Original Research Article

COMPARATIVE ANALYSIS OF ARIMA, PRE-INTERVENTION AND POST-INTERVENTION MODELING OF CRUDE OIL PRICE IN NIGERIA

Abstract

The study applied Autoregressive Integrated Moving Average intervention in modelling crude oil prices in Nigeria betweenJanuary 1986 to June 2017. The time plot of the series showed an abrupt increase in the series and this called for an intervention model. The data was divided into three sets (actual series, pre-intervention and post-intervention series).The Augmented Dickey Fuller (ADF) test was used to test for unit root on each of the variables at level and the series were non-stationary. The first differences showed the present of unit root in all the three series (actual series, pre and post- intervention). Eighteen models were estimated and the best model was the pre-intervention model that minimised the Akaike information criterion (AIC) (ARIMA (111) with AIC of (4.4.578). The plot of the residual correlogram show adequacy of the model. The model was adequate since there was no spike that cut the level of the correlogram and the histogram of the residual was normally distributed.

KEY WORDS: Comparative Analysis, ARIMA, PRE- Intervention, Post-intervention, Crude oil Prices, Nigeria.

1.0 INTRODUCTION

The major source of income to Nigeria government is crude oil production and sales. The production and sales of the commodity has been on the decrease for some period and then a sundered increase,this calls for intervention modelling. The intervention model is used to study the increase and decrease that occur in an event of interestAmadi and Etuk (2017).The purpose of applying autoregressive integrated moving average (ARIMA) intervention model to any series is to find out the dynamic effect on the means level of the variable and other event that affect the series.Jeffrey and Eric (2011)The aim of the study is to apply Box-Tiao (1987) ARIMA intervention model on the crude oil price in Nigeria from January, 1986 to June, 2017.

2.0 LITERATURE REVIEW

Intervention modelling was introduced by Box and Tiao (1975) to examined the impact of air pollution control on smog-producing oxidant level in the Los Angeles area and of economic controls on the consumer price index in the United States. Jeffrey and Eric (2011) used ARIMA intervention model to analyse the Chinese stock price. Etuk *et al.* (2012) fitted a SARIMA $(011)*(011)_{12}$ model for Nigeria inflation rate. Etuk, *et al* (2015) studied monthly Nigeria Treasury Bill Rates using Box-Jankins techniques. The acceptable model for Treasury bill rates was SARIMA $(011)*(011)_{12}$ model. Abdul-Aziz, *et al* (2013) studied rainfall pattern in Ghana as a seasonal ARIMA process using the Box- Jenkins method. Four model were estimated for the series but the best model was choose base on the least BIC, which was estimated as SARIMA $(0,0,0)*(2,1,0)_{12}$.Mrinmoy et al (2014) examined time series intervention model and forecasting cotton yield in Gujarat and Maharashtra in India. Intervention was found to besuperior to the conventional ARIMA model. Etuk and Vincent (2018) fitted intervention model of daily Moroccan Dirhan to Nigeria Naira exchange rate. The best model account on ARIMA intervention modelling can be found in Box et al. (1994).

3.0 METHODOLOGY

The conditional means and the error terms of a series is modelled using autoregressive integrated moving average (ARIMA) model. The movement of the crude oil price in Nigeria has the component of the ARIMA model and an intervention term.

3.1 **ARIMA Model**

Many series are non-stationary, Box-Jenkins (1976) proposed that differencing up to an appropriate order make it stationary. Suppose (d) is the minimum order of differencing necessary for stationarity to be attained, then the series $(c_t)$is said to follow an autoregressive integrated moving average of order p, d and q denoted as (ARIMA(p d q)). If the series is seasonal in nature, the ARIMA model will incorporate both the non-seasonal and the seasonal component in a multiplicative model. The notation for the model is

SARIMA(p d q)×$(P\ D\ Q)_{S.}$ (3.1)

Where p = non-seasonal AR, d = non-seasonal differencing, q = non-seasonal MA, P = seasonal AR, D = seasonal differencing, Q = seasonal MA, and S = time span of repeating seasonal pattern. Without differencing operations, the model could be written more formally as Abdul-Aziz *et al* (2013)

$\phi(B^s)\psi(B)(C_t)$-μ= $\theta(B^s)\Theta(B)\varepsilon_t$ (3.2)

The non-seasonal components are:

AR: $\psi(B)$ = 1 – $\varphi_1 B_1$ - ... – $\varphi_p B_p$ (3.3)

MA: $\Theta(B)$ = 1 + $\Theta_1 B_1$ + ... +$\Theta_q B_q$ (3.4)

The seasonal components are: Seasonal

AR:$\phi(B^s)$= 1 – $\phi_1 B^s$ - ... -$\phi_P B^{sP}$ (3.5)

Seasonal MA: $\theta(B^s)$= 1 + $\theta_1 B^s$ + ... +$\theta_Q B^{sQ}$ (3.6)

Seasonal differencing is defined as a difference between a value and a value with lag that is a multiple of *S*. Where *S* = 12, which may occur with monthly data, a seasonal difference is

$B^{12}c_t$= c_t- c_{t-12} (3.7)

The differences (from the previous year) may be about the same for each month of the year giving us a stationary series.Seasonal differencing removes seasonal trend and can also get rid of a seasonal random walk type of non-stationary.Non-seasonal differencing: If trend is present in the series after seasonal differencing, we may also need non-seasonal differencing. Often a first non-seasonal difference will “de-trend” the data.Wiri and Essi (2018)

4.0 INTERVENTION

The simple ways to study intervention analysis (event study) is to consider some simple dynamic models which involved two stages, pulse function and step function.

4.1 Pulse Function

A pulse function is a function which shows that intervention only occur in a single time index (t_1). Mathematically the pulse function is given as;

$$P_t = \begin{cases} 0 & if \;\; T \neq t_1 \\ 1 & if \;\; T = t_1 \end{cases} \tag{4.1}$$

4.2 Step Function

A step function is function which define the intervention process as a continual stage starting with time index (t_1). Mathematically the step function is

$$S_t = \begin{cases} 0 & if \;\; t < t_1 \\ 1 & if \;\; t \geq t_1 \end{cases} \tag{4.2}$$

4.3 **ARIMA Intervention Model**

The intervention model discussed by [3]is of the form

$$Y_t = \Gamma(\mathrm{B}) I_t + K_t \tag{4.3}$$

Where, Y_t = dependent variable, I_t= is the time of intervention (indicator variable),I_t=P_t=S_t

$\Gamma(\mathrm{B}) = \frac{\xi(B)}{\eta(B)}\mathrm{B}^{\mathrm{r}}$, $K_t = \frac{\theta(B)}{\varphi(B)}\varepsilon_t$, B^{r} = backshift operator

$$Y_t = \frac{\xi(B)}{\eta(B)}\mathrm{B}^{\mathrm{r}} I_t + \frac{\theta(B)}{\varphi(B)}\varepsilon_t \tag{4.4}$$

4.2.0 Step Involve in ARIMA Intervention Model

The general step for estimation of ARIMA intervention model consists of the following three stages:

I Time plot of the original series.

2 Tet for stationality of the data using Augmented Dickey-Fuller (ADF) test where the null hypothesis of unit root exists.

3 Model Estimation and selection.

4 Diagnosis check of the parameters of the model

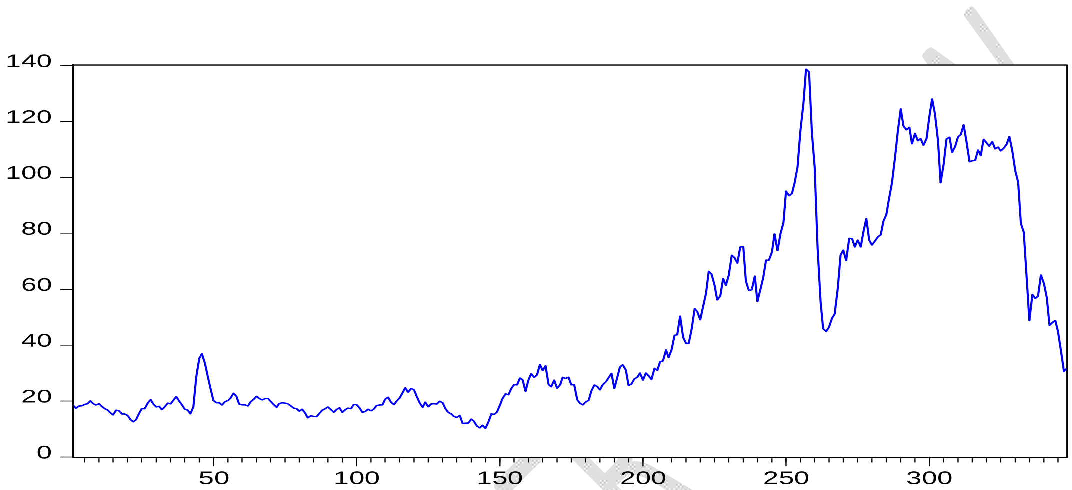
5 Residual diagnostic check using correlogram of Q-statistics, ACF and PACF of the residual is used for residual diagnostic check.

5.0 RESULTS AND DISCUSSION

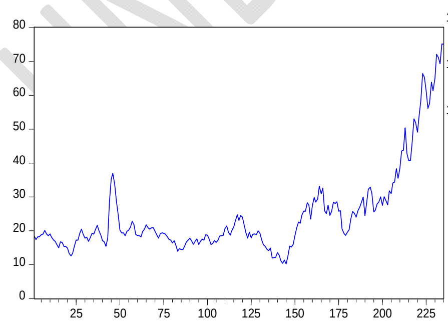
The series is a monthly crude oil prices in US dollars per barrel from January1986 to

June 2017 from Central Bank of Nigeria website. www.cenbank.org. The researcher used eviews 10 in the statistical analysis.

Figure 1.0. Time Plot of Crude Oil Price



Examining Figure 1.0, we noticed an irregular movement, with sudden jump in the year 250the effect beginning at time t_1= 251 Suggesting a new set of governmental intervene in crude oil production and sale. Therefore, there is one intervention point, meaning production of crude oil and the sale was on increase. Thus, we identify the intervention point; it can be defined as follows; pre-intervention period (0 to 235) and post-intervention period (235 to 366). The data was divided into two part, see Figure 1.1 and figure 1.2 for pre-intervention and post-intervention time plot.



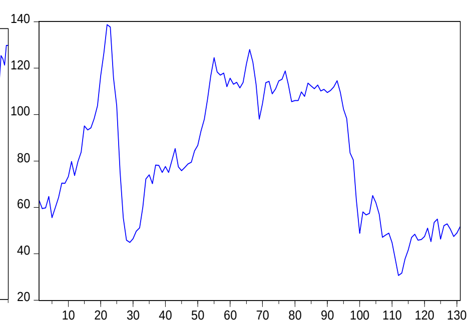


Figure 1.1. Pre-Intervention *Figure 1.2 Post-Intervention*

The pre-intervention series shows irregular and linear trend, with gradual increase to 235 (meaning irregular increase in the price of crude oil). From figure 1.2 the post-intervention graph show irregular movernment upward and downward trend (meaning increase and decrese in the sales of crude oil price)

5.1 Stationarity Test

Table (1.0) Unit Roots Test

Variable	Levels	1st difference	Test critical value	
Crude oil price	-1.9555 (0.3067)	-13.036 (0.000)	1% level	-3.4816
Pre-intervention	1.266(0.9976)	-13.225 (0.000)	5% level	-2.8829
Post-intervention	-2.153(0.332)	-7.2933 (0.000)	10% level	-2.5787

The series are required to be stationary in order to carry out joint significant test on the lags of the variable and the method used to test for stationary is the Augmented Dickey Fuller (ADF) test. The test is used to test for unit root on each of the variables(Brooks 2008).Table (1.0) represent result of The Augmented Dickey Fuller (ADF) test at level and first differences and probability values in brackets. The probability values (p-values) at level is greater than 0.05 (p-values >0.05), the result showed the presence of unit root. The p-value of all the variables at first difference were tested for stationarity and the series was stationary. The probability values is (0.000) for all the variables hence the null hypothesis was rejected and the series concluded stationary. Etuk *et al* (2017)

5.2 Model Estimation and AIC and SIC Values

Eighteen models were estimated in all, six each for estimated for ARIMA, PRE-INTERVENTION AND POST-INERVENTIONrespectively with Akaike information criterion (AIC) and schwarz information criterion (SIC) shown in appendix(1). The best model for Nigeria crude oil price was ARIMA-intervention (pre-intervention series in appendix (4)) model (ARIMA (111)) with minimise information criterion AIC (4.579) and SIC (4.638).Akaike (1975)

The pre-intervention (ARIMA (111)) model for crude oil price in Nigeria is given below

$$C_t = \frac{\xi(B)}{\eta(B)} B^r I_t + \frac{\theta(B)}{\varphi(B)} \varepsilon_t \qquad (5.1)$$

Where

C_t = crude oil price at time t, $\xi(B)$= Impact parameter, $\eta(B)$= slop parameter, $\varphi(B)$= AR(1) parameter, $\theta(B)$= MA(1) parameter

I_t= indicator variable coded according to the type of intervention involved in the study. The type of intervention in this study is call a pulse function (intervention only occur in a single time index t_1 =235). Chung *et al* (2009)

The pre-intervention model obtained is given as follow

$$C_t = \frac{-7.88}{1-0.0439B} BI_t + \frac{1-0.764B}{1+0.61B} \varepsilon_t \quad (5.2)$$

The model can also be represented lineally as

$$C_t = 1.045C_{t-1} + 0.268C_{t-2} - 7.88I_{t-1} - 4.81I_{t-2} - 1.2\varepsilon_{t-1} + 0.374\varepsilon_{t-2} + \varepsilon_t \quad (5.3)$$

5.3 Diagnostic Test

The plot of the residual correlogram showed adequacy of the model since there is no spike that cut off level in appendix (2). The histogram of the residual is normally distributed with probability values (0.000) in appendix (3). The test statistics of the residual showed that the data is normally distributed with constant mean and variance (White noise Process). Box and Jenkins (1976)

5.4 Conclusion

The ARIMA-Intervention model was used to measure the impact of unusual increase in the crude of price in Nigeria. The study investigated the time series intervention modelling of (actual series, pre and post intervention analysis). It was found that in all the three models, pre-intervention analysis was found to be superior to the conventional ARIMA models and post intervention.The results indicate that pre- intervention analysis is much appropriate in modelling trend of Nigeria crude oil price.

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Appendix (1)

Parameter Estimation Of Arima And Arima+Interventions Models

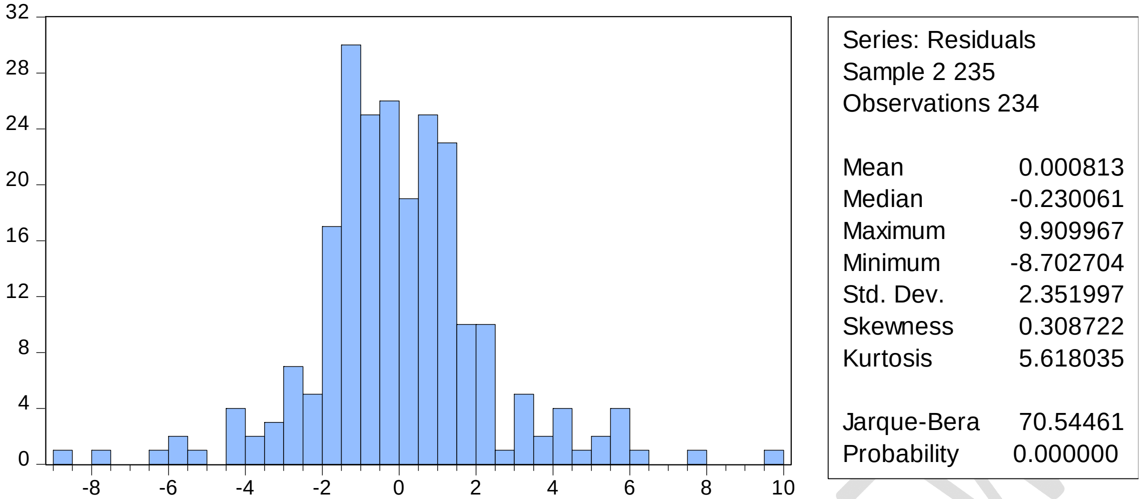
MODELS	PARAMETER CO-EFFICIENT		AIC	SIC
	AR(p)	MA(q)		

ARIMA MODEL OF CRUDE OIL PRICES				
ARIMA(111)	0.3823	-0.0260	5.785	5.800
ARIMA(011)		0.3386	5.766	5.798
ARIMA(110)	0.3598		5.7528	5.784
ARIMA(210)	0.356 0.00923		5.758	5.80
ARIMA(012)		0.344 0.0972	5.764	5.80
ARIMA(212)	-0.2806 0.334	0.6552 -0.1337	5.75	5.823
ARIMA-INTERVENTION (PRE-INTERVENTION)				
ARIMA (111)	**-0.6095**	**0.7638**	**4.578**	**4.637**
ARIMA (110)	0.1383		4.587	4.892
ARIMA (011)		0.16456	4.584	4.627
ARIMA (210)	0.1526 -0.1014		4.586	4.644
ARIMA (012)		0.1492 -0..1111	4.58	4.644
ARIMA (212)	0.158 0.372	-0.0274 -0.542	4.59	4.67
ARIMA-INTERVENTION (POST-INTERVENTION)				
ARIMA(111)	0.477	-0.0834	6.55	6.66
ARIMA(110)	0.40766		6.5366	6.58
ARIMA(011)		0.37067	6.564	6.617
ARIMA(210)	0.922 0.0373		6.55	6.617
ARIMA(012)		0.366 0.136	6.564	6.63
ARIMA(212)	-0.2056 0.3811	0.6249 -0.1583	6.58	6.717

Appendix (2). Corrrlogram of Nigeria Crude Oil Price.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.139	0.139	4.5621	0.033
		2	-0.078	-0.099	6.0195	0.049
		3	-0.080	-0.056	7.5481	0.056
		4	-0.156	-0.149	13.414	0.009
		5	0.029	0.064	13.622	0.018
		6	-0.028	-0.077	13.818	0.032
		7	-0.010	-0.004	13.841	0.054
		8	-0.041	-0.071	14.242	0.076
		9	0.039	0.068	14.616	0.102
		10	0.217	0.184	26.234	0.003
		11	0.117	0.074	29.623	0.002
		12	0.093	0.102	31.778	0.001
		13	-0.035	-0.004	32.080	0.002
		14	-0.096	-0.008	34.399	0.002
		15	-0.099	-0.078	36.855	0.001
		16	-0.105	-0.073	39.673	0.001
		17	0.076	0.076	41.150	0.001
		18	0.020	-0.019	41.255	0.001
		19	0.107	0.099	44.174	0.001
		20	0.117	0.045	47.697	0.000
		21	0.009	-0.001	47.720	0.001
		22	-0.029	-0.076	47.944	0.001
		23	-0.103	-0.077	50.720	0.001
		24	0.009	0.049	50.743	0.001
		25	0.024	0.051	50.895	0.002
		26	-0.026	0.013	51.079	0.002
		27	-0.049	-0.060	51.722	0.003
		28	-0.037	-0.009	52.094	0.004
		29	0.001	-0.081	52.095	0.005
		30	0.139	0.085	57.314	0.002
		31	0.021	-0.075	57.429	0.003
		32	0.001	0.058	57.430	0.004
		33	-0.089	-0.045	59.622	0.003
		34	-0.074	-0.003	61.152	0.003

Appendix (3) Histogram of residuals of Nigeria crude oil price



Appendix (4) ARIMA(1,1,1)

Dependent Variable: DE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/30/18 Time: 15:57
Sample: 2 235
Included observations: 234
Convergence achieved after 27 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.239790	0.177461	1.351225	0.1780
AR(1)	-0.609500	0.119080	-5.118389	0.0000
MA(1)	0.763892	0.099669	7.664325	0.0000
SIGMASQ	5.508249	0.340418	16.18086	0.0000

R-squared	0.036335	Mean dependent var	0.242521
Adjusted R-squared	0.023765	S.D. dependent var	2.395928
S.E. of regression	2.367286	Akaike info criterion	4.578684
Sum squared resid	1288.930	Schwarz criterion	4.637750
Log likelihood	-531.7061	Hannan-Quinn criter.	4.602500
F-statistic	2.890700	Durbin-Watson stat	1.977482
Prob(F-statistic)	0.036222		

Inverted AR Roots	-.61
Inverted MA Roots	-.76

Appendix (5)

Dependent Variable: Z
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 10/30/18 Time: 16:58
Sample (adjusted): 2 131
Included observations: 130 after adjustments
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients
Z = C(1)*(1 - C(2))^(T - 235)/(1 - C(2))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-7.875241	351.5401	-0.022402	0.9822
C(2)	-0.043943	0.398930	-0.110152	0.9125

R-squared	0.000277	Mean dependent var	-0.008154
Adjusted R-squared	-0.007533	S.D. dependent var	1.747367
S.E. of regression	1.753936	Akaike info criterion	3.976867
Sum squared resid	393.7653	Schwarz criterion	4.020983
Log likelihood	-256.4963	Hannan-Quinn criter.	3.994793
Durbin-Watson stat	1.063710		