,1,1)_{12}$ and $(0,1,1)x(0,1,1)_{7}$ respectively.

Intervention analysis (IA) was introduced by Box and Tiao (1975) [3]. Ever since it has been widely and extensively applied by scholars in ascertaining of the degree (if any) of intervention necessary for a time series, given some perturbation of its trend by some phenomenon. For instance, Wichem and Jones (1977) used IA to examine the effects of Proctor and Gamble's promotion of the American Dental Association on the market shares of Crest and Colgate dentifrice between 1958 and 1963 [4]. Thompson *et al.* (1982) applied IA to determine the ventilator reaction of the bluegill to sublethal concentrations of zinc sulphate [5]. It has been demonstrated by Nelson (2000) that the Bankruptcy Reform Act of 1978 in the US increased consumer bankruptcies by 36% [6]. Lam *et al.* (2009) determined intervention effects of business process re-engineering on the performance of some enterprises [7]. Economic recession was shown to adversely affect casino hotel firms by Zheng *et al.* (2015) [8]. Unnikrishnan and Suresh (2016) have shown that the imposition of a 10% import duty on gold in April 2013 in India caused a decrease in the domestic supply of gold by 56%. This is to mention just a few cases [9].

Materials and Methods

Data

The data for this work are 156 monthly EUR/NGN exchange rates from 2004 to 2016 from the website of the Central Bank of Nigeria (CBN) www.cbn.gov.ng/rates/exrates.asp . They are read as the amounts of NGN in a EUR.

Box-Tiao (1975) [3] Intervention Analysis

The point at which the trend of the time series in question changes drastically is called the intervention point. The pre-intervention series is modelled by an ARIMA model. Suppose this is an ARIMA(p, d, q) model. Then according to Box *et al.* (1994) [10]

$$A(L)(1-L)^d X_t = B(L)\varepsilon_t \qquad (1)$$

where $\{X_t\}$ is the time series studied, $\{\varepsilon_t\}$ is a white noise process, L a backshift operator defined by $L^k X_t = X_{t-k}$, $A(L) = 1-\alpha_1 L - \alpha_2 L^2 - \dots - \alpha_p L^p$ and $B(L)=1 + \beta_1 L + \beta_2 L^2 + \dots + \beta_q L^q$ and the α's and β"s constants such that the model is both stationary and invertible. That means

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

On the basis of the model (2) post –intervention forecasts are obtained. Suppose these forecasts are given by $\widehat{X_t}, t$>T the difference between the observations and the forecasts is given by

$$Z_t = X_t - \widehat{X_t}\ , \ t>T$$

As could be found in The Pennsylvania State University (2016) [11], if the equation

$$Z_t = \frac{C(1)*(1-C(2)^{(t-T+1)})}{(1-C(2))},\ t > T, \qquad (3)$$

is estimated by the least squares procedure for C(1) and C(2), this is the intervention model. The overall intervention model is therefore given by combining (2) and (3) as

$$Y_t = \frac{B(L)\varepsilon_t}{A(L)(1-L)^d} + I_t Z_t \qquad (4)$$

where I_t =1, t> T and zero elsewhere.

In practice the model (1) is fitted first, by the determination of the orders p, d and q. The differencing order is determined sequentially starting from 0 if the series is stationary. If not, with d=1, the series is tested for stationarity. If non-stationary, d=2. Stationarity may be tested with the Augmented Dickey Fuller (ADF) unit-root test procedure. The autoregressive (AR) order may be determined by the lag at which the partial autocorrelation function (PACF) cuts off. The moving average (MA) order may be estimated as the lag at which the autocorrelation function (ACF) cuts off. Estimation of the α's and β's may be done by the method of least squares. Data analysis was done by the use of Eviews 7.

Results and Discussion

A time plot of the series in Figure 1 shows that there is a slight positive trend up to May 2016 after which there is an abrupt rise in the trend. This means that the intervention point is June 2016. The pre-intervention time plot in Figure 2 shows a generally positive trend and with a test statistic value of -1.27 the ADF test adjudges the series as non-stationary. This necessitated differencing of the series. The first order differences are plotted in Figure 3 and, with an ADF test statistic of -10.89 and 1%, 5% and 10% critical values of -3.48, -2.88 and -2.58 respectively, are adjudged stationary. Their correlogram of Figure 4 shows positive spikes at lags 11 for both the ACF and the PACF. On the basis of this an ARIMA(11, 1,11) model is identified and estimated in Table 2 α_{11} = 0.6784 and β_{11} = 0.4972. It is noteworthy that these estimates are highly statistically significant.

On the basis of these estimates forecasts have been made for the post-intervention period. The observation/forecast difference is modelled using equation (3) and as obtainable from Table (2), C(1) = 44.4282 and C(2) = 0.6252 and these coefficients are as well highly statistically significant, indicating that the model is adequate.

The overall intervention model is therefore

$$Y_t = \frac{(1+0.4972L^{11})\varepsilon_t}{(1-0.6784L^{11})(1-L)} + I_t \frac{44.4282*(1-0.6252)^{(t-148)}}{(1-0.6252)} \qquad (5)$$

where I_t =1, t>149; zero elsewhere.

A plot of the post-intervention observations and the post-intervention forecasts in Figure 6 reveals a good fit between the two. Figure 7 gives a superimposition of the two for the entire period of study.

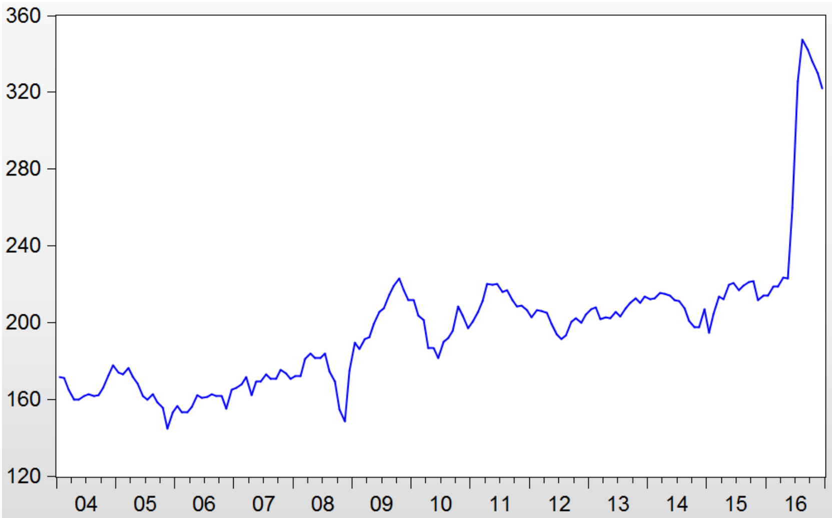


Figure 1: Monthly Euro-Naira Exchange Rates

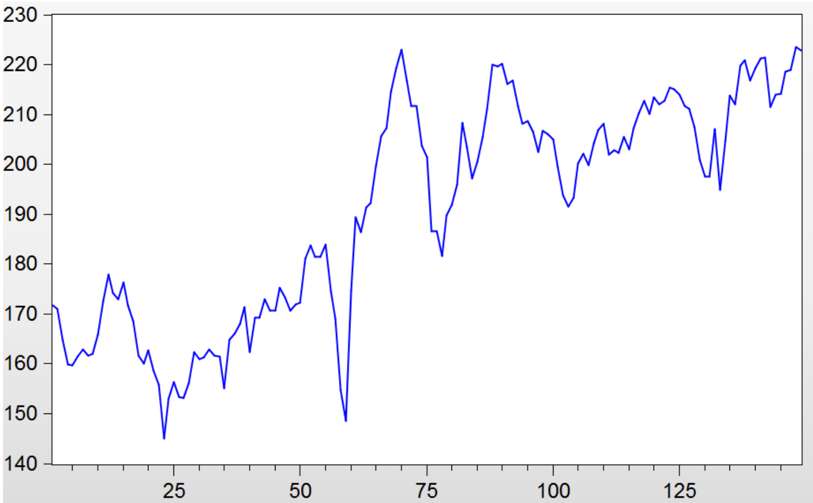


Figure 2: Pre-Intervention Observations

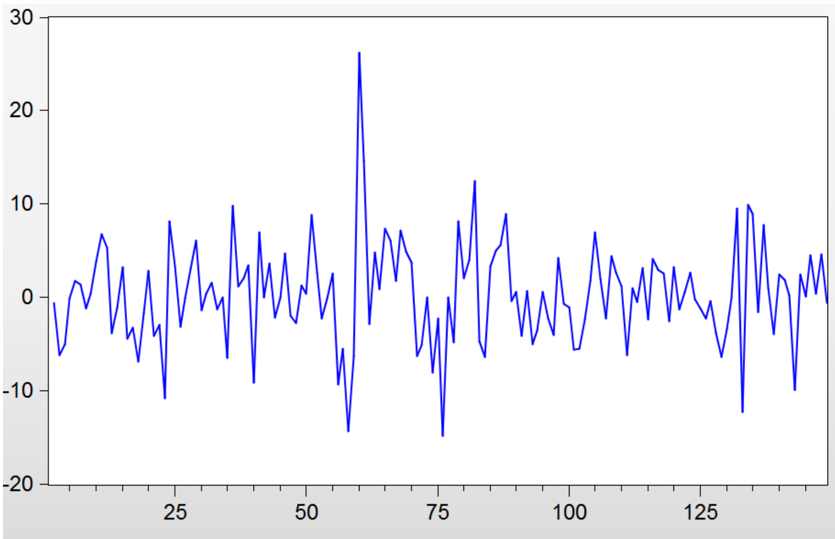
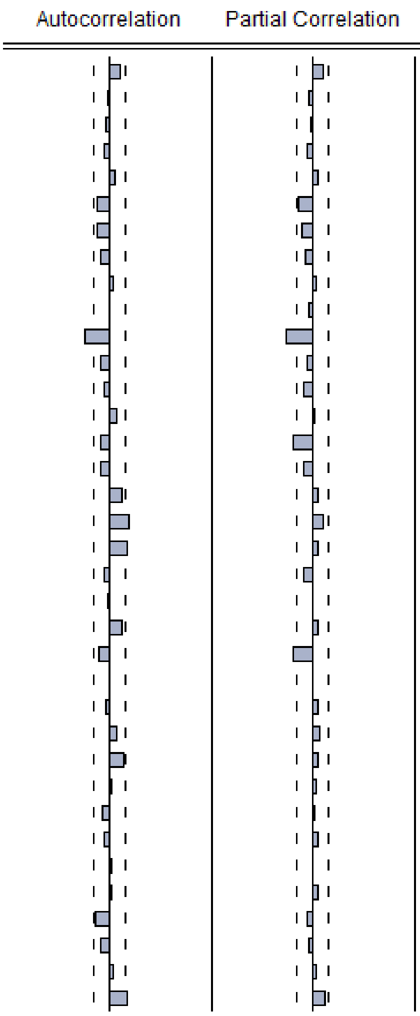


Figure 3: Difference of Pre-intervention Series



Lag	AC	PAC	Q-Stat	Prob
1	0.100	0.100	1.5087	0.219
2	-0.022	-0.033	1.5849	0.453
3	-0.029	-0.024	1.7136	0.634
4	-0.059	-0.055	2.2463	0.691
5	0.047	0.058	2.5874	0.763
6	-0.138	-0.155	5.5567	0.475
7	-0.129	-0.102	8.1913	0.316
8	-0.083	-0.073	9.2928	0.318
9	0.030	0.040	9.4356	0.398
10	0.004	-0.037	9.4378	0.491
11	-0.259	-0.272	20.281	0.042
12	-0.085	-0.063	21.450	0.044
13	-0.058	-0.094	21.994	0.055
14	0.067	0.016	22.737	0.065
15	-0.093	-0.193	24.188	0.062
16	-0.087	-0.083	25.472	0.062
17	0.123	0.047	28.054	0.044
18	0.189	0.099	34.124	0.012
19	0.188	0.065	40.196	0.003
20	-0.050	-0.087	40.633	0.004
21	-0.019	-0.003	40.697	0.006
22	0.118	0.055	43.139	0.005
23	-0.113	-0.195	45.395	0.004
24	-0.003	-0.005	45.397	0.005
25	-0.038	0.063	45.660	0.007
26	0.066	0.071	46.456	0.008
27	0.136	0.054	49.857	0.005
28	0.017	0.035	49.909	0.007
29	-0.075	0.018	50.951	0.007
30	-0.058	0.065	51.575	0.008
31	0.023	0.000	51.678	0.011
32	0.017	0.049	51.731	0.015
33	-0.151	-0.062	56.131	0.007
34	-0.087	-0.034	57.620	0.007
35	0.027	0.039	57.762	0.009
36	0.174	0.119	63.743	0.003

Figure 4: Correlogram of Difference of Pre-Intervention Data

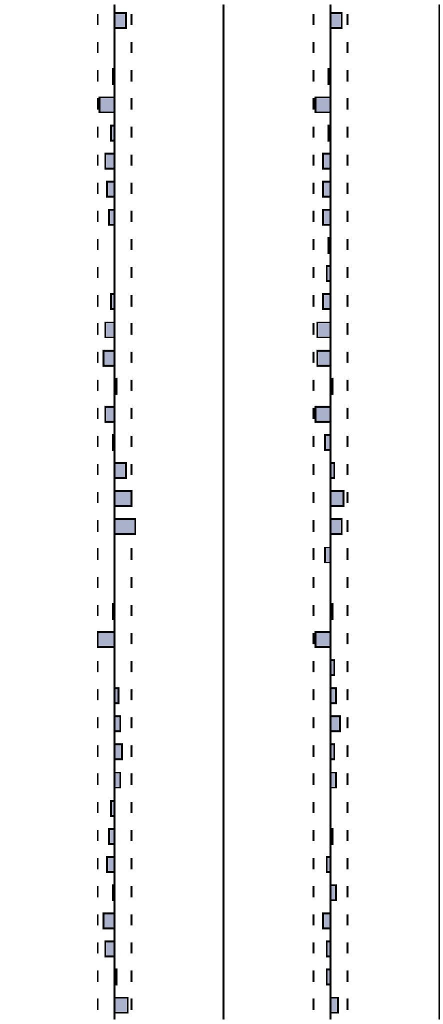
Table 1: Estimation of the Arima(11,1,11) pre-intervention model

Dependent Variable: DNNEU
Method: Least Squares
Date: 02/05/17 Time: 20:04
Sample (adjusted): 13 149
Included observations: 137 after adjustments
Convergence achieved after 8 iterations
MA Backcast: 2 12

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(11)	-0.678409	0.153342	-4.424148	0.0000
MA(11)	0.497180	0.181798	2.734787	0.0071

R-squared	0.094304	Mean dependent var	0.327737
Adjusted R-squared	0.087595	S.D. dependent var	5.570043
S.E. of regression	5.320499	Akaike info criterion	6.195502
Sum squared resid	3821.541	Schwarz criterion	6.238130
Log likelihood	-422.3919	Hannan-Quinn criter.	6.212825
Durbin-Watson stat	1.772203		

Inverted AR Roots	.93+.27i	.93-.27i	.63-.73i	.63+.73i
	.14-.96i	.14+.96i	-.40+.88i	-.40-.88i
	-.81+.52i	-.81-.52i	-.97	
Inverted MA Roots	.90+.26i	.90-.26i	.61+.71i	.61-.71i
	.13+.93i	.13-.93i	-.39+.85i	-.39-.85i
	-.79+.51i	-.79-.51i	-.94	



Lag	AC	PAC	Q-Stat	Prob
1	0.107	0.107	1.6110	
2	0.005	-0.007	1.6140	
3	-0.024	-0.024	1.6958	0.193
4	-0.149	-0.145	4.8643	0.088
5	-0.045	-0.014	5.1532	0.161
6	-0.082	-0.079	6.1333	0.189
7	-0.077	-0.068	6.9963	0.221
8	-0.054	-0.066	7.4249	0.283
9	-0.007	-0.009	7.4327	0.385
10	-0.007	-0.035	7.4401	0.490
11	-0.041	-0.069	7.6968	0.565
12	-0.095	-0.121	9.0759	0.525
13	-0.111	-0.122	10.974	0.445
14	0.024	0.012	11.062	0.524
15	-0.097	-0.154	12.527	0.485
16	-0.011	-0.054	12.544	0.563
17	0.101	0.039	14.150	0.514
18	0.171	0.129	18.833	0.277
19	0.202	0.114	25.409	0.086
20	0.001	-0.061	25.410	0.114
21	0.000	0.007	25.410	0.147
22	-0.012	0.022	25.435	0.185
23	-0.171	-0.155	30.322	0.086
24	0.004	0.031	30.325	0.111
25	0.027	0.059	30.450	0.137
26	0.052	0.083	30.919	0.156
27	0.068	0.035	31.708	0.167
28	0.053	0.044	32.203	0.186
29	-0.031	0.002	32.372	0.219
30	-0.049	0.009	32.807	0.243
31	-0.082	-0.037	34.005	0.239
32	-0.024	0.047	34.106	0.277
33	-0.101	-0.079	35.959	0.247
34	-0.092	-0.042	37.536	0.230
35	0.012	-0.027	37.561	0.268
36	0.131	0.079	40.795	0.196

Figure 5: Correlogram the Arima(11,1,11) Model Forecasts

Table 2: Estimation of the Intervention Model

Dependent Variable: Z
Method: Least Squares
Date: 02/10/17 Time: 19:54
Sample: 150 156
Included observations: 7
Convergence achieved after 1 iteration
Z=C(1)*(1-C(2)^(T-148))/(1-C(2))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	44.42815	13.85841	3.205862	0.0238
C(2)	0.625193	0.164235	3.806698	0.0125

R-squared	0.504680	Mean dependent var	100.7143
Adjusted R-squared	0.405616	S.D. dependent var	29.63659
S.E. of regression	22.84871	Akaike info criterion	9.330623
Sum squared resid	2610.318	Schwarz criterion	9.315169
Log likelihood	-30.65718	Hannan-Quinn criter.	9.139611
Durbin-Watson stat	1.168307		

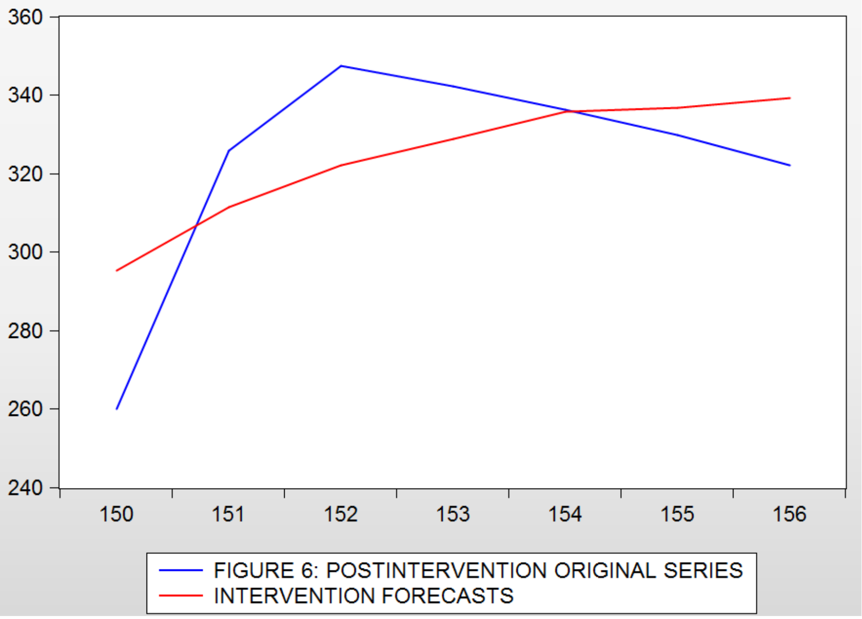


Figure 6: Post-intervention Original Series and Intervention Forecasts

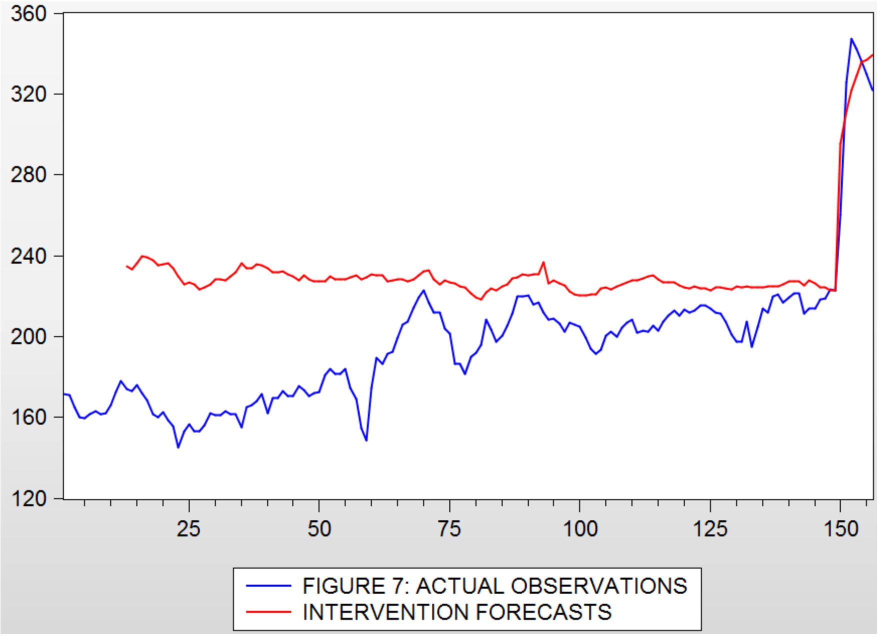


Figure 7: Actual Observations and Intervention Forecasts

Conclusion

It may therefore be concluded that an intervention model for the monthly EUR-NGN exchange rates is given by equation (5). The post-intervention fit is quite good as evident from Figure 6. Intervention may therefore be based on the model.

References

[1]. Etuk, E. H. (2013). The fitting of a Sarima Model to Monthly Naira-Euro Exchange rates. Mathematical Theory and Modelling, 3(1): 17-26.

[2]. Etuk, E. H. (2013). Multiplicative Sarima Modelling of Daily Naira-Euro Exchange Rates. International Journal of Mathematics and Statistics Studies, 1(3): 1-8.

[3]. Box, G. E. P. and Tiao, G. C. (1975). Intervention Analysis with applications to economic and environmental problems. Journal of American Statistical Association, 70, 70-79.

[4]. Wichem, D. W. and Jones, R. H. (1977). Assessing the impact of Market Disturbances Using Intervention Analysis, Management Science, 24(3): 329-337.

[5]. Thompson, K. W., Deaton, M. L., Foutz, R. V., Cairns, J. and Hendricks, A. C. (1982). Application of Time-Series Intervention Analysis to Fish Ventilatory Response Data Respone Data. Canadian Journal of Fisheries and Aquatic Sciences, 39(3): 518-521.

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

[7]. Lam, C. Y., Ip, W. H. and Lau, C. W. (2009). A business process activity model and performance measurement using a time series ARIMA intervention analysis. Expert Systems with Applications, 36(3): 6986-6994.

[8]. Zheng, T., Farrish, J. and Kitterlin, M. (2015). Performance Trends of Hotels and Casino Hotels Through the Recession: An ARIMA with Intervention analysis of Stock Indices. Journal of Hospitality Marketing & Marketing, 25(1): 49-68.

[9]. Unnikrishnan, I. and Suresh, K. K. (2016). Modelling the Impact of Government Policies on Import on Domestic Price of Indian Gold Using ARIMA Intervention Method. International Journal of Mathematics and Mathematical Sciences, 2016(2016). Article ID 6382926. http://dx.doi.org/10.1155/2016/

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

[11]. The Pennsylvania State University (2016). Welcome to STAT 510! Applied Time Series Analysis. Department of Statistics Online Program. www.onlinecourses.science.psu.edu/stat510/