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Statistical Modeling of Crude Oil Price Volatility in Nigeria

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Abstract

This study investigated the effects of price volatility on Nigeria crude oil price over eighteen years beginning from 1997 to 2014. Time series analysis was carried out on the data collected as extracts from the annual Bulletin of Nigerian Petroleum Corporation (NNPC). The behavior of the price of crude oil in Nigeria was examined using suitable time series model over the study period. Results from the analysis showed that the crude oil price experienced an upward movement in 2008. This indicated that the crude oil prices in Nigeria were characterized with high volatility. It can therefore be concluded that the up and down movement of the series became stable through application of time series tools.

Keywords: ARIMA, Crude oil price, Non Stationarity Time series, Stationarity, Volatility

1.0 Introduction

Crude oil is naturally occurring, unrefined petroleum product composed of hydrocarbon deposits. Crude oil can be refined to produce usable products such as gasoline, diesel and various forms of petrochemicals (see www.investopedia.com). Crude oil is a commodity of great importance to any nation that is naturally endowed with the resources. In the last years, crude oil prices have presented large variations, they have steadily risen from about 30 dollars a barrel in August, 2003 to over 140 dollars a barrel in May, 2008 and then dramatically dropped down during the crisis of 2008.

Volatility is a statistical measure of the dispersion of returns for a given security or market index. In other words, crude oil volatility refers to the amount of uncertainty or risk about the size of changes in the price of crude oil. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security's value does not fluctuate dramatically, but changes in value at a steady pace over a period of time.(http://www.investopedia.com).The Black Scholes equation assumes predictable constant volatility, this is not observed in real markets, and amongst the models are Dermanand Kani (1994) and Dupire's (1994) Local Volatility, Poisson Process where volatility jumps to new levels with a predictable frequency, and the increasingly popular Heston model of stochastic volatility.It is common knowledge that types of assets experience periods of high and low volatility. The main objective of this paper is to examine the volatility in the price of crude oil in Nigeria.

2.0 Literature review

Crude oil markets are covering a number of different areas and issuesand examine the characteristics of these markets in various respects. Many empiricalstudies show evidence that time series of crude oil prices, likewise other financial timeseries, are characterized by fat tail distribution, volatility clustering, asymmetry andmean reverse (Morana, 2001; Bina and Vol, 2007). Concerning the most recent time period mentioned in different studies, oil price dynamics during 2002-2006 havebeen characterized by high volatility, high intensity jumps, and strong upward drift andwere concomitant with underlying fundamentals of oil markets and world economy(Askari and Krichene, 2008).

The ARIMA approach was first popularized by Box and Jenkins, and ARIMA models are often referred to as Box-Jenkins models. The general transfer function model employed by the ARIMA procedure was discussed by Box and Tiao (1975). When an ARIMA model includes other time series as input variables, in several early papers standard deviation of price differences is commonly used as a measure of volatility of commodity prices (Ferderer, 1996; Fleming and Ostdiek, 1999).

Kang et al. (2009) investigates the efficiency of a volatility model with regard to its ability to forecast for crude oil price the number of research papers investigating the impact of crude oil determinants on the price series is not as significant. Kaufmann et al. (2004) applies statistical models to estimate the causal relationship between crude oil prices and several factors, such as capacity utilization, production quotas, and production levels. Kaufmann et al. (2008) investigates the factors that might have contributed to the quarterly oil price increase in more details, by expanding a model for crude oil prices to include refinery utilization rates, a non-linear effect of OPEC capacity utilization and conditions in futures markets as explanatory variables and finds that this model performs relatively well in terms of forecasting.

3.0 Research methodology

The data employed secondary data which involved 18years of Nigerian crude oil price from 1997-2014 were collected from NNPC statistical bulletin was used in the analysis in order to tentatively identify Box-Jenkins model, we must first determine whether the time series we wish to analyze is stationary. Time plots of each of the data analyzed in gretland R were found to have an increasing trend and this was verified by the slow decay of the ACF plots. Thus, the data is a non – stationary. Descriptive analysis of the crude oil price data was done using the time plots. Thus, the data is a non – stationary. Descriptive analysis of the crude oil price data was done using the time plots.

The data was made stationary by removing the trend and this was done by differencing. Time plots were subsequently produced to verify whether the data is stationary. The data was made stationary, we used the sample ACF and PACF plots in order to identify various Box-Jenkins models for each of the Nigerian crude oil prices data. Estimates of the models parameters were produced and their statistical significance tested. Residuals from the models were also checked in order to identify if the residuals are white noise.

Suitable models were each selected and fitted for each differenced data based on their AIC (Akaike Information Criterion), AIC_C corrected version of AIC, and BIC (Bayesian information criterion) values and finally the models selected were used in making forecasts for the values of the Nigerian crude oil price.

3.1. ARIMA MODELING

Box and Jenkins (1976) introduced the ARIMA model and ever since then the method has turned out to be one of the most famous approach used in predicting the future value of a variable. ARIMA model is presumed to be a linear combination of past errors. ARIMA Model is the generalization of ARMA models which incorporates a wide class of non-stationary time-series is obtained by introducing the differencing into the model. The simplest example of a non-stationary process which reduces to a stationary one after differencing is Random Walk. A process {yt} is said to follow an Integrated ARMA model, denoted by ARIMA (p, d, q), if is $\nabla^d y_t = (1-B)^d \varepsilon_t$ARMA

The model is written as equation$\varphi(B)(1-B)^d\, y_t = \theta(B)\varepsilon_t$

Where $\varepsilon_t \sim WN(0,\sigma^2)$and WN indicates white noise. The integration parameter d is a non-negative integer. When d = 0, ARIMA (p, d, q) ≡ ARMA (p, q). The ARIMA methodology is carried out in three stages, by identificating, estimating and diagnostic checking. Parameters of the tentatively selected ARIMA model at the identification stage are estimated at the estimation stage and adequacy of tentatively selected model is tested at the diagnostic checking stage. If the model is found to be inadequate, the three stages are repeated until satisfactory ARIMA model is selected for the time-series under consideration. An excellent discussion of various aspects of this approach is given in Box et al. (2007).

3.2 STATIONARITY TEST

The basic assumption in time-series econometrics is that the underlying series is stationary in nature. Thus, the test for stationarity of the series under consideration was done using Augmented Dickey-Fuller (ADF). The ADF test relies on parametric transformation of the model.

Akaike's Information Criteria (AIC)

The AIC which was proposed by Akaike uses the maximum likelihood method in the implementation of the approach, a range of potential ARMA models is estimated by maximum likelihood methods, and for each, the AIC is calculated, given by:

$$AIC_{(p,q)} = \frac{-2\ln(maximum\ likelihood) + 2r}{n}$$

Schwarz's bayesian criterion (BIC)

Schwarz's BIC like AIC uses the maximum likelihood method. It is given by

$$BIC_{(p,q)} = \ln(\delta_e^2) + r\frac{\ln(n)}{n}$$

Where all parameters remained defined as above.

AUTOCORRELATION FUNCTION

Autocorrelation refers to the correlation of a time series with its own past and future values. Autocorrelation is also sometimes called "lagged correlation" or "serial correlation", which refers to the correlation between members of a series of numbers arranged in time. Positive autocorrelation might be considered a specific form of "persistence", a tendency for a system to remain in the same state from one observation to the next.

PARTIAL AUTOCORRELATION FUNCTION

Partial autocorrelation function measures the degree of association between Y_t and Y_{t+k} when the effect of other time lags on Y are held constant. The partial autocorrelation function PACF denoted by $\{r_{kk}$:k=1,2,3…$\}$ The set of partial autocorrelations at various lags k are defined by

$$r_{kk} = \frac{r_k - \sum_{j=1}^{k-1} r_{k-1,j}\, r_{k-j}}{1 - \sum_{j=1}^{k-1} r_{k-1,j}\, r_j}$$

AUTOREGRESSIVE (AR) MODEL

The notation $AR_{(p)}$ refers to the autoregressive model of order p. A model in which future values are forecast purely on the basis of past values of the time series is called an Autoregressive (AR) process. An autoregressive model of order p, denoted by AR (p) with mean zero is generally given by the equation:

$$y_t = \mu + \varphi_{1X_{t-1}} + \varphi_{2X_{t-2}} + \cdots + \varphi_{pX_{t-p}}$$

MOVING AVERAGE (MA) MODELS

A model in which future values are forecast based on linear combination of past forecast errors is called moving average model. A moving average model of order q, with mean zero, denoted by MA (q) is generally given by:

$$y_{t=}V_t - \theta_{1V_{t-1}} - \theta_{2V_{t-2}} - \cdots - \theta_{qV_{t-q}}$$

AUTOREGRESSIVE MOVING AVERAGE (ARMA) MODELS

Autoregressive and Moving Average processes can be combined to obtain a very flexible class of univariate processes (proposed by Box and Jenkins), known as ARMA processes.

The time series $y_t$is an ARMA (p, q) process, if it is stationary.

$$y_t = \mu + \varphi_{1X_{t-1}} + \varphi_{2X_{t-2}} + \cdots + \varphi_{pX_{t-p}} - V_t - \theta_{1V_{t-1}} - \theta_{2V_{t-2}} - \cdots - \theta_{qV_{t-q}}$$

AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA) MODEL

The time series models above are only used when the time series data is stationary. However many real time series are not stationary hence those models cannot be used for the data. Differencing the data one or two times will reduce the non-stationary time series to stationary series. ARIMA also called Box-Jenkins models are the models based on this idea.

In general, an ARIMA model is characterized by the notation ARIMA (p, d, q), where p, d and q denote orders of auto-regression, integration (differencing) and moving average respectively.This time series method was used to model the crude oil price in Nigeria.

4.0 DATA ANALYSIS

TIME SERIES ANALYSIS OF NIGERIA CRUDE OIL PRICE IN USD/BARREL

TIME PLOT

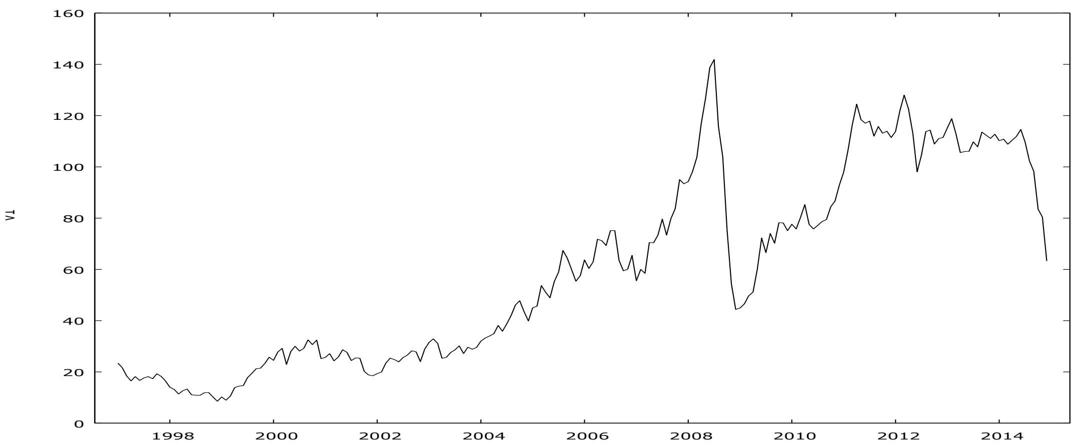

Figure 4.1:Figure 4.1 above is the time plot of crude oil price in Nigeria (in USD/barrel) from 1997 to 2014, which is a graph that describes a point moving with the passage of time, the time plot shows some sudden changes, particularly the big shut in 2008. The volatility in oil prices is ordinarily quite high because the underlying demand and supply curves are so inelastic.Nothingunusual about the time plot and there appears to be no need to do any data adjustment, the data are clearly non-stationary as the series wanders up and down for long periods. Consequently, we will take a first difference of the data to make it stationary.

Autocorrelation function (ACF) and Partial Autocorrelation function (PACF) plots of Nigeria crude oil price in USD per barrel

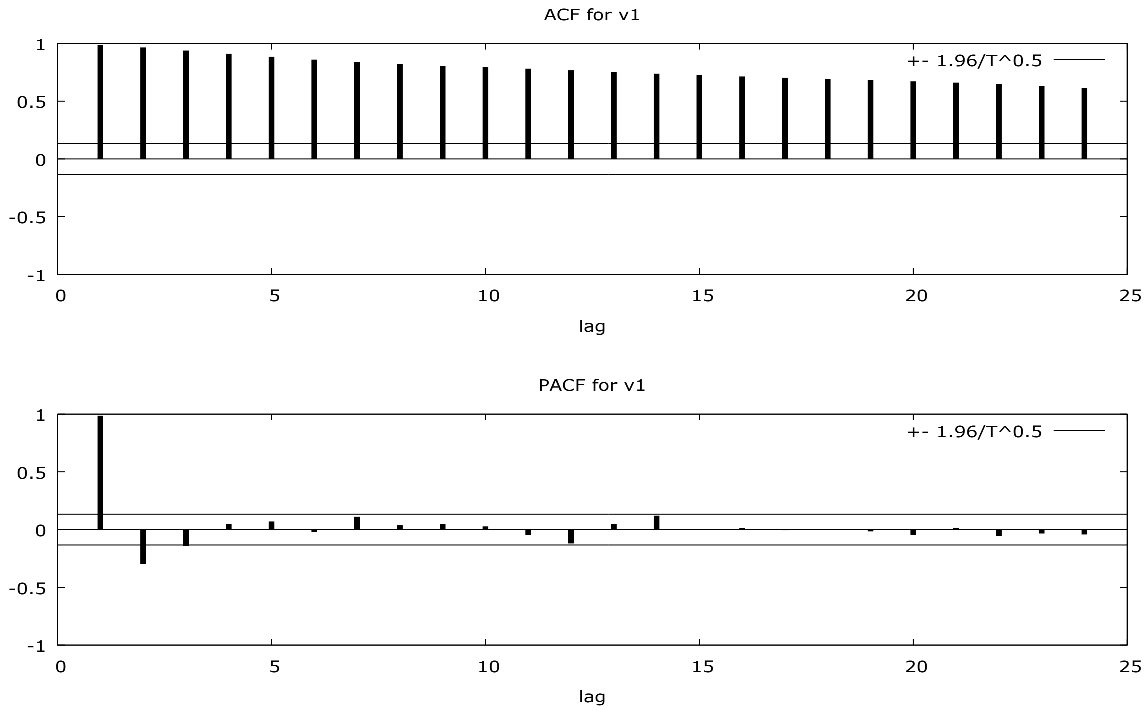

Figure 4.2: Autocorrelation and Partial Autocorrelation function plot can be used to detect non randomness in data and also to identify an appropriate time series model if they are not stationary. Figure 4.2 shows that the autocorrelation function decays slowly to zero which means the time series is non-stationary. These clearly reveal that non stationarity is inherent in the data. The Augmented dickey fuller test is also used to check for stationarity of the series as describe in the table below.

Table 4.2: UNIT ROOT AND STATIONARY TEST

TEST TYPE	TEST STATISTIC	P-VALUE

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Augmented Dickey fuller (ADF)	-3.3111	0.0706

Initial analysis of data: The time plot in fig 1 shows the original series. The time plot of crude oil price in Nigeria (in USD/barrel) from 1997 to 2014, which is a graph that describes a point moving with the passage of time, the time plot shows some sudden changes, particularly the big shut in 2008. The volatility in oil prices is ordinarily quite high because the underlying demand and supply curves are so inelastic. Nothing unusual about the time plot and there appears to be no need to do any data adjustment, the data are clearly non-stationary as the series wanders up and down for long periods. Consequently, we will take a first difference of the data to make it stationary. The Fig 2 is the correlogram (ACF and PACF) of the crude oil price's the data series before differencing. Autocorrelation and Partial Autocorrelation function plot can be used to detect non randomness in data and also to identify an appropriate time series model if they are not stationary. Fig 2 shows that the autocorrelation function decays slowly to zero which means the time series is non-stationary. These clearly reveal that non stationarity is inherent in the data.

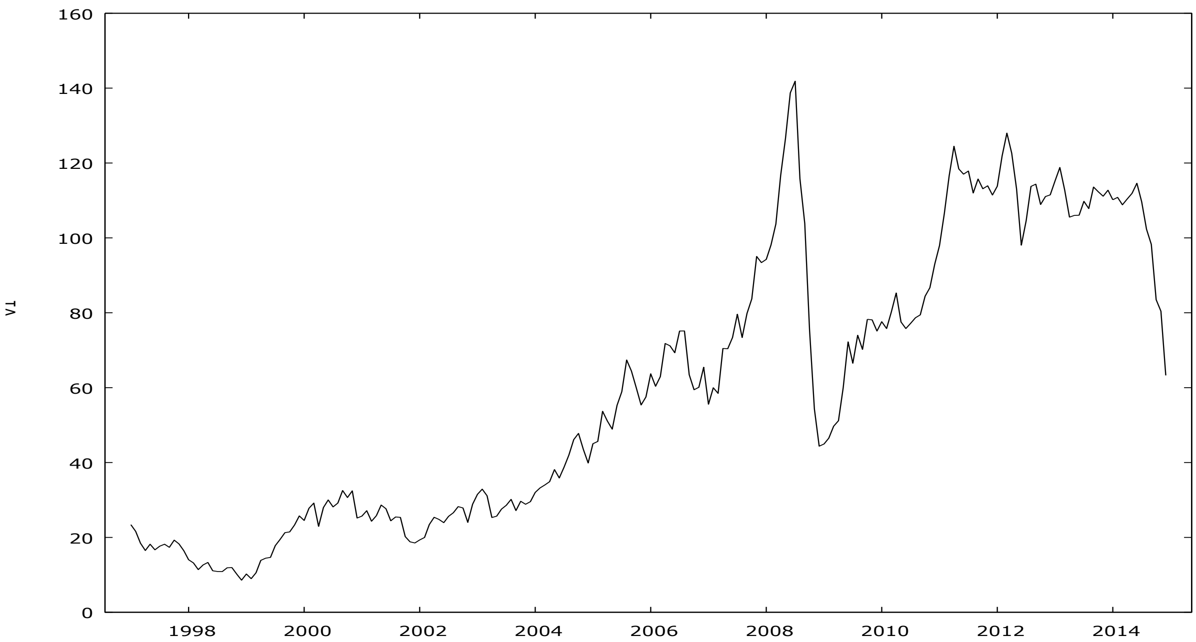

Fig. 1: Time plot of the monthly crude oil price in USD/BARREL

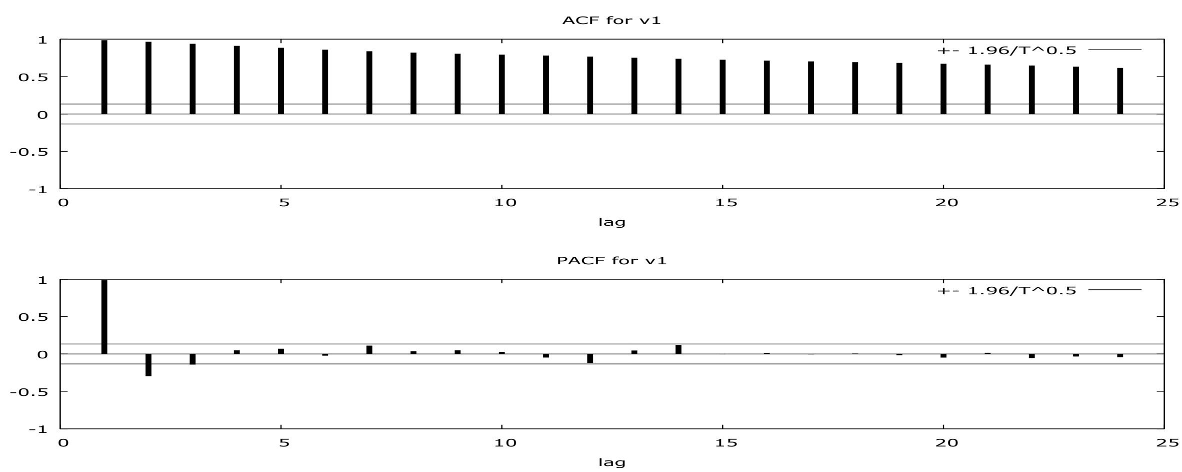

Fig. 2: The ACF and PACF of the monthly crude oil price **in USD/BARREL**

Unit root tests before differencing: The Augment Dickey Fuller (ADF)test was conducted to test for the unit root (stationary). The results of the test are given in Table 1 which show that the confirming the crude oil price series is not stationary, since the tests statistics are greater than the p/critical values at some levels. Since the time series is not stationary, we have to make it stationary before we can apply the Box- Jenkins methodology. Therefore the series has to be differenced to stationaries' the data.

Table 1Unit Root and Stationary Test

TEST TYPE	TEST STATISTIC	P-VALUE
Augmented Dickey fuller (ADF)	-3.3111	0.0706

Time plot of the first difference: Figure 3 is the time plot of the first order difference of Nigerian crude oil price. The observations revert to its mean value and the variability is also approximately constant.which imply that the Nigeria crude oil price data is now stable and stationary as the series stays roughly constant over time it is clear that the mean is exactly zero which means we will not consider further differencing due to the absent of trend component. The correlogram is shown in figure 4: The ACFs at lag 1 seem statistically different from zero (at the 95% confidence limit, those lags are asymptotic and so can be considered approximate), but at all other lags, they are not statistically different from zero. This is suggesting AR (1) and the PACF show a sharp cut-off at lag1 and lag 6. We therefore conclude that the data series is now stat ionary.

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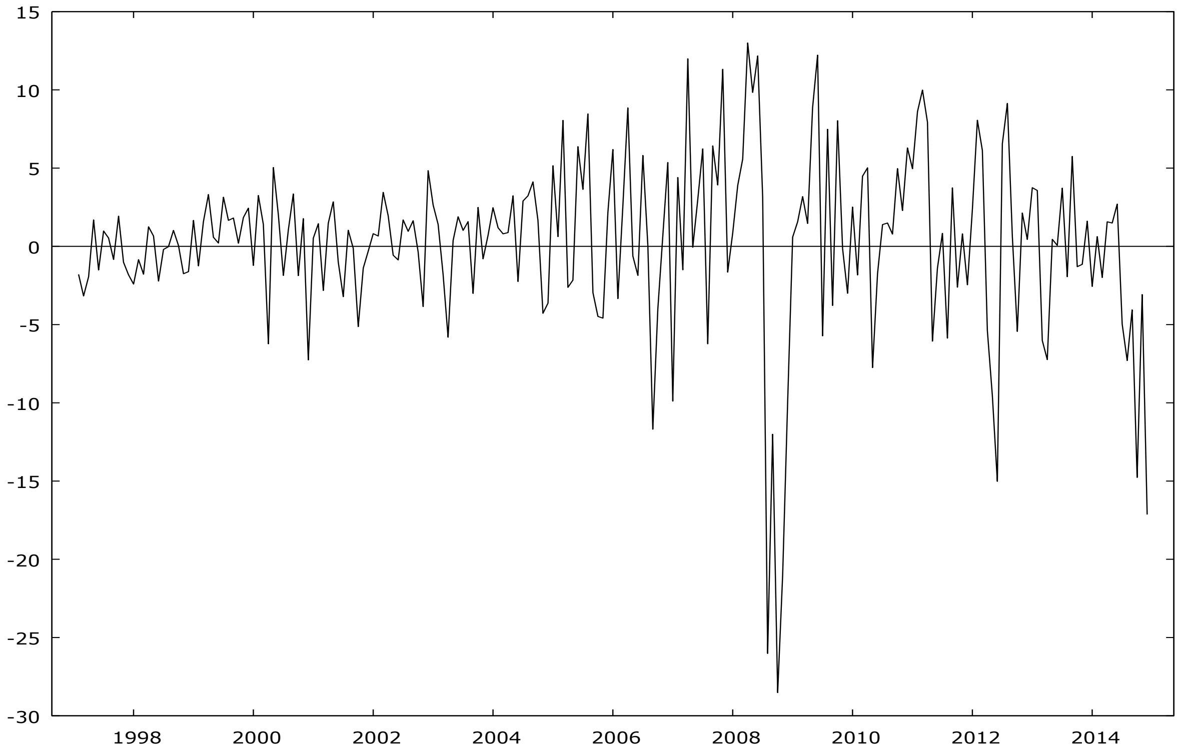

Figure 3: First difference time plot of the Crude oil Price data.

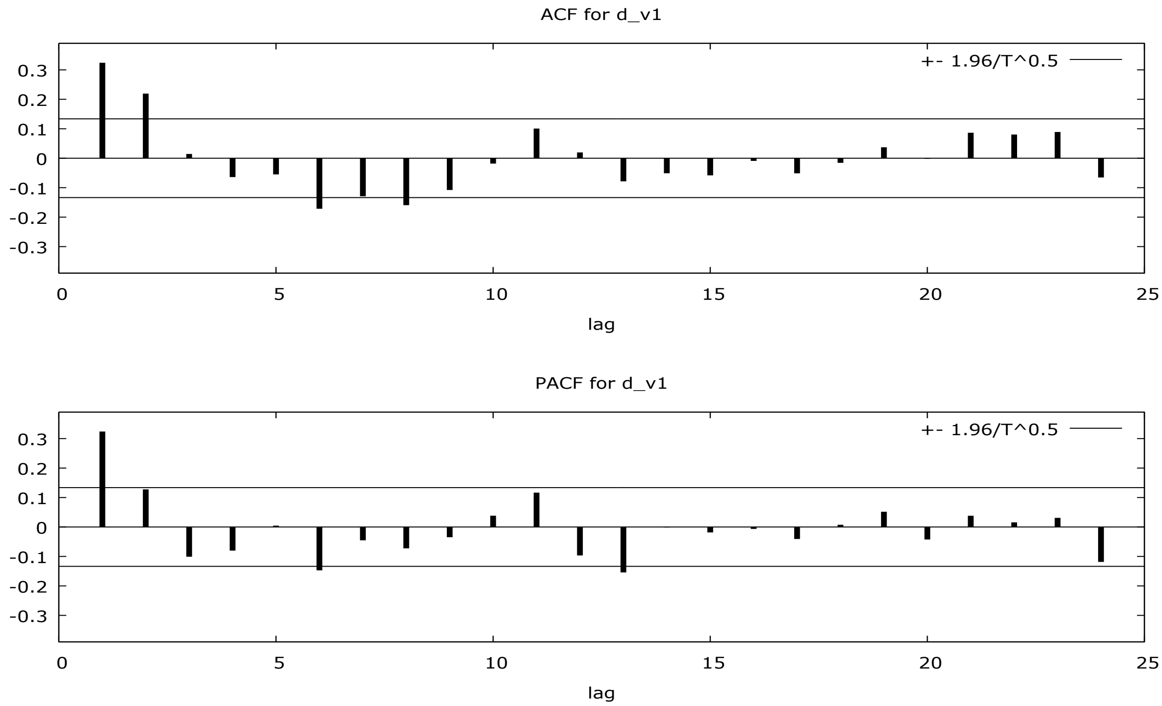

Figure 4: Plot (ACF) and(PACF) of the first difference of crude oil price

Unit root tests after differencing: The Augment Dickey Fuller (ADF) test was conducted to test for the unit root (stationary). The results of the test are given in Table 2 which show that the confirming the log of the crude oil price series is stationary, since the tests statistics with p-value of 0.001 is less than the p/critical values at some levels. Therefore there is no need for further difference since the series is now stationary. We then conclude that crude oil price data is stable at the first difference.

Table 2 Unit Root and Stationary Test for first differenced

TEST TYPE	TEST STATISTIC	P-VALUE

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Augmented Dickey fuller (ADF)	-6.1970	0.001

Formulation of the ARIMA model for the crude oil price data: from the initial analysis (time plot and correlogram of the data) it is clearly shown that the series is non-stationary. This led to the first differencing d=1.

Model Identification and selection: Comparing the ARIMA Models in Table 3, ARIMA(0,1,2) has the smallest Akaike Information criterion (AIC) which became the suitable time series model for modeling crude oil price volatility in Nigeria. The summary of the estimate for ARIMA (0,1,2) is given in the table 4 below.

Table 3: Summary of some selected ARIMA Model.

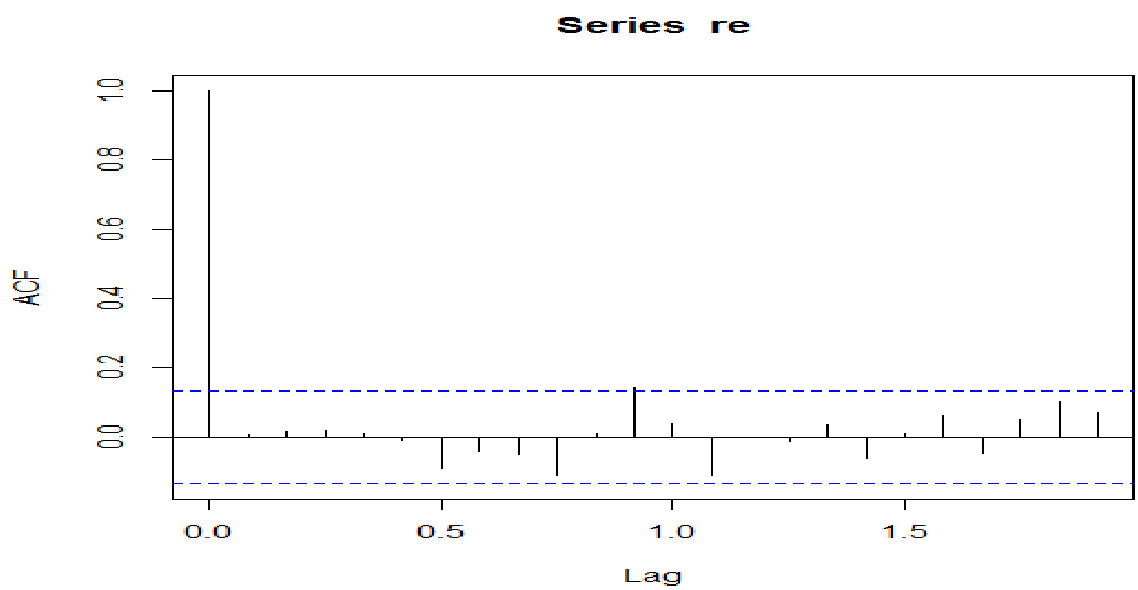
Model	ARIMA (0,1,1)	**ARIMA (0, 1, 2)**	ARIMA (1, 1, 0)	ARIMA (1, 1, 1)	ARIMA (1, 1, 2)	ARIMA (2, 1, 0)	ARIMA (2, 1, 1)	ARIMA (2, 1, 2)
AIC	1337.46	**1326.85**	1330.55	1330.41	1328.61	1328.91	1330.14	1330.60

Table 4: Parameter estimate of ARIMA (0,1,2)

Parameter	**Coefficient**	**Std. Error**	**t-ratio**	**p-value**

AR(0)	-	-	-	-
MA1	0.2916	0.0662	4.4048	0.0252
MA2	0.2556	0.0666	3.8378	0.0375

Table 4 indicates that MA (1) and MA (2) models are significant at the 0.05 significance level.



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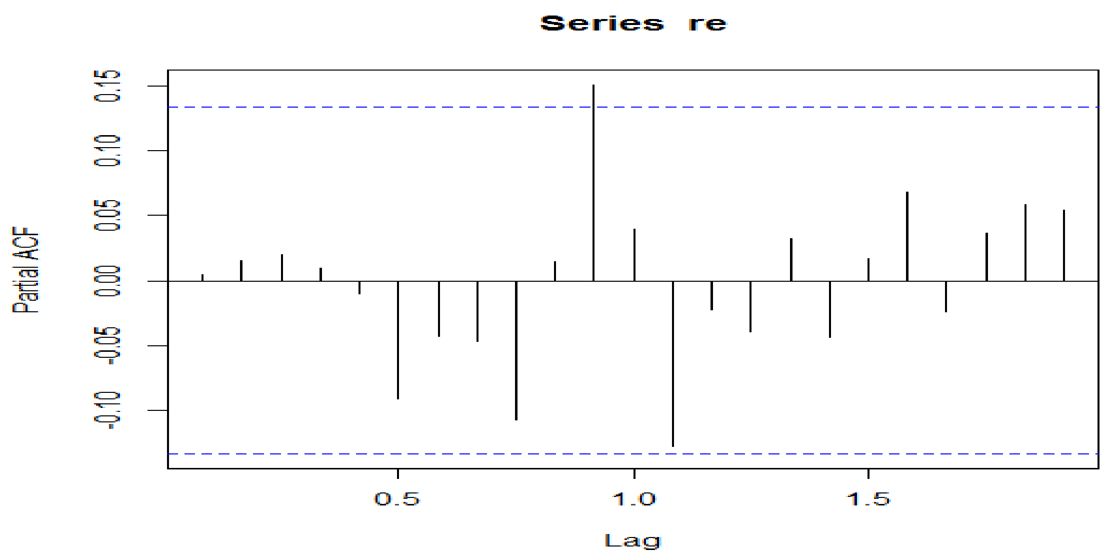

Figure 5: Residual of Autocorrelation and Partial Autocorrelation function plot of ARIMA (0.1.2) Model

Figure 5 shows the Residual ACF and PACF plot of the ARIMA(0,1,2) model and it shows no systematic pattern they all fall within the critical boundary which means they are significant and can be used to make forecast.

From Table 5 report the box pierce test for Nigeria crude oil price data has a corresponding P-value of 0.9455,since the P-value is greater than critical value,which implies that the test is not significant and therefore we do not reject the H0 hypothesis,thus the residuals appear to be uncorrelated. This indicate that the residuals of the fitted ARIMA(0,1,2) model are white noise,that means the model fits the series quite well,the parameter of the model are significant and the residuals are uncorrelated,i.e it can be used to make forecast

Table 5 check for autocorrelation

Test type	Chi-squared	Degree of freedom	p-value
Box-pierce test	0.015	1	0.9026

ARIMA (0, 1, 2) Forecast Evaluation: After a good ARIMA model has been fitted, we finally study its forecast value. Two years crude oil price forecast from January 2015 to December 2016 using ARIMA (0, 1, 2) model. The prediction is similar to the observed value in pattern; this testified the adequacy of our model. Although the forecast sample is better.

Table 6: Two Years Crude Oil Price Forecast From January 2015 To December 2016 Using ARIMA (0,1,2) Model

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2015	59.40515	52.716426	66.09387	49.1756299	69.63467
Feb 2015	55.80499	44.879118	66.73086	39.0953114	72.51467
Mar 2015	55.80499	40.756054	70.85392	32.7896299	78.82035
Apr 2015	55.80499	37.541194	74.06878	27.8729253	83.73705
May 2015	55.80499	34.813039	76.79694	23.7005718	87.90940
Jun 2015	55.80499	32.400764	79.20921	20.0113159	91.59866
Jul 2015	55.80499	30.214883	81.39509	16.6682996	.94168
Aug 2015	55.80499	28.201560	83.40842	13.5891877	98.02079
Sep 2015	55.80499	26.325419	85.28456	10.7198772	100.89010
Oct 2015	55.80499	24.561736	87.04824	8.0225578	103.58742
Nov 2015	55.80499	22.892429	88.71755	5.4695725	106.14040
Dec 2015	55.80499	21.303795	90.30618	3.0399667	108.57001
Jan 2016	55.80499	19.785159	91.82482	0.7174133	110.89256
Feb 2016	55.80499	18.328010	93.28197	-1.5111032	113.12108
Mar 2016	55.80499	16.925435	94.68454	-3.6561567	115.26613

Apr 2016	55.80499	15.571726	96.03825	-5.7264767	117.33645
May 2016	55.80499	14.262105	97.34787	-7.7293694	119.33935
Jun 2016	55.80499	12.992526	98.61745	-9.6710228	121.28100
Jul 2016	55.80499	11.759526	99.85045	-11.5567326	123.16671
Aug 2016	55.80499	10.560116	101.04986	-13.3910728	125.00105
Sep 2016	55.80499	9.391690	102.21829	-15.1780258	126.78800
Oct 2016	55.80499	8.251965	103.35801	-16.9210848	128.53106
Nov 2016	55.80499	7.138924	104.47105	-18.6233338	130.23331
Dec 2016	55.80499	6.050777	105.55920	-20.2875116	131.89749

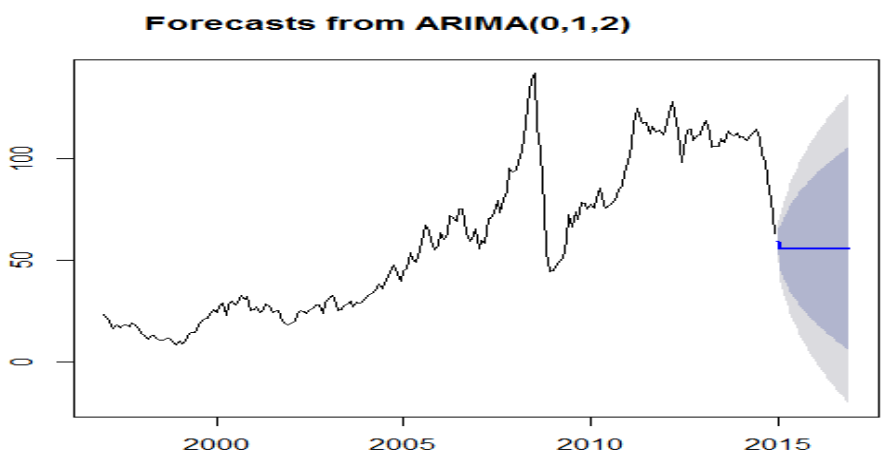

Figure 5 forecasts from ARIMA (0, 1, 2)

The above Figure 5 shows the visual representation of the Nigerian crude oil price data with its forecast values in black line and its 2years forecast(Start = Jan 2015,End = Dec 2016) shaded in light blue with its point forecast in deep blue and its 95%confidence interval in dark blue and its 80% confidence interval in light blue.From the forecast plot it can be seen that there is a straight trend in the forecast which predicts a stable price for the Nigerian crude oil price in future.

5.0 CONCLUSIONS

Crude oil price affects economy and governments therefore knowledge of its future movements can lead to better decisions in various managerial levels. However oil price forecasting is not a trivial procedure since oil price time series proved to have high volatility. And it was observed that fluctuations in oil prices often have great impacts on economies in general such as

1. High volatility of oil prices creates uncertainty, as a result, the economic instability may be observed for both oil-exporting and oil-importing countries. In particular, resource-based economies or economies that extremely depend on oil are characterized by significant uncertainty and high volatility of exports and therefore government revenues. In such economies oil price fluctuations not only affect the government budget considerably, but also have strong effects on stock markets and macroeconomic variables. For instance, higher crude oil prices contribute to inflation, the result is recession in oil-consuming countries.

2. Variation of oil prices significantly affects financial markets. Moreover, there is considerable empirical evidence causally linking oil price changes with stock market variables including interest rates, real exchange rates, etc.

3. Understanding oil price evolution and its forecasting is very important for oil industry. Producers make oil price forecasts for general purposes of strategic planning and for specific purposes of evaluating investment decisions related to resource exploration, reserve development and production.

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