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An Example of Intervention: The Case of Ukraine Because of Russian Invasion

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ABSTRACT
For more than a month now Russia has invaded Ukraine militarily. That in itself is an intervention. A lot of time series will show intervention because of this sudden and, perhaps, unexpected attack. A look at the time series of Ukranian Hryvnia (UAH)/ Nigerian Naira (NGN) from 1 January 2022 to 13 March 2022 shows the emergence of an intervention on 24 February 2022 the day of the invasion. By 13 March 2022 the intervention was still existent. By the algorithm of Box and Tiao (1975) a model of intervention is fitted to the data and shown to be adequate. This will be useful for planning purposes.
Keywords: Ukrainian Hyrvnia (UAH), Nigerian Naira (NGN), exchange rates, intervention, Russian invasion

INTRODUCTION

Relatively Ukraine is the victim of the war with Russia from 24 February till date. It may be observed that this war has created an intervention in the UAH/NGN time series up to 13 March 2022. By the pioneer work of Box and Tiao (1975), the intervention is being analyzed in the sequel and shown to be adequate. Not a few authors have applied the algorithm successfully. Chapter 19 of the book of Hipel and McLeod (1994) has been devoted to comprehensive discussion of intervention models. For instance Etuk and Amadi (2016) fitted an intervention model to the GBP/USD time series which was observed to fall sharply with the Brexit. Analysis of intervention in Yu Ebao yield was made by Su and Deng (2014). Wang and Houston (2015) by autoregressive moving average (ARMA) modeling estimated the impact of change in futures price on genetically modified soybeans in China. Analysis of intervention to assess the effect of congestion charge on traffic casualties in London has been done by Noland *et al.* (2008). Makatjane *et al.* (2018) using the SARIMA model to analyse the 2008 US financial crisis showed the forecasting supremacy of the SARIMA intervention model over the ordinary SARIMA model. By the use of an ARIMA (2,2,0) pre-intervention model, Siedono *et al.* (2021) were able to demonstrate that the intervention model of data obtained from Bank Indonesia was good. Li *et al.*(2021) have published a work on three methods of intervention analysis including the ARIMA technique. Using Box/Tiao's (1075) algorithm Okogbaa and Peng (1998) examined the possibility that rather than assume that new components of a system work as new, they relax this assumption and use a postulate that depend on time varying model to study the behavior of the system failure.

MATERIALS AND METHODS

Data

The data analyzed herein are 72 UAH/NGN exchange rates from 1 January 2022 to 13 March 2022 obtainable from the website https://www.exchangerates.org.uk/UAH-NGN-spot-exchange-rates-history-2022.html . They are to be read as the amount of NGN going for one UAH ($\emptyset 1\ UAH$).

Intervention Modelling

Let $X_1, X_2, \ldots, X_n$ be a realization of a time series $\{X_t\}$ with an intervention at t = T. Let an ARIMA(p, d, q) be proposed and fitted to the realization. That is, the model

$$\nabla^d X_t = \alpha_1 \nabla^d X_{t-1} + \alpha_2 \nabla^d X_{t-2} + \cdots + \alpha_p \nabla^d X_{t-p} = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_q \varepsilon_{t-q} \quad \text{……} (1)$$

where $t < T$, $\nabla = 1 - L$ where L is a backshift operator defined as $LX_t = X_{t-1}$, $\{\alpha_i\}$ and $\{\beta_j\}$ are constants chosen so that (1) might be

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stationary as well as invertible and $\{\varepsilon_t\}$ is a white noise process. That means

$\nabla^d(1-\alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_p L^p)X_t = (1 - \beta_1 L - \beta_2 L^2 - \cdots . -\beta_q L^q)\varepsilon_t$ …………………………………………………………………………………………… (2)

$\nabla^d A(L) X_t = B(L)\varepsilon_t$ ………………………………………………………… (3)

where $A(L)$ is the autoregressive operator $1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha_p L^p$ and $B(L)$ is the moving average operator $1 - \beta_1 L - \beta_2 L^2 - \ldots - \beta_q L^q$.

From (3), the noise part of the intervention model is given by

$X_t = \frac{B(L)\varepsilon_t}{\nabla^d A(L)}$ ………………………………………………………………………………… (4)

Let f(t), $t \geq T$ be the post-intervention forecasts on the basis of (1) and $z = X_t - f$, $t \geq T$. Then the transfer function is given by

$Z_t = c_1(1-c_2\hat{}(t-T+1))/(1-c_2)$, $t \geq T$ ……………………………………………… (5)

where c_1 and c_2 are constants.

The intervention model is given by a combination of (4) and (5) into

$Y_t = \frac{B(L)\varepsilon_t}{\nabla^d A(L)} + I_t Z_t$ ………………………………………………………………………… (6)

where $I_t = 0$, $t < T$ and 1 elsewhere.

Computer Software

The reviews 10 was used for all computational needs in this paper.

RESULTS:

The time plot of the original series is in Figure 1. The intervention point is T = 55. That is, on 24 February 2022, the day Russia struck Ukraine. There is a generally negative trend. The time-plot for the pre-intervention data is presented in figure 2. The trend is generally negative. The unit root test in Table 1 adjudges the series non-stationary. There is therefore need for differencing.

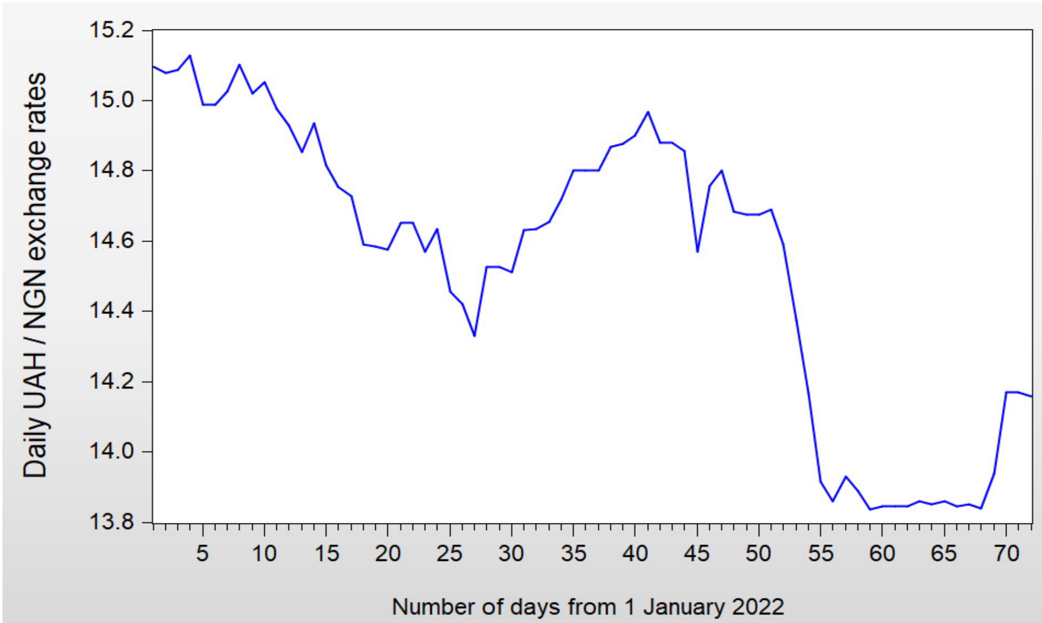

Figure 1: Time Plot of the daily UAH/NGN exchange rates

The time-plot of the difference of the pre-intervention series is displayed on Figure 3. There is now no trend and the unit root test on it in Table 2 adjudges it as stationary. The correlogram of the difference on Figure shows the autocorrelation structure of a white noise process. With the white noise proposal the forecast for the post-intervention part is 14.1665 for all post-intervention points.

That is, $f(t) = 14.1665$, $t > 54$.

Then, $z = X_t - 14.1665$, $t \geq 55$

By Table 3, the transfer function yields $c_1 = -0.250752$ and $c_2 = -0.006593$.

The intervention model is therefore

$Y_t = \frac{\varepsilon_t}{\nabla} - 0.2508 * (1 - (-0.0066)^{t-54})/1.0066$, $t > 54$……………………(7)

Table 4 has a display of the Pearson's chi-square goodness-of-fit test of the post-intervention data to the intervention forecasts. With a statistical value of 0.0169, it is not significant, being less

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than 27.587=$\chi^2_{0.05}$ at 17 degree-of-freedom. Hence the model is adequate.

CONCLUSION

The model (7) is an adequate model fitted for the intervention. The model is significant to planners, administrators and managers of both countries.

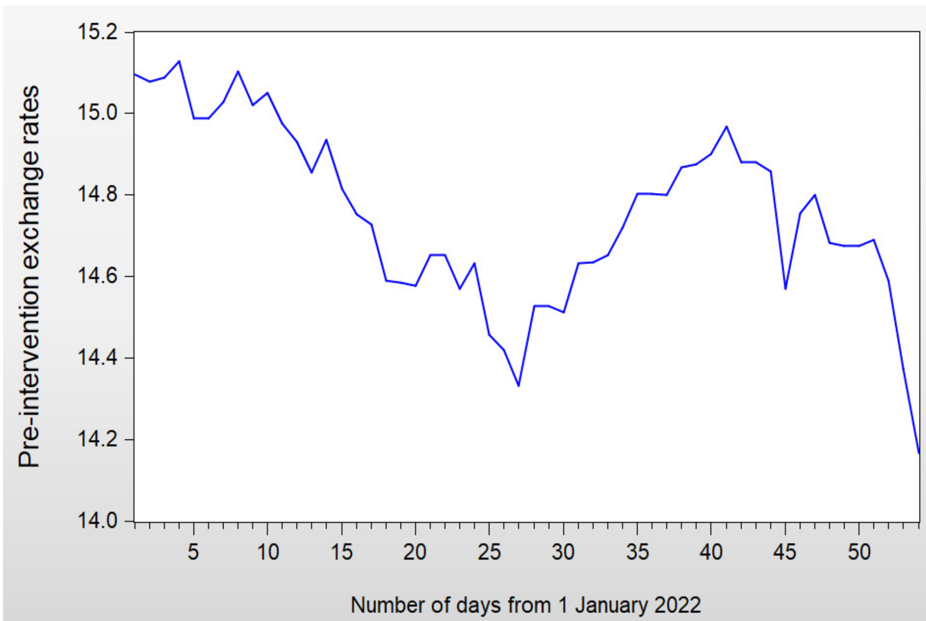

Figure 2: Time plot of the pre-intervention rates

Table 1: Unit root test for the pre-intervention data

Null Hypothesis: UAHN has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.261397	0.8866
Test critical values:	1% level	-4.140858	
	5% level	-3.496960	
	10% level	-3.177579	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UAHN)
Method: Least Squares
Date: 03/15/22 Time: 00:48
Sample (adjusted): 2 54
Included observations: 53 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UAHN(-1)	-0.091543	0.072572	-1.261397	0.2130
C	1.365085	1.084751	1.258432	0.2141
@TREND("1")	-0.001139	0.000959	-1.187017	0.2408

R-squared	0.038764	Mean dependent var	-0.017545
Adjusted R-squared	0.000315	S.D. dependent var	0.093120
S.E. of regression	0.093105	Akaike info criterion	-1.855229
Sum squared resid	0.433431	Schwarz criterion	-1.743703
Log likelihood	52.16358	Hannan-Quinn criter.	-1.812342
F-statistic	1.008180	Durbin-Watson stat	1.923275
Prob(F-statistic)	0.372178		

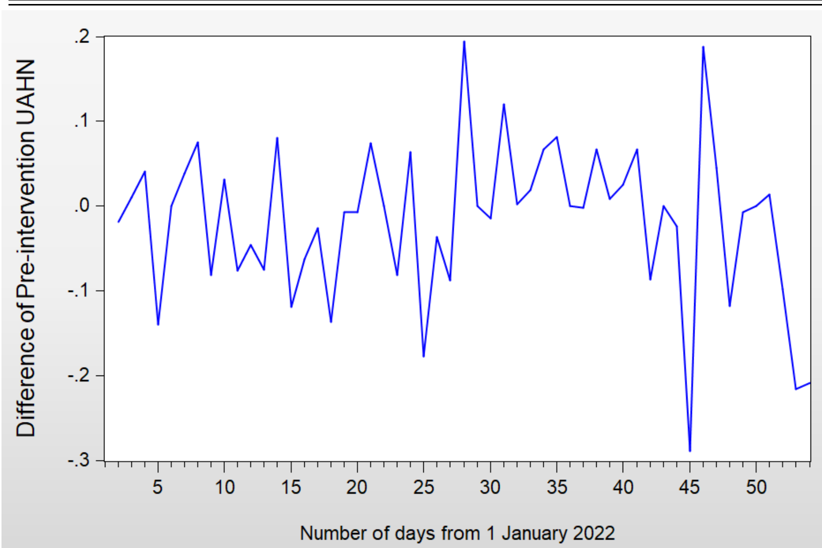

Figure 3: Time plot of the difference of the pre-intervention data

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Table 2: Unit root test for the difference of the pre-intervention data

Null Hypothesis: DUAHN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

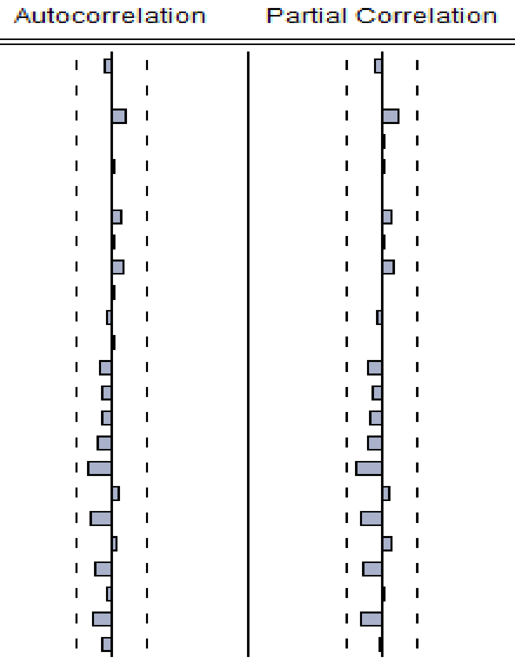
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.147825	0.0000
Test critical values:	1% level	-3.562669	
	5% level	-2.918778	
	10% level	-2.597285	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DUAHN)
Method: Least Squares
Date: 03/15/22 Time: 01:00
Sample (adjusted): 3 54
Included observations: 52 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DUAHN(-1)	-1.054012	0.147459	-7.147825	0.0000
C	-0.018264	0.013310	-1.372280	0.1761

R-squared	0.505398	Mean dependent var	-0.003648
Adjusted R-squared	0.495506	S.D. dependent var	0.133521
S.E. of regression	0.094837	Akaike info criterion	-1.835615
Sum squared resid	0.449701	Schwarz criterion	-1.760568
Log likelihood	49.72600	Hannan-Quinn criter.	-1.806844
F-statistic	51.09140	Durbin-Watson stat	1.907783
Prob(F-statistic)	0.000000		



	AC	PAC	Q-Stat	Prob
1	-0.050	-0.050	0.1375	0.711
2	0.002	-0.001	0.1377	0.933
3	0.115	0.115	0.9029	0.825
4	0.001	0.012	0.9029	0.924
5	0.009	0.009	0.9078	0.970
6	0.007	-0.006	0.9105	0.989
7	0.076	0.076	1.2791	0.989
8	0.016	0.022	1.2950	0.996
9	0.084	0.087	1.7626	0.995
10	0.017	0.008	1.7812	0.998
11	-0.044	-0.049	1.9159	0.999
12	0.024	-0.001	1.9581	0.999
13	-0.097	-0.102	2.6475	0.999
14	-0.068	-0.078	2.9889	0.999
15	-0.074	-0.092	3.4059	0.999
16	-0.103	-0.110	4.2338	0.998
17	-0.180	-0.198	6.8432	0.985
18	0.059	0.047	7.1287	0.989
19	-0.162	-0.156	9.3794	0.967
20	0.027	0.075	9.4447	0.977
21	-0.138	-0.155	11.177	0.959
22	-0.043	0.015	11.353	0.969
23	-0.144	-0.161	13.365	0.944
24	-0.078	-0.014	13.980	0.947

Figure 4: Correlogram of the difference of the pre-intervention data F = 14.1666, t > 54

Table 3: Transfer Function determination for the intervention model

Dependent Variable: Z
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 03/15/22 Time: 01:14
Sample: 55 72
Included observations: 18
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Z=C(1)*(1-C(2)^(T-54))/(1-C(2))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.250752	0.122123	-2.053279	0.0568
C(2)	-0.006593	0.504243	-0.013075	0.9897

R-squared	0.000016	Mean dependent var	-0.249200
Adjusted R-squared	-0.062483	S.D. dependent var	0.118487
S.E. of regression	0.122133	Akaike info criterion	-1.262979
Sum squared resid	0.238662	Schwarz criterion	-1.164049
Log likelihood	13.36681	Hannan-Quinn criter.	-1.249338
Durbin-Watson stat	0.320150		

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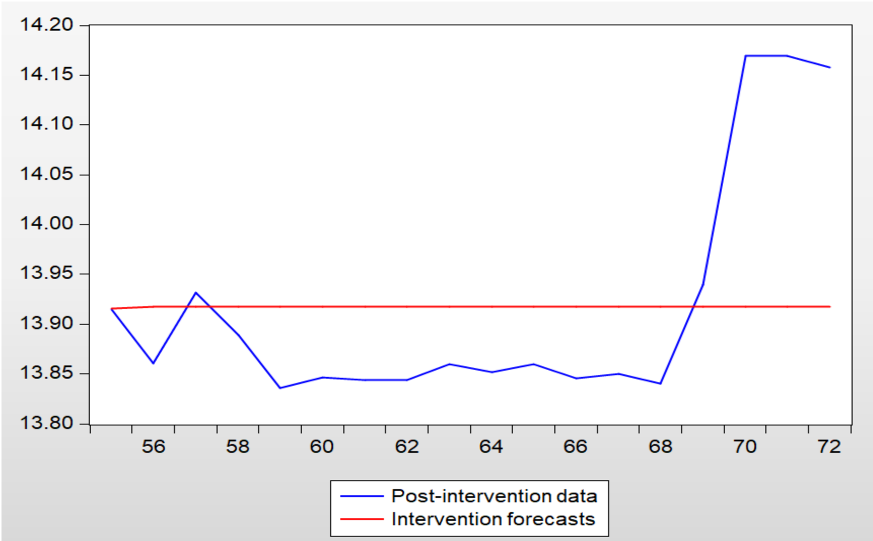

Figure 4: Superimpositon of the post-intervention forecasts and the data

TABLE 4: Goodness-of-fit test of the intervention model with post-intervention data

Intervention forecasts (1)	Post-intervention data (2)	((1)-(2))^2/(1)
13.91575	13.9150	0.00000402
13.91740	13.8608	0.00023000
13.91739	13.9315	0.00001430
13.91739	13.8888	0.00005870
13.91739	13.8362	0.00047400
13.91739	13.8463	0.00036300
13.91739	13.8440	0.00038700
13.91739	13.8442	0.00038500
13.91739	13.8599	0.00023700
13.91739	13.8516	0.00031100
13.91739	13.8601	0.00023600
13.91739	13.8455	0.00037100
13.91739	13.8505	0.00037100
13.91739	13.8401	0.00042900
13.91739	13.9399	0.00003640
13.91739	14.1696	0.00457100
13.91739	14.1695	0.00456700
13.91739	14.1579s	0.00415600

Total 0.01691142

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