Statistical Assessment of Government's Interventions on Nigerian Crude Oil Prices

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***Abstract* — Nigerian crude oil price has been characterized by series of breaks, jumps, and through indicative of very important events called intervention. A lot of work has gone into the assessment of this intervention by records over the years but most current events have not been captured. This paper, therefore, attempts to assess the impact and mean effect of these interventions using the ARIMA-Intervention model and Intervention model using Lag Operator to determine the better model for analyzing time data in the presence of interventions. Data used is the monthly crude oil price from January 1985 to December 2017. The results showed that the second, third, fourth, fifth, seventh, and eighth interventions had a negative impact on the crude price with the respective interventions being the OPEC 10% Quota Increase and Asian Financial Crisis of 1998, OPEC reduction of members production Quotas of 2000, The Financial crisis of 2008, the Political Unrest in Egypt of 2011, the effect of the Nuclear Agreement of 2014 and China's low economic growth of 2016 while the first and the sixth interventions impacted on the crude oil price positively with the respective interventions being the Gulf War of 1990 and the carried-over effect of the Political Unrest of 2011 in Egypt. ARIMA-Intervention model was found to be superior to the Intervention model using Lag Operator as indicated by the RMSE, MAE and MAPE, Since the smaller the error the better the forecastability of the model. Hence, the ARIMA-Intervention model can be usefully employed for forecasting crude oil prices.**

Keywords - *Intervention analysis, Crude oil, Financial crisis, Prices.*

I. Introduction

The world economy needs the energy to run and much of that energy is crude oil. Therefore, sustainable access to crude oil has remained a key aspect of international politics and relations by Import-dependent countries and exporting countries alike. Import-dependent countries are interested in how to maintain sustainable, secure access to oil at low prices, whereas oil-exporting countries are interested in balancing their desire to uphold prices and revenues while maintaining market share, Bromley et al (2006). This has formed a key basis of the relationship between these two categories of countries and their actions and inactions since the discovery of oil and its importance in powering the world economy became known.

The economics law of free-market based on demand and supply has been severally manipulated by politics and global events aimed at putting pressures on demand or supply depending on the interest of the political actors. One of the major factors that affect the prospects of an oil-dependent economy is the crude oil price in the international market. Since the first oil price shock of 1974, the shocks have kept reoccurring. Between 1991 and 2016 these distortions have been so obvious and as such caused uncertainties in the exchange rates, planning, and execution of vital projects in the economy.

Unfortunately, Nigeria, whose crude oil export currently accounts for 90% of her total exports and roughly 75% of her consolidated budgetary revenues. Except through OPEC (which is largely controlled by the Arab member countries), Nigeria does not have any effective hold on global oil price and so, is essentially a price taker and vulnerable to the vagaries of global oil price and its politics. These distortions in the prices of crude oil have been due to interventions such as 1990(The Gulf War), 1998(OPEC 10% Quota Increase and Asian Financial Crisis), 2000(OPEC Reduce Members Production Quotas), 2008(The Financial Crisis), 2011(Political unrest in Egypt), 2015(Nuclear Agreement of 2014) and 2016(China's Economy hit the lowest Growth).

II. REVIEW OF LITERATURE

The most widely used technique for modeling and forecasting in time series is the Box Jenkins ARIMA methodology. However, when the patterns of the time series under study are affected by some external event such as mentioned above, then the forecasting performance of the ARIMA model may be affected. However, it can be improved by employing appropriate techniques such as the ARIMA-Intervention model.

In this study, the data on monthly crude oil prices is analyzed using the ARIMAIntervention model with a view to comparing the result with that of the intervention model using the lag operator. Intervention analysis is a method that measures the effect of external or exogenous intervention on a time series data of interest.

This model has been successfully applied by scholars. For example, Roy *et al* (2009), used ARIMA – Intervention Analysis in Modeling the Financial Crisis in China's Manufacturing Industry. Shittu (2009), Modeled the Exchange Rate in Nigeria in the Presence of Financial and Political Instability using the multiple regression model to compare the result with that of the intervention model with lag operator L. Jarrett and Kyper (2011), used ARIMA Modeling with Intervention to Forecast and Analyze Chinese Stock Prices. Mrinmoy *et al* (2014), used time-series Intervention Modelling for Modelling and Forecasting Cotton Yield in India. Etuk and Eleki (2017), used the ARIMA Intervention model to analyze the Monthly Xaf – Ngn Exchange Rates occasioned by Nigerian Economic Recession.

This paper, therefore, attempts to assess the impact and mean effect of these interventions using the ARIMA-Intervention model and Intervention model using Lag Operator with a view to determining the better model for analyzing time data in the presence of interventions.

III. MODEL SPECIFICATION

Two approaches were considered in modeling the crude oil price dataset.

Model I

The first scheme for intervention analysis is based on the time series models of Box - Jenkins and Tiao (Box and Jenkins, 1970; Box and Tiao, 1965, 1973). Box- Tiao and Box-Jenkins models represent time-series observations as the realization of a linear stochastic process of autoregressive, moving average, or mixed autoregressive-moving average form.

$$Y_t = \frac{\omega(B)}{\delta(B)} B^b I_t + \frac{\theta(B)}{\phi(B)} \varepsilon_t \qquad (3.1)$$

Let

$$\delta(B) = 1 - \delta_1 B - \ldots - \delta_r B^r$$

$$\omega(B) = \omega_0 - \omega_1 B - \ldots - \omega_s B^s$$

$$\phi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$$

$$\theta(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$$

where:

Y_t = the observed crude oil price, b = delay parameter, ω = impact parameter, δ = slope parameter, ϕ = autoregressive parameter, θ = moving average parameter, B= backshift operator, ε_t = white noise, I_t = is the intervention variable that is defined as

$$I_t = \begin{cases} 1, t = T \\ 0, t \neq T \end{cases} \qquad (3.2)$$

Model II

Using the assumption that the full impact of intervention might not be felt until the second month and following Enders, Sandlers, and Cauley (1990), we consider the intervention model using lag operator L as:

$$y_t = c_0 + a_1 y_{t-1} + \sum_i^k b_i S_i + \varepsilon_t, \qquad (3.3)$$

Simplifying (3.3), we obtain equation (3.4)

$$y_t = (1 - a_1 L)^{-1} c_0 + (1 - a_1 L)^{-1} \sum_i^k b_i S_i + (1 - a_1 L)^{-1} \varepsilon_t \qquad (3.4)$$

Since $(1 - a_1 L)^{-1}$ is the limit of the convergent geometric series $(1 + a_1 L + a^2{}_1 L^2 + \ldots)$, then equation (3.4) becomes:

$$y_t = (1 + a_1 L + a^2{}_1 L^2 + \ldots) c_0 + (1 + a_1 L + a^2{}_1 L^2 + \ldots) \sum_i^k b_i S_i + (1 + a_1 L + a^2{}_1 L^2 + \ldots) \varepsilon_t \qquad (3.5)$$

$$y_t = \frac{c_0}{1 - a_1} + \sum_j^k b_j \sum_i^\infty a^i{}_1 S_{t-i} + \sum_i^\infty a^i{}_1 \varepsilon_{t-i} \qquad (3.6)$$

where:

y_t = the observed crude oil price, k= maximum number of interventions in the series, c_0 = The intercept term, b_i = impact of the intervention variables, ε_t = The white noise disturbance term, a_1 = Serial correlation coefficient, S_{it} = The intervention variable.

The various transitional effects are obtained from the impulse response function y_t as follows:

$\frac{c_0}{1-a_1}$, (The long-run mean effect of the intervention on the series) (3.7)

$\frac{c_0+b_i}{1-a_1}$, (The long-run mean effect at each intervention S_i) (3.8)

$\frac{c_0+\sum_{j=1}^{k} b_j}{1-a_1}$, (The long-run mean effect after each intervention S_i) (3.9)

IV. Sources of Data

The data used for this study are on the monthly crude oil prices for the period January 1985 - December 2017. They were collected from US Energy Information Administration.

V. Results and Discussions

Intervention analysis is a method that measures the effect of an external or exogenous intervention on time series data. The dataset considered for the analysis is the monthly crude oil price from January 1985 to December 2017.

The time series so defined is analyzed to determine candidate ARIMA models. Then, the ARIMA-Intervention model and Intervention model using Lag Operators as defined in section three, are analyzed and interpreted. Thus, the following are the special events or interventions on crude oil price from January 1985 to December 2017: **1990** (The Gulf War), **1998**(OPEC 10% Quota Increase and Asian Financial Crisis), **2000** (OPEC Reduce Members Production Quotas), **2008**(The Financial Crisis), **2011**(Political unrest in Egypt), **2015** (Nuclear Agreement of 2014) and **2016**(China's Economy hit the lowest Growth). The statistical package used for the analysis of this work is R language (R-3.4.4-win).

The Time Plot

The time plot showing the monthly crude oil Price from January 1985 to December 2017 is given in Figure 1. The graph of the series shows an upward trend as it rises and falls at random. From the plot, we can observe a significant drop in crude oil Price in December 1998, January 2015, and January 2016. While October 1990, September 2000, July 2008, June 2011, and March 2012 testify a period of increase in crude oil price.

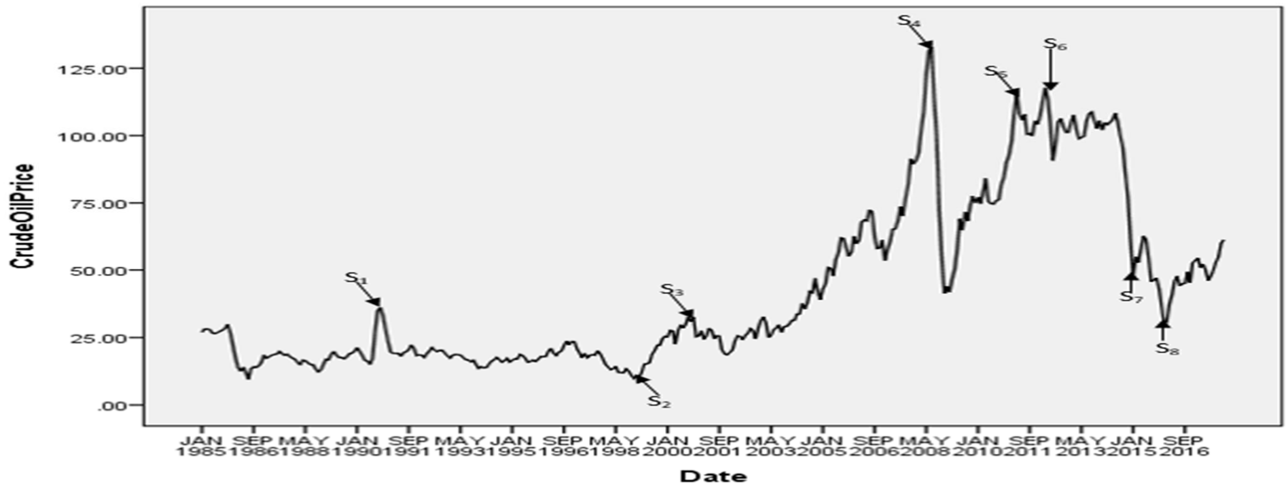

Figure 1: Time plot of the series from 1985 to 2017

Eight points were identified on the time plot. These points were suspected to be those points where the intervention took place on the crude oil price dataset. These points were labelled by indicator functions as:

$$I_{1t} = \begin{cases} 0, t < October, 1990 \\ 1, t \geq October, 1990 \end{cases}, I_{2t} = \begin{cases} 0, t < December, 1998 \\ 1, t \geq December, 1998 \end{cases},$$

$$I_{3t} = \begin{cases} 0, t < September, 2000 \\ 1, t \geq September, 2000 \end{cases}, I_{4t} = \begin{cases} 0, t < July, 2008 \\ 1, t \geq July, 2008 \end{cases}$$

$$I_{5t} = \begin{cases} 0, t < June, 2011 \\ 1, t \geq June, 2011 \end{cases}, I_{6t} = \begin{cases} 0, t < March, 2012 \\ 1, t \geq March, 2012 \end{cases},$$

$$I_{7t} = \begin{cases} 0, t < January, 2015 \\ 1, t \geq January, 2015 \end{cases}, I_{8t} = \begin{cases} 0, t < January, 2016 \\ 1, t \geq January, 2016 \end{cases}$$

Model I

After fitting model I, we obtained the following Estimates:

Table 1: Parameter Estimates of the ARIMA-Intervention Models

Parameter/ Intervention	First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth
AR(1)	-	0.4196	0.4339	-0.2877	0.4458	0.4656	0.4218	0.9901
MA(1)	0.3625	-	-	-	-	-	-	0.3108
MA(2)	0.1777	-	-	-	-	-	-	-
Impact(ω)	9.7934	-0.8109	-1.3298	-2.2877	-9.3587	5.9835	-12.1372	-2.8712
Slope(δ)	0.8872	0.7035	-0.6538	-0.6106	0.9426	0.8661	0.9247	0.7949
IRF(b)	1	1	0	1	1	2	0	0

The dataset on monthly crude oil price was divided into pre-intervention observations for ARIMA modeling and post-intervention observations for determining the intervention component form. The series was adjudged stationary across the eight pre-intervention observations.

From the impulse response function, it can be inferred that b=1 i.e. though the intervention occurred in Oct.1990, Dec.1998, July2008, June2011 for the 1st, 2nd, 4th, 5th interventions respectively but its effect was felt only in Nov.1990, Jan1999, Aug2008, July2011 respectively. For b=2, for the 6th intervention, that is, though the intervention occurred in Mar2012 and its effect was felt after a delay of two periods. b=0 for the 7th and 8th interventions, that is the effect of the intervention was felt at the point of intervention exactly (i.e. Jan2015 and Jan2016 respectively).

The interventions had a positive impact on the crude oil price for the 1st and 6th interventions. While the impact parameter implies a negative change due to the interventions for the 2nd, 3rd, 4th, 5th, 7th and 8th interventions. Slope parameter is near one for the 1st, 2nd, 5th, 6th, 7th and 8th interventions, which implies that the effect of the intervention increases over time. But for the 3rd and 4th interventions, the slope parameter indicates a constant effect over time since it is near zero.

Model II

Intervention model using Lag Operator in Equation (3.6) described in section three is used in this section to model the crude oil price dataset.

Table 2: Parameter Estimates of Intervention Model using Lag Operator

Parameters	Estimate	S.E	t-Statistics
c_0	1.9467	0.6572	2.962
a_1	0.8913	0.0160	55.717
b_1 (1990)	0.2731	0.7593	0.360
b_2 (1998)	-0.9092	1.1634	-0.782
b_3 (2000)	2.8569	1.2385	2.307
b_4 (2008)	4.9886	1.0631	4.692
b_5 (2011)	1.0613	1.8643	0.569
b_6 (2012)	-0.5012	1.7084	-0.293
b_7 (2015)	2.6413	1.8143	1.456
b_8 (2016)	-6.0572	1.8078	-3.351

We have the intercept term to be 1.9467 and the impact of each intervention S_i (i=1, 2, 3, 4, 5, 6, 7, 8) on the monthly crude oil price is measured by the coefficient b_i (0.2731,-0.9092,2.8569,4.9886,1.0613,-0.5012,2.6413,-6.0572) and the serial correlation coefficient a_1 (0.8913). It is seen that the first, third, fourth, fifth and seventh impact parameters are all positive (0.2731, 2.8569, 4.9886, 1.0613, 2.6413) implying a positive change due to intervention while the second, sixth and eighth impact parameters are negative (-0.9092, -0.5012 and -6.0572) indicating a negative change due to intervention. Thus, the value 0.92661 indicates a persistent effect. The residual shows that the model is adequate and this was confirmed by the F-statistic of 1800 on 9 and 386 degrees of freedom with p-value of 2.2e-16 which is significant, indicating that the model is a good fit.

Table 3: Summary of Transition Effects of Intervention Variables

Intervention Variables	Impact of s_i	Long-run mean at each s_i	Long-run mean after each s_i
b_1 (1990)	0.2731	20.4213	20.4213
b_2 (1998)	-0.9092	9.5446	12.0570
b_3 (2000)	2.8569	44.1914	38.3395
b_4 (2008)	4.9886	63.8022	84.2328
b_5 (2011)	1.0613	27.6725	93.9963
b_6 (2012)	-0.5012	13.2981	89.3855
b_7 (2015)	2.6413	42.2079	113.6845
b_8 (2016)	-6.0572	-37.8151	57.9604

The long-run mean effect of interventions on the series is obtained as 17.9089. And from the Table 3 are the various transitional effects of intervention variables such as the impact, the long-run mean effect before and after each intervention variable. From Table 3 we observed that there is a significant change between the long-run mean effect before and after each intervention.

VI. Conclusion

The Gulf War of 1990 which was identified as the 1st intervention had a positive impact on crude oil price with an increasing effect. The OPEC 10% Quota Increase/Asian Financial Crisis of 1998 (2nd intervention) had a negative impact on the crude oil price with an increasing effect. September 2000 was the third intervention; the intervention was the OPEC reduction of members' production Quotas. Despite this effort by OPEC in reducing members' production, there was still a negative impact on crude oil price may be due to the effect of OPEC's 10% increase of 1998.

The fourth intervention was the financial crisis, in July 2008. We observed an astronomical rise in crude oil price shortly followed by a sharp fall in price and this was confirmed by the impact parameter with a negative effect. The Political unrest in Egypt of 2011 impacts negatively on the crude oil price although with a relative increase in oil price.

The effect of the fourth intervention caused an increased in crude oil price with a positive impact on oil price in year 2012. The effect of the Nuclear Agreement of 2014 had a negative impact with increasing effect in year 2015. China's low economy growth of 2016 had a negative impact on crude oil price with an increasing effect.

Table 4: Model Evaluation

Models	ARIMA-Intervention Model	Intervention Model using Lag Operator L
AIC	2196.83	2383.027
RMSE	3.838	4.7691
MAE	2.597	2.700
MAPE	6.747	6.9352

It can be inferred that the accuracy of forecasting with the ARIMA-Intervention model is more than that of the Intervention model using Lag Operator, since the smaller the error the better the forecasting ability of the model.

VII. Recommendation

Based on this work, the following recommendations were made:

- In order to obtain better forecasts for the crude oil price, it is recommended that this should be modeled using the ARIMA-Intervention model.
- In modelling the crude oil price dataset of January 1985 to December 2017, it is recommended that the model:

$$Y_t = 0.1952Y_{t-1} + 0.7870Y_{t-2} - 2.8712I_{t-2} + 2.8428I_{t-3} + 0.4841\varepsilon_{t-1} - 0.2471\varepsilon_{t-2} + \varepsilon_t$$

be adopted, since the forecast values appeared to be more reliable and closer to reality.

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