# Estimating the Impact on the Nigeria Crude Oil Export from 2002 to 2013. (An Arima-Intervention Analysis)

Obinna Adubisi, E.T. Jolayemi

**Abstract:** This research was done within the framework of intervention analysis to evaluate and estimate the impact of the financial crisis which became a global issue from January 2008, on Nigeria crude oil export. Secondary data on monthly crude oil export was obtained from the Nigeria National Petroleum Cooperation (NNPC) annual statistical bulletin from 2002 to 2013. The 72 months pre-intervention series was used to identify a seasonal ARIMA (0, 1, 1) $(0, 1, 1)_{12}$ model, with differencing required at lags 1 and 12 to achieve stationarity. Based on the pre-intervention series model, the full intervention model was obtained. The parameters of the SARIMA and intervention models were found to be statistically significant, p-value $< 0.05$ respectively. The study revealed a significant 11.6 million barrels reduction in crude oil export and a significant long run effect of 7.6 million barrels. The overall intervention model was significant at 5% level based on the Ljung-Box test.

**Keywords:** Crude oil export, Global financial crisis, Intervention analysis, SARIMA.

## 1. INTRODUCTION

The global financial debacle is considered as a periodic plunge in international monetary and global payment system often occasioned by the breakdown of financial institutions and international megabanks as well as the loss of confidence by investors in the system and the devaluation of financial assets of affected countries as in [25]. The financial crisis which emanated from the United States as a liquidity crisis due to overvaluation of financial assets in the United States banking system in 2007, became a global issue starting from the first quarter of 2008.

In most modern industrialized societies, crude oil is considered as the prime mover and basis of most of the process in these societies but notwithstanding its importance, oil sales by crude oil exporting countries was adversely affected as a result of the economic meltdown experienced by these industrialized nations. Crude oil exporting countries during the financial crisis recorded lower total revenues from crude oil sales including other petroleum products as a result of reduced demands. The magnitude of the impact on crude oil and other petroleum products sales is not yet disclosed as the effect of the global financial crisis varies from one crude oil producing country to another.

### 1.1 Statement of the problem

The financial crisis by both local and international analysts is said to have affected Nigeria export leading to less demand for Nigeria crude oil contrary to the believe by many Nigerians, since the major oil trading partners like America, Europe and Asia were the hardest hit by the crisis. Furthermore, given that the Organization of Petroleum Exporting Countries (OPEC) in 2008, cut supply of crude oil by 4.2 million barrel per day to shore up oil price in the international market due to reduced demand for crude oil. This research is therefore carried out to determine the magnitude of the decline in Nigeria crude oil export due to the aforementioned crisis using a statistical approach called impact assessment or Intervention time series analysis.

### 1.2 Significance of the study

Since the oil boom of 1970's, crude oil has been the major export commodity for the past decades. It continues to play the major roles as the foreign exchange earner to the country and provides the major source of the Nigeria government revenue. Since the Nigeria economy is crude oil export oriented, this study would reveal from its results that the economic crisis declined the demand for crude oil indirectly affecting our nation's economy within the study period, so need for appropriate policies by the government to avert such impact on the economy in the nearest future.

### 1.3 Objectives of the study

This study is aimed at achieving the following objectives:

I. To model the crude oil export from 2002 to 2013 given the impact of the global financial crisis.
II. To estimate the magnitude of the global financial crisis impact on Nigeria crude oil export.
III. To evaluate the pattern of the fitted intervention effect model.

## 2. Literature review

The perusal review of previous published literature by different authors regarding the application of intervention analysis. Intervention analysis or impact assessment is used to assess the effect of some input events or intervention events on a well-defined time series dataset in the time domain. In 1975, Box and Tiao [9] developed the autoregressive integrated moving average (ARIMA) model version of interrupted time series analysis which was found to be statistically valid for the assessment of the significance of the input event or events on a given time series. Many analysts over the years have used intervention analysis approach in a wide variety of applications in different fields to assess the effect of certain events or policies on a given time domain series. Chung et al. [14], carried out a study to model and analyze the impact of the financial crisis on China manufacturing industry, using data collected from China National Bureau of Statistics from the year 2005 to 2008. The results showed that the manufacturing industry in China tolerated a significant negative impact as a result of the global financial debacle. The impact of the global financial debacle on china manufacturing industry was abrupt and temporary. Comparison between ARIMA without intervention and ARIMA with intervention was carried out and the results confirmed that ARIMA with intervention produced the best fitted model.

Rusco et al. [27], investigated the long-run impact of lifting the Alaskan crude oil export ban through the use of intervention analysis. The results from the study revealed that the oil prices in Alaskan increased relative to prices of comparable crude oils in the west coast spot market as a result of export ban lifting. However, the paper concluded that were no real evidence to prove that prices for diesel fuel, refined oil, unleaded gasoline and jet fuel increased in the Western Coaster region as a result of export ban lifting.

Maurice [22], used intervention analysis to examine the effectiveness of the cocoa Hi-technology and the national mass spraying introduced by the Ghanaian Government on cocoa production in 2003 and 2002 respectively. Annual data from the year 1984 to 2011, used for the study was obtained from Ghana COCOBOD institution. The results from the study revealed that both Programmes significantly increased cocoa production in Ghana by 266,515.1 and 182,398.2 metric tons per annum and others like; the tourism forecasting [13], [17]; China economic factors investigation [14]; demand in telemarketing centers [5], and Air travel demand investigation [20]. The above reviews have mainly stated the use of ARIMA models with intervention analysis as an analytical tool for estimation and also as a forecast tool in a wide variety of fields. However, no published research study has being extended to assess the effect of the financial debacle on the Nigeria crude oil export using (ARIMA) intervention analysis. Hence this present study attempts to assess the nature and quantify the impact of the global financial crisis on Nigeria crude oil export.

# 3. MATERIAL AND METHODS

## 3.1 Date source

A secondary data on monthly export of Nigeria crude oil from January 2002 to December 2013 were obtained from the Nigeria National Petroleum Cooperation (NNPC) annual statistical bulletin [23], to quantify the intervention effect being studied in this research paper. Data which spans for 72 months before and 72 months after the suspected intervention event date (Global financial crisis) was used to fit an adequate ARIMA intervention model using the ARIMA intervention modeling technique. The next subsection describes the intervention analysis approach or impact analysis technique.

## 3.2 Intervention analysis approach

Intervention analysis which was developed by Box and Tiao [9], as special form of dynamic regression model (stochastic modeling technique) used to assess the effect of special events such as labour strikes, government policy changes, financial policy changes, import regulations and many similar events which are commonly referred to as intervention events on a time series data. In many ways these external events most times causes several patterns of distortions in the observed time series data and are assumed to affect the series process by changing the mean function or trend. Intervention analysis technique is being applied in many fields of research study. In intervention analysis modeling approach, the response variable $Y_t$ is a function of the pre-intervention ARIMA noise model plus the input function of the deterministic intervention indicator (intervention component) which incorporates the intervention events into the research study. Mathematically, the time series intervention technique model may be written as:

$$Y_t = f(I_t) + N_t \tag{1}$$

Where, $Y_t$ is the response series, $f(I_t)$ is the intervention function of a discrete deterministic intervention indicator (intervention component) at time $(t)$ and $N_t$ is the ARIMA noise model for the preintervention series. In other to fit the intervention model, the preintervention series ARIMA noise model will first be identified. This approach known as ARIMA was popularized by Box and Jenkins, which combines the autoregressive and the moving average approaches together [7], [8], was described in 1951 by Peter Whittle [29], in his thesis titled: Hypothesis testing in time series analysis. The model formed as a result of the combination is known as the autoregressive integrated moving average (ARIMA) model, given that the series is nonstationary. It comprises three tentative stages namely: model identification, model estimation and model diagnostic checking.

The form and order of tentative ARIMA models are facilitated by the sample autocorrelation function (ACF) and the partial autocorrelation function (PACF) under the model identification stage. The characteristics of the theoretical ACF and PACF for identifying simple tentative models are presented in Table 1. The parameters of the selected model at the model estimation stage is best estimated with the maximum likelihood estimation method. The three main penalty function statistics used to penalize fitted ARIMA models with respect to the parsimonious principle are the Akaike information criteria (AICc) and the Schwarz Bayesian information criteria (BIC). Furthermore, the optimal model adequacy is examined based on the residual series analysis, the Lung-Box Portmanteau test and the Shapiro-Wilk Normality test.

The pre-intervention series is used to obtain an adequate ARIMA noise model before an intervention function is added to the ARIMA noise model to fit a full ARIMA intervention model. The intervention function can be coded as either a step function or impulse (pulse) function depending on the onset and duration of the event(s) being considered. A step intervention function is coded 0 prior to the beginning of the event(s) and as 1 at both the onset $(T)$ and for the entire duration of the presence of the event (s).

$$I_t = S_t^{(T)}, \text{ where } S_t^{(T)} = \begin{cases} 1, t \geq T \\ 0, t < T \end{cases} \quad (2)$$

The intervention function can also be modeled as an impulse (pulse) function coded 1 at the point of intervention event(s) and 0 otherwise.

$$I_t = P_t^{(T)}, \text{ where } P_t^{(T)} = \begin{cases} 1, t = T \\ 0, t \neq T \end{cases} \quad (3)$$

The full intervention model residuals are subjected to diagnostic check in other to assess the adequacy of the fitted intervention model using the Ljung-Box and Shapiro-Wilk Normality tests including the residual plots.

### 3.3 Intervention model specification

The focus of this research is to assess the nature and quantify the effect of the financial crisis which emanated from the United States as a liquidity crisis due to overvaluation of financial assets in the United States banking system in 2007, which became a global issue starting from the first quarter of 2008, on Nigeria crude oil export within the time frame of the collected data on crude oil export from the Nigeria National Petroleum Cooperation (NNPC) annual statistical bulletin. The intervention model was used to quantify the impact of this event and modeled with a step intervention function due to its mode of occurrence. The hypothesized full intervention model for this study is given as:

$$Y_t = c + f(w, \delta)I_t + \frac{\theta(B)}{\varphi(B)}\varepsilon_t \quad (4)$$

$$Y_t = c + f(w, \delta)I_t + N_t \quad (5)$$

Where: $c$ is a constant term, $f(w, \delta)$ is the resultant transfer function during the intervention period, $Y_t$ is the monthly increase or decrease in crude oil export extracted from NNPC annual Statistics bulletin, $I_t$ is the step intervention indicator variable scored (0) for absence or (1) for presence of the intervention event (financial crisis) while the $N_t$ represent the ARIMA noise model. The intervention indicator function for this study is formulated as;

$$I_t = S_t^{(2008)} = \begin{cases} 1, t \geq 2008 \\ 0, \text{Otherwise} \end{cases} \quad (6)$$

Where: $t$ is the time and $I_t$ is the intervention indicator. The form of the pre-intervention series model is considered as a seasonal ARIMA noise model given as:

$$N_t = ((1 - \theta_1 B)(1 - \Theta_1 B^{12}))\varepsilon_t \quad (7)$$

Where $\theta(B), \Theta(B)$ are the back shift operators and $\varepsilon_t$ is the error term as represented in the full intervention. The transfer function $f(w, \delta)$ during the intervention period can be written in this form $\frac{\omega_0}{(1 - \delta B)}$ as a result of the observed sharp drop in the year 2008 (January, 2008). Hence, the full intervention model for this study reduces to a first decay function given as:

$$Y_t = c + \frac{\omega_0}{(1 - \delta B)} I_t + ((1 - \theta_1 B)(1 - \Theta_1 B^{12}))\varepsilon_t \quad (8)$$

Where $\omega_0$ is the impact parameter which indicates the size of gain or loss in the response series mean level while the decay parameter $\delta$ represent the first order dynamic decay which estimates the reduction subsequent to the impact and must lie within the parameter estimation bound $(-1 < \delta < 1)$. The long term behaviour of the intervention effect for an integrated data series is estimated from equation (8) and is given by:

$$\lim_{t \to \infty} Y_t = \frac{\omega_0}{(1 - \delta)} \quad (9)$$

## 4. Results and Discussion

The research analysis was carried out using the R (3.0.3) statistical package [24]. There are various estimation techniques but the preferred estimation method used in this study to estimate the reported parameters of the models is the maximum likelihood estimation method. The descriptive statistics of the crude oil export, before and after the impact of intervention event is shown in Table 1. The preintervention series spans from January 2002 to December 2007, while the post-intervention period marks from January 2008 to December 2013.

Table 1: Descriptive Statistics of the Crude Oil Export.

| | Before the Intervention | After the Intervention |
|---|---|---|
| Sum | 66.5476 | 66.2955 |
| Mean | 6.6611 | 6.29426 |
| Median | 67.7475 | 66.3998 |
| SD | 50.5527 | 53.0003 |
| Max | 78.7147 | 79.6378 |

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| | | |
|---|---|---|
| Min | 4791.43 | 4773.28 |
| Range | 1 - 72 | 73 - 144 |

The data in this study consist of the monthly crude oil export by Nigeria from January 2002 to December 2013. The time plot in Figure 1 represents the crude oil export series. The plot displays observations (Crude oil export data) on the y-axis against equally spaced time intervals (Year/month) on the x-axis. The plot is used to evaluate identifiable patterns and behaviour in the crude oil export data over the years used in this study.

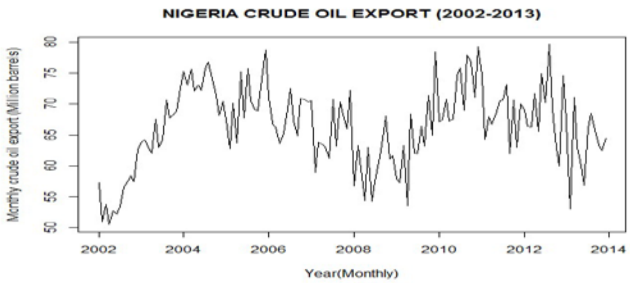


Figure 1: Monthly Crude Oil Export Series.

## 4.1 Pre-intervention model results

The time plot in Figure 2 is the graphical representation of the data series before the global financial crisis started. This period from January 2002 to December 2007 is called the pre-intervention period which basically did not reveal any visible characteristics except for the sharp decrease and increase in oil export at specific periods in each year suggesting some seasonal influence in the pre-intervention series. This pre-intervention data series was used to fit an ARIMA noise model.

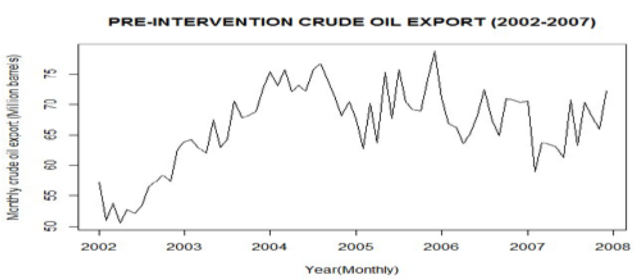


Figure 2: Preintervention monthly crude oil export series.

The preintervention series was checked for stationarity and possible identification of tentative ARIMA model using the correlogram with two other objective test statistics: The KPSS test proposed by Kwiatkowski-Phillips-Schmidt-Shin [19] and the ADF test proposed by Dickey and Fuller [16]. A critical observation of Figure 3, shows that the autocorrelation function (ACF) displays high positive spikes which slowly dies out not to zero with spikes further alternating in sign resulting in damped sine wave like form while the partial autocorrelation function (PACF) shows a significant non-zero positive spikes at the first two lags and geometrically decays to zero. This depicts a clear situation of a pre-intervention series that is either non-stationary in its mean or perhaps in its variance.

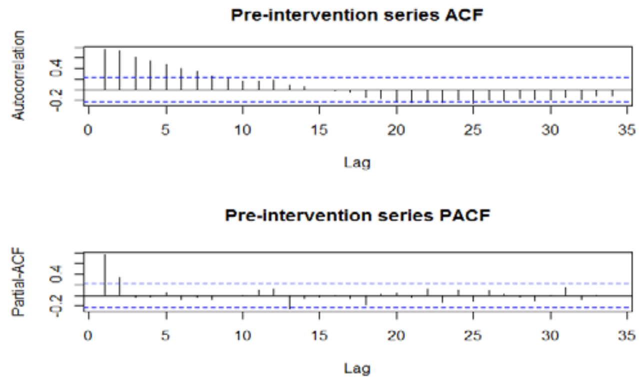


Figure 3: Preintervention series ACF and PACF.

The nonstationarity of the pre-intervention series as expressed by the correlogram was re-affirmed from the KPSS and ADF tests results in Table 3. The ADF test statistic of -2.3318 with P-value of 0.4402, did not reject the null hypothesis of a unit root at 5% significance level. On the other hand, the KPSS test statistic of 1.2107 with P-value of 0.01 rejected the null hypothesis of a stationary series implying that the series has a unit root. The results confer that the pre-intervention series is non-stationary and needs to be differenced.

Table 3: Unit root and Stationary tests

| Summary of Test statistics | | | |
|---|---|---|---|
| Test type | Test statistics | Lag order | P-value |
| KPSS | 1.2107 | 1 | 0.01 |
| ADF | -2.3318 | 3 | 0.4402 |

The preintervention series is transformed by first order differencing. Figure 4, presents the time plot for the differenced data series with the mean superimposed as the line.

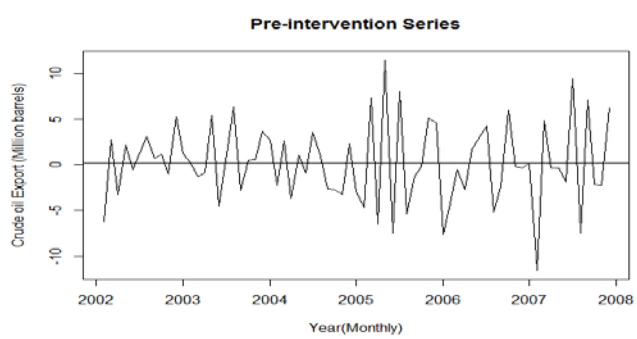


Figure 4: First-order differenced preintervention series.

From Figure 5, the correlogram indicates that the first order differenced preintervention series is seasonally influenced.

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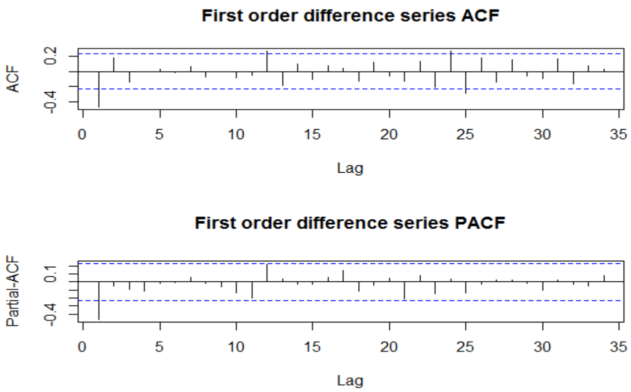


Figure 5: Differenced series ACF and PACF.

The first order differenced series was seasonally differenced to eliminate the influence of seasonality in the series with the mean superimposed as the line. It is evident from the time plot in Figure 6 that the mean, variance and auto-covariances are constant which confers that the preintervention series is stationary.

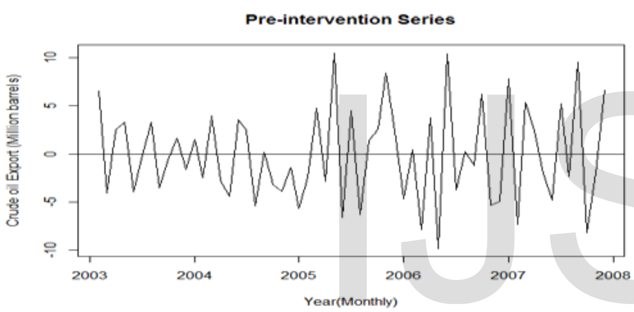


Figure 6: Seasonally differenced preintervention series

From Figure 7, the autocorrelation function (ACF) shows a significant spike at lag 1 and at the seasonal lag 12 while the partial autocorrelation function (PACF) shows a significant spike at lag 1 and thereafter slowly decays. This attribute of the first order and seasonally differenced preintervention series signifies a mean stationary series.

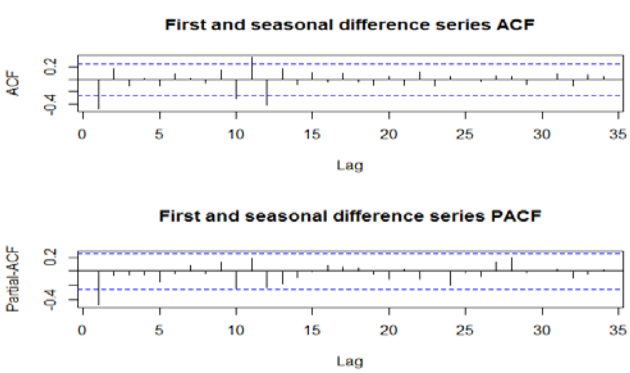


Figure 7: Seasonally differenced series ACF and PACF.

Table 4, the KPSS test statistic of 0.0575 with P-value of 0.100 greater than the pre-chosen significance value of 0.05 implies that the null hypothesis of having a level stationary is not rejected while the ADF test with test statistic of -4.6245 with P-value of 0.01 implies that the null hypothesis of a unit root in the series is rejected since the P-value is less than 0.05 which indicates that the first order and seasonally differenced preintervention series is stationary.

Table 4: Unit root and stationary test.

| Summary of Test statistics | | | |
|---|---|---|---|
| Test type | Test statistics | Lag order | P-value |
| KPSS | 0.0575 | 1 | 0.1 |
| ADF | -4.6245 | 3 | 0.01 |

Based on the correlogram patterns in Figure 7, the following seasonal candidate models; Seasonal ARIMA (0, 1, 1) (0, 1, 1)12 and Seasonal ARIMA (0, 1, 2) (0, 1, 1)12 were identified. The Akaike Information Criterion [4], the Corrected Akaike Information Criterion [11] and the Schwartz Bayesian Information Criterion [28], were used to select the optimal model for the preintervention data series among the two identified seasonal ARIMA models. According to Burnham and Anderson [11], the AIC penalizes the number of parameters less strongly than does the BIC and the AIC has more theoretical advantages over BIC. Yang [30], on the other hand stated that the AIC is asymptotically optimal in choosing the model with the least mean squared error than the BIC and they highly recommend using the AIC over the BIC but Robert and McGee [26], advised that the optimal model should be the model with the smallest BIC. Notwithstanding all the statements the three penalty statistics were used in this study to select the best optimal model.

Table 5: Parameter estimates of
Seasonal ARIMA (0, 1, 1) (0, 1, 1)12 model.

| Model Fit Statistics | | | |
|---|---|---|---|
| AIC | AICc | BIC | |
| 334.74 | 335.17 | 340.97 | |
| Coefficients | Estimate | STD Error | t-value |
| Ma1 | -0.4444 | 0.1147 | -3.8745 |
| Sma1 | -0.5504 | 0.1709 | -3.2206 |

Table 6: Parameter estimates of
Seasonal ARIMA (0, 1, 2) (0, 1, 1)12 model.

| Model Fit Statistics | | |
|---|---|---|
| AIC | AICc | BIC |
| 336.46 | 337.2 | 344.77 |

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| Coefficients | Estimate | STD Error | t-value |
|---|---|---|---|
| Ma1 | -0.4665 | 0.1286 | -3.6275 |
| Ma2 | 0.0681 | 0.1290 | 0.5279 |
| Sma1 | -0.5436 | 0.1701 | -3.1958 |

From Table 5 and Table 6, the estimated AIC, AICc and BIC penalty statistics for seasonal ARIMA (0, 1, 1) (0, 1, 1)12 model are smaller compared to that of seasonal ARIMA (0, 1, 2) (0, 1, 1)12 model. Hence, seasonal ARIMA (0, 1, 1) (0, 1, 1)12 in Table 5, was chosen to be the optimal preintervention data series noise model. The estimated parameters from the optimal noise model are presented in Table 5. The coefficients of the chosen noise model are statistically significant from zero based on their Student t-values and strictly conforms to the bounds of Invertibility parameters $(-1 < \theta < 1)$. The fitted preintervention noise model is written as:

$$Y_t = \varepsilon_t - 0.4444\varepsilon_{t-1} - 0.5504\varepsilon_{t-12} \qquad (10)$$

From Table 7, the Box- Ljung test failed to reject the null hypothesis of uncorrected residuals with a P-value of 0.8861 while the Shapiro-Wilk Normality test also failed to reject the null hypothesis that the model residuals are normally distributed with P-value of 0.2693, given a 5% pre-chosen significance level.



Table 7: Ljung-Box and Shapiro-Wilk Normality tests.

| Ljung-Box Test statistics | | |
|---|---|---|
| Chi-Square | df | P-value |
| 12.7928 | 20 | 0.8861 |
| Shapiro-Wilk Test statistics | | |
| W | P-value | |
| 0.9789 | 0.2693 | |

This is confirmed from the residual plots shown in Figure 8, which comprises the residuals histogram, the time plot of the residuals, the ACF plot of the residuals and the probability plot of the residuals respectively. The time plot generally shows no clear pattern and may be conceived as independent and identically distributed (i.i.d) sequence with a constant variance and a zero mean. Also, no evidence exist in the plot that the error terms are correlated with one another as well as no evidence of the existence of an outlier. The ACF plot shows no evidence of a significant spike, all the spikes are within the ACF confidence limit indicating that the residuals seem to be uncorrelated. Finally, the individual probabilities of the residuals are above 0.05 (the line) as indicated in the probability plot. It is therefore concluded that the residuals of the preintervention data series follow a white noise process.

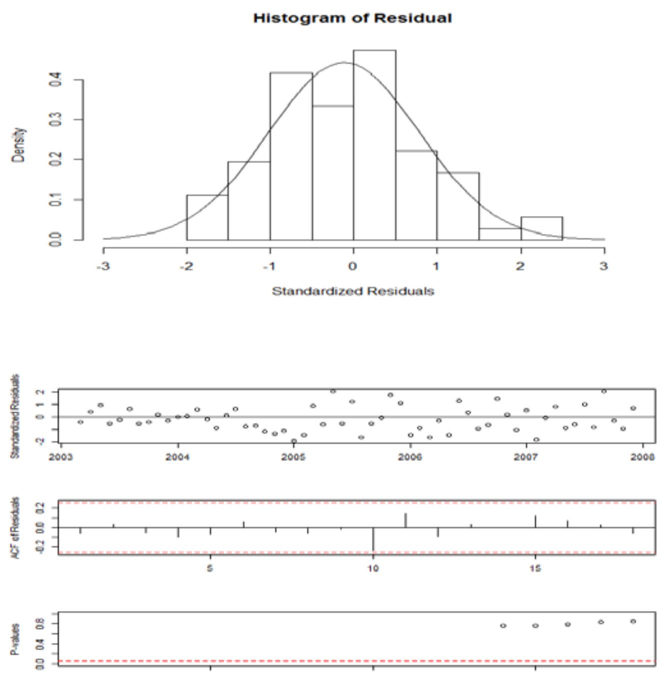


Figure 8: Preintervention noise model Residual plots.

## 4.2 ARIMA-Intervention model

The optimal preintervention noise model is fitted together with the intervention function. The intervention function is coded 1 for presence and 0 for absence, of the Global financial crisis event. The estimated parameters of the full intervention model are presented in Table 8.

Table 8: Parameter estimates of the full ARIMA intervention model.

| Model Fit Statistics | | | |
|---|---|---|---|
| AIC | AICc | BIC | |
| 781.07 | 781.55 | 795.44 | |
| Coefficients | Estimate | STD Error | t-value |
| Ma1 | -0.6207 | 0.0630 | -9.8524 |
| Sma1 | -0.8520 | 0.1396 | -6.1031 |
| T1-AR1 $(\delta)$ | -0.5603 | 0.1806 | -3.1024 |
| T1-MA0 $(\omega_0)$ | -11.5942 | 4.0047 | -2.8951 |

From the table, all the estimated coefficients are significantly different from zero. The penalty statistics reported in terms of AIC, AICc and BIC with corresponding

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values of 781.07, 781.55 and 795.44 respectively penalizes the fitted model based on the principle of parsimony. Mathematically, the full ARIMA-intervention model is written as:

$$Y_t = \frac{-11.5942}{(1-(-0.5603))} I_t - 0.6207\varepsilon_{t-1} - 0.85204\varepsilon_{t-12} + \varepsilon_t \quad (11)$$

The T1-AR1$(\delta)$ reflects the rate of decay or reduction in the impact of the financial crisis while the T1-MA0$(\omega_0)$ denotes the magnitude of the change in mean level after the impact of the global financial crisis. The results from the ARIMA-intervention model in Table 8, indicates that global financial crisis reduced the crude oil export by a monthly average estimate of approximately 11.6 million barrels during the period under study and the effect of the global financial crisis in the long run was 7.4 million barrels while the decay or reduction $(\delta)$ parameter of -0.5603, reflects the rate at which the actual level of the series is approached. The parameters were both found to be statistically significant with t-values greater than 1.96 in absolute value. Furthermore, the full intervention model residuals confirms that the residuals are uncorrelated and normally distributed with zero mean and a constant variance using the Box-Ljung and Shapiro-Wilk normality tests. The test failed to reject the null hypothesis which implies that the residuals are white noise as show in Table 9.

Table 9: Ljung-Box and Shapiro-Wilk Normality tests

| Ljung-Box Test Statistics | | |
|---|---|---|
| Chi-square | df | P-value |
| 14.1347 | 20 | 0.8236 |
| Shapiro-Wilk Test Statistics | | |
| W | P-value | |
| 0.9922 | 0.6201 | |

The diagnostic residual plots in Figure 9, do not show any anomalies for the full fitted intervention model. There are no significant spikes in the ACF residuals plot as well as the probability plot of the residuals also indicates that the individual probabilities of the residuals are above 0.05 (the dotted line). The time plot of the residuals also show that the residuals appear to be randomly scattered about zero, hence no existence of correlation between the error terms (white noise residuals).

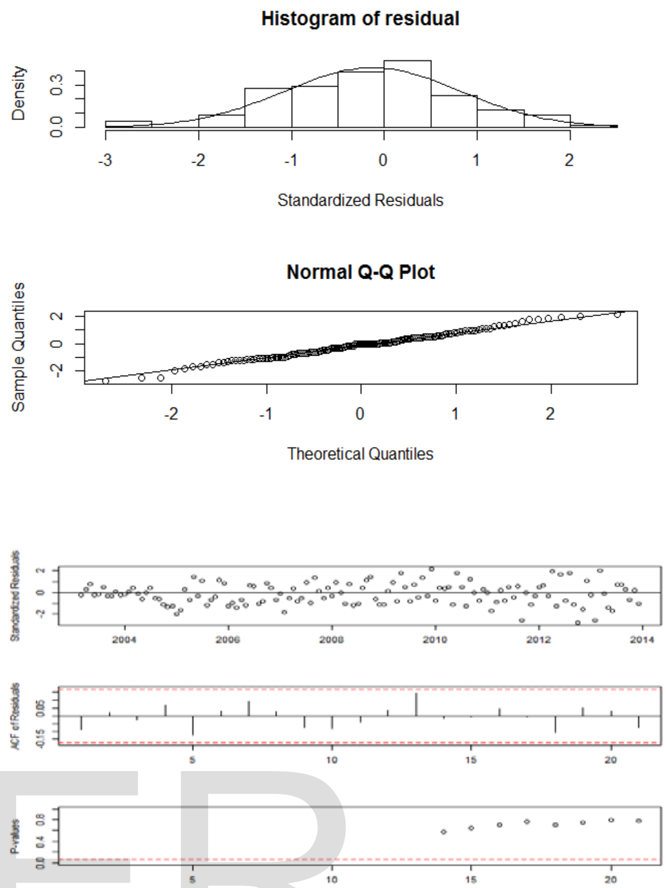


Figure 9: Full ARIMA-intervention residual plots

The study revealed that the full intervention model fairly fits the data very well because the full fitted intervention model adjusts the data for trends, seasonality and persistence of the random shock and thus, more accurately reflects the financial crisis impact on crude oil export as portrayed in Figure 10.

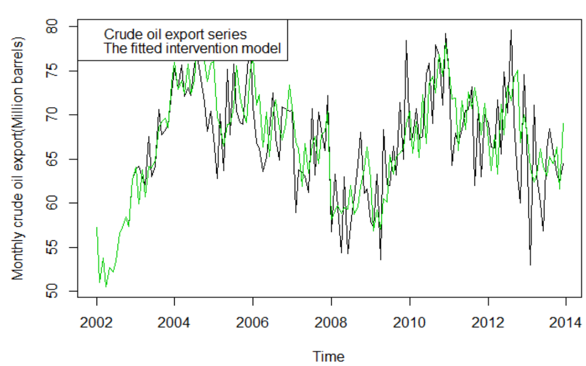


Figure 10: Full fitted ARIMA-intervention model verses the observed data series plot

## 5. CONCLUSION

This research study was carried out to assess and estimate the effect of the financial crisis on Nigeria crude oil export based on the objectives, the literature reviewed as well as the discussions made from the analysis. The following conclusions are drawn:

The first objective, was to model the crude oil export given the global financial crisis impact. It can be concluded with regard to the first objective that the full ARIMA-intervention model was found to be significant and adequate by the Box-Ljung test, the Shapiro-Wilk Normality test as well as the diagnostics residual plots. It can be concluded based on the second objective that the global financial crisis had a significant impact of reducing the crude oil export over the period of study by a monthly significant average estimate of 11.6 million barrels and also a long term effect of 7.6 million barrels. Furthermore, evaluation of the effect in the long run revealed that the global financial crisis had a temporary declining effect on crude oil export. Finally, based on the full intervention model plots, it can be concluded that it fairly fits the original series.

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