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SEASONAL ARIMA MODELLING OF NIGERIAN MONTHLY CRUDE OIL PRICES

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ABSTRACT

The time plot of the series NCOP reveals a peak in 2008 and a depression in early 2009. The overall trend is horizontal and no seasonality is obvious. Twelve-month differencing yields SDNCOP exhibiting still a peak in 2008 and a trough in 2009, the overall trend being slightly positive and seasonality not easily discernible. Nonseasonal differencing of SDNCOP yields DSDNCOP with an overall horizontal trend and no obvious seasonality. However its correlogram reveals an autocorrelation structure of a seasonal model of order 12. Moreover it suggests the product of two moving average components both of order one, one non-seasonal and the other 12-month seasonal. The partial autocorrelation function suggests the involvement of a seasonal (i.e. 12-month) autoregressive component of order one. A $(0, 1, 1)x(1, 1, 1)_{12}$ autoregressive integrated moving average model was therefore proposed and fitted. It has been shown to be adequate.

Keywords: Seasonal time series, ARIMA models, Crude oil prices, Nigeria.

INTRODUCTION

Many economic time series are seasonal. Its volatility notwithstanding, Nigerian monthly crude oil price series tends to exhibit some seasonality. Box and Jenkins (1976), Madsen (2008) and Boubaker (2011) are a few of authors that have written extensively on seasonal ARIMA models which are specially articulated for seasonal time series. This paper is focussed on the modelling of the prices by a multiplicative seasonal ARIMA model. Crude oil being the mainstay of the Nigerian economy, the modelling of its prices has engaged the attention of many researchers, a few of whom are Bolton (2012), King *et al.* (2012) and Salisu and Fasanya (2012).

Seasonal ARIMA Models

ARIMA modelling, proposed by Box and Jenkins (1976) is well known. However for the purpose of this paper, seasonal ARIMA modelling is briefly highlighted.

A time series $\{X_t\}$ is said to follow an autoregressive moving average model of order (p, q) (denoted by ARMA(p, q)) if it satisfies the following difference equation

$$X_t - \alpha_1 X_{t-1} - \alpha_2 X_{t-2} - \dots - \alpha_p X_{t-p} = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \dots + \beta_q \varepsilon_{t-q} \qquad (1)$$

Or

$$A(L)X_t = B(L)\varepsilon_t \qquad (2)$$

Here $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \dots - \alpha_p L^p$ and $B(L) = 1 + \beta_1 L + \beta_2 L^2 + \dots + \beta_q L^q$ where L is the backward shift operator defined by $L^k X_t = X_{t-k}$. Moreover the α's and the β's are constants such that the model is stationary and invertible, i.e. A(L) and B(L) have zeros all outside the unit circle respectively, and $\{\varepsilon_t\}$ is a sequence of uncorrelated random variables each with mean zero and constant variance called a *white noise process*.

Most real life time series are non-stationary. Box and Jenkins (1976) proposed that differencing to an appropriate degree could render such a series stationary. Let $\nabla^d X_t$ denote the d^{th} difference of X_t. Then $\nabla = 1 - L$. If X_t is replaced by $\nabla^d X_t$ in (1), then the series $\{X_t\}$ is said to follow an autoregressive integrated moving average of order (p, d, q) designated ARIMA(p, d, q). Suppose the time series is seasonal of period s. Let D be the degree of seasonal differencing applied to the series $\nabla^d X_t$. The resultant series may be denoted by $\nabla^d \nabla_s^D X_t$.

A time series $\{X_t\}$ is said to follow a multiplicative $(p, d, q)x(P, D, Q)_s$ seasonal ARIMA model if it satisfies the following equation

$$A(L)\Phi(L^s)\nabla^d \nabla_s^D X_t = B(L)\Theta(L^s)\varepsilon_t \qquad (3)$$

where $\Phi(L) = 1 + \phi_1 L + \dots + \phi_P L^P$ and $\Theta(L) = 1 + \theta_1 L + \dots + \theta_Q L^Q$ and the ϕ's and θ's are constants such that the zeros of Φ(L) and Θ(L) are all outside of the unit circle for seasonal stationarity and invertibility, respectively. Box and Jenkins (1976), Priestley (1981), Madsen (2008), Surhatono. (2011) and Etuk (2012) are a few of the authors that have written extensively on seasonal ARIMA modelling.

MATERIALS AND METHODS

Data

The data for this work are monthly Nigerian (Bonny Light) crude oil prices in US$/barrel from 2006 to 2011 obtainable from the website of the Central Bank of Nigeria, www.cenbank.org. This 72-point time series shall be referred to as NCOP.

Model Estimation

A knowledge of the theoretical properties of ARIMA models helps a lot in their identification and estimation. An existent seasonality can be revealed by the time-plot. Where it is not so obvious from the time plot, the autocorrelation plot or the *correlogram* shows it up. A significant spike at the seasonal lag on the correlogram suggests seasonality. A negative spike at the seasonal lag suggests the involvement of a seasonal moving average component. A positive spike at the seasonal lag suggests the involvement of a seasonal autoregressive component. In addition, if the autocorrelation function cuts off, the cut-off lag is an estimate of the non-seasonal moving average order, q. If, however, the partial autocorrelation plot cuts off, the cut-off lag is an estimate of the non-seasonal autoregressive order p. It has been advised that $D + d < 3$ to avoid undue model complexity.

Once the model orders have been estimated, the model parameters may be estimated. Optimization criteria like the least error sum of squares criterion, the maximum likelihood criterion, the maximum entropy criterion, etc. may be used. Involvement of the white noise process in the definition of an ARMA process necessitates the application of non-linear optimization techniques for their estimation. Such a process involves iterations after an initial estimate has been made, each iteration being an improvement on the previous one until the process converges to an optimal solution. However, efforts have been made with some measure of success to use linear optimization techniques to estimate ARMA models (See for example, Oyetunji (1985), (Etuk, 1987; Etuk, 1998). In this work, the software Eviews, which is based on the least squares approach, shall be used.

Diagnostic Checking

A fitted model must be checked for goodness-of-fit to the data. Eviews has facilities for such purposes. In particular, some residual analysis shall be performed. Under the hypothesis of an adequate model, the residuals should be uncorrelated with zero mean and should follow a Gaussian distribution.

RESULTS

The time plot of the original series NCOP in Figure 1 reveals a peak in 2008 and a trough in 2009. A twelve-month differencing yields the series SDNCOP with a deep trough in 2009 (See Figure 2). A non-seasonal differencing of SDNCOP yields the series DSDNCOP which exhibits an overall horizontal trend with no obvious seasonality (See Figure 3). Its correlogram in Figure 4 shows significant spikes at lags 1, 11, 12 and 13, with autocorrelations at lags 11 and 13 fairly comparable. That can be interpreted as the autocorrelation structure of the product of two moving average components, each of order one: one seasonal (i.e. 12-month) and the other nonseasonal. Moreover the partial autocorrelation function, PAC, has a significant spike at lag 12, indicating the involvement of a seasonal autoregressive component of order one. The following $(0, 1, 1)\mathrm{x}(1, 1, 1)_{12}$ multiplicative seasonal model is hereby proposed. That means the model is

$$DSDNCOP_t = \alpha_{12}DSDNCOP_{t-12} + \beta_1\varepsilon_t + \beta_{12}\varepsilon_{t-12} + \beta_{13}\varepsilon_{t-13} \quad (4)$$

An estimate of (4) is given in Table 1 as

$$DSDNCOP_t + 0.3523DSDNCOP_{t-12} = 0.1241\varepsilon_{t-1} + 0.5349\varepsilon_{t-12} + 0.4621\varepsilon_{t-13} + \varepsilon_t \quad (5)$$
$$(\pm 0.1043) \qquad (\pm 0.1169) \quad (\pm 0.0846) \quad (\pm 0.0866)$$

In the model (5), only the MA(1) coefficient is not statistically significant, being less than twice its standard error. As much as 55% of the variation in DSDNCOP is explained by the model. The fitted model has been shown to agree closely with observations (See Figure 5). The residuals follow a fairly normal distribution with zero mean(except for two outliers between 20 and 30)(See Figure 6) and they are uncorrelated (See Figure 7). Therefore the model is adequate.

CONCLUSION

The Nigerian monthly crude oil price series has been shown to follow a $(0, 1, 1)x(1, 1, 1)_{12}$ seasonal ARIMA model. This has been shown to be adequate by various techniques.

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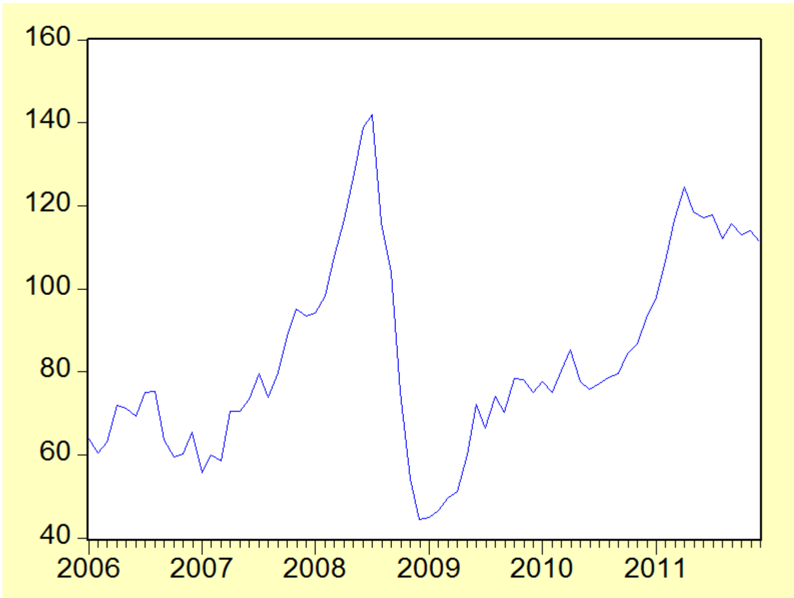

FIGURE 1: NCOP

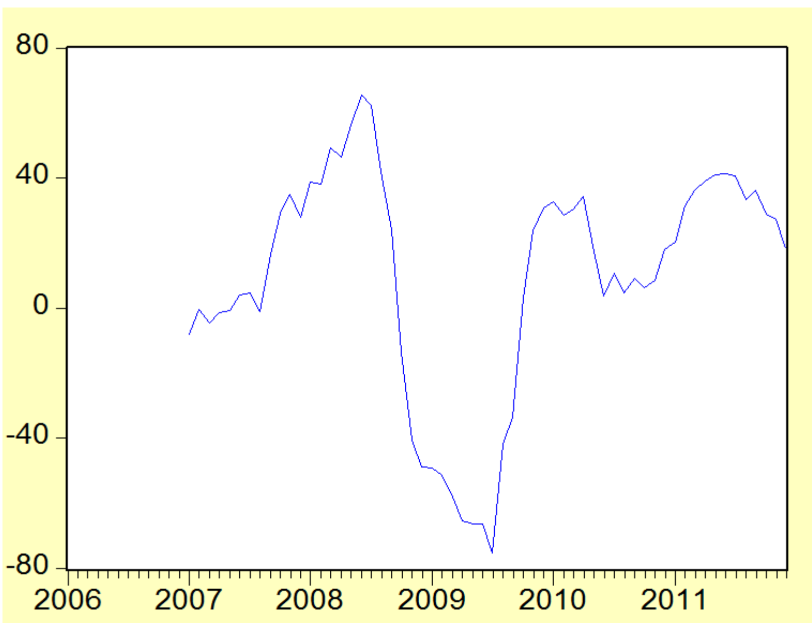

FIGURE 2: SDNCOP

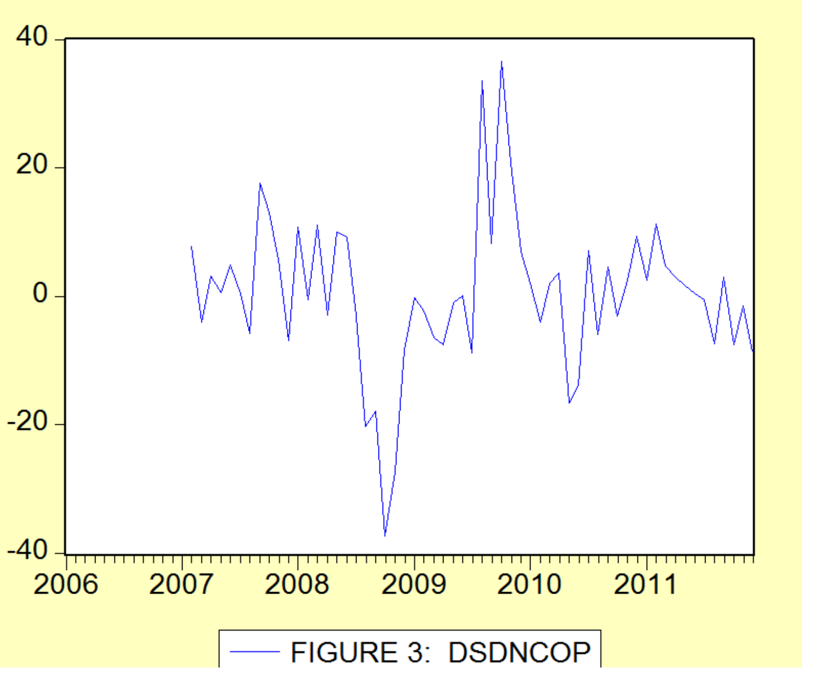

Figure-4. Correlogram of Dsdncop

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.448	0.448	12.472	0.000
		2	0.411	0.263	23.139	0.000
		3	0.151	-0.137	24.613	0.000
		4	0.044	-0.105	24.737	0.000
		5	-0.040	-0.027	24.846	0.000
		6	-0.130	-0.092	26.001	0.000
		7	-0.165	-0.074	27.876	0.000
		8	-0.101	0.074	28.598	0.000
		9	-0.226	-0.187	32.269	0.000
		10	-0.360	-0.347	41.806	0.000
		11	-0.261	0.072	46.926	0.000
		12	-0.471	-0.320	63.949	0.000
		13	-0.292	-0.079	70.636	0.000
		14	-0.122	0.331	71.824	0.000
		15	0.036	0.072	71.927	0.000
		16	0.101	-0.244	72.789	0.000
		17	0.121	0.044	74.037	0.000
		18	0.105	0.018	75.003	0.000
		19	0.210	-0.069	78.959	0.000
		20	0.038	-0.091	79.089	0.000
		21	0.050	0.024	79.321	0.000
		22	0.024	-0.329	79.377	0.000
		23	0.032	-0.031	79.482	0.000
		24	-0.060	-0.080	79.853	0.000

Table-1. Model Estimation

Dependent Variable: DSDNCOP
Method: Least Squares
Date: 10/07/12 Time: 17:21
Sample(adjusted): 2008:02 2011:12
Included observations: 47 after adjusting endpoints
Convergence achieved after 26 iterations
Backcast: 2007:01 2008:01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	-0.352279	0.104337	-3.376370	0.0016
MA(1)	0.124116	0.116939	1.061370	0.2944
MA(12)	0.534889	0.084587	6.323545	0.0000
MA(13)	0.462138	0.084657	5.458953	0.0000

R-squared	0.548421	Mean dependent var	-0.430426
Adjusted R-squared	0.516916	S.D. dependent var	12.80220
S.E. of regression	8.898074	Akaike info criterion	7.290812
Sum squared resid	3404.556	Schwarz criterion	7.448271
Log likelihood	-167.3341	F-statistic	17.40717
Durbin-Watson stat	2.470250	Prob(F-statistic)	0.000000

Inverted AR Roots	.89+.24i	.89 -.24i	.65+.65i	.65 -.65i
	.24+.89i	.24 -.89i	-.24 -.89i	-.24+.89i
	-.65+.65i	-.65+.65i	-.89+.24i	-.89 -.24i
Inverted MA Roots	.96+.25i	.96 -.25i	.71+.68i	.71 -.68i
	.29 -.94i	.29+.94i	-.20+.95i	-.20 -.95i
	-.61+.71i	-.61 -.71i	-.79	-.82+.32i
	-.82 -.32i			

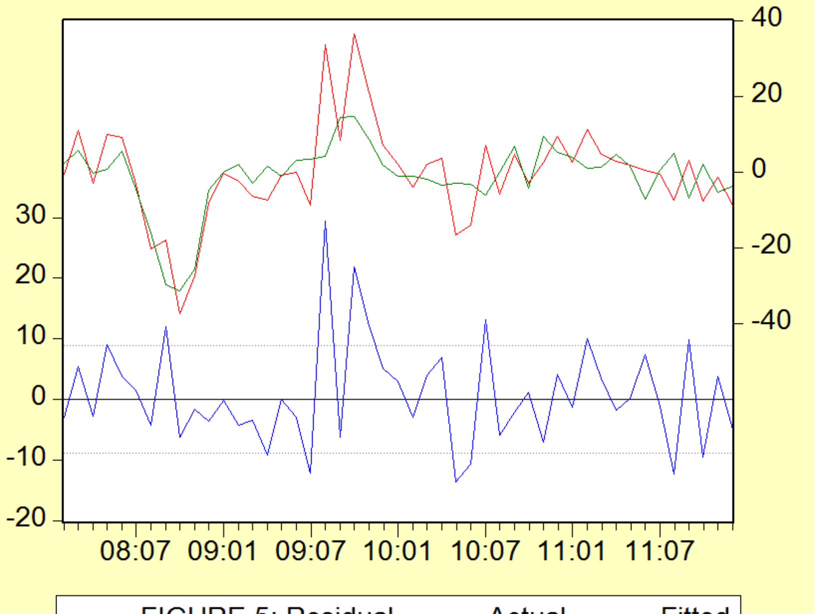

FIGURE 5: Residual

Figure-6. Histogram of the Residuals

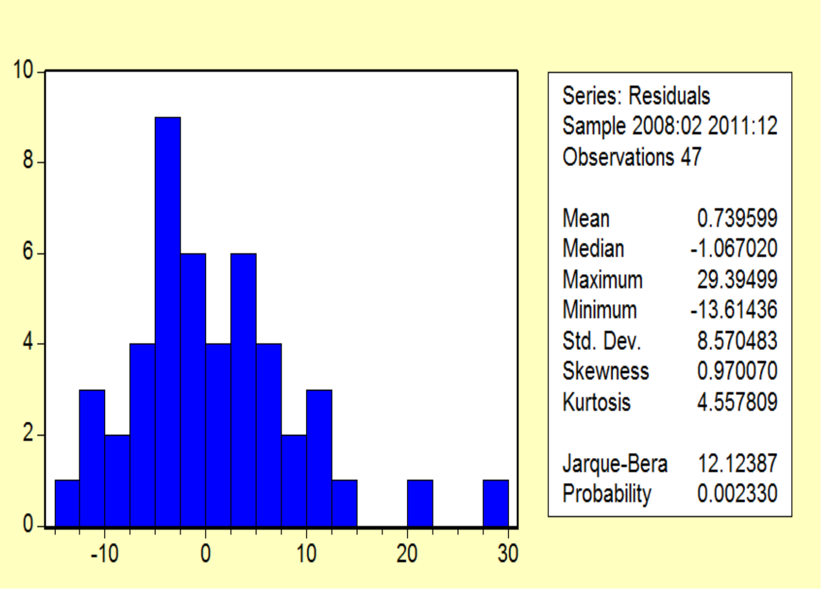

Figure-7. Correlogram of the Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.251	-0.251	3.1588	
		2	0.203	0.149	5.2642	
		3	0.123	0.222	6.0526	
		4	-0.048	-0.002	6.1750	
		5	-0.027	-0.125	6.2164	0.013
		6	-0.152	-0.237	7.5117	0.023
		7	-0.167	-0.264	9.1247	0.028
		8	-0.076	-0.109	9.4679	0.050
		9	-0.131	-0.031	10.507	0.062
		10	-0.319	-0.345	16.831	0.010
		11	0.314	0.214	23.145	0.002
		12	-0.276	-0.060	28.145	0.000
		13	-0.059	-0.346	28.378	0.001
		14	0.230	0.037	32.076	0.000
		15	0.006	0.140	32.078	0.001
		16	0.097	-0.073	32.778	0.001
		17	0.106	0.002	33.641	0.001
		18	0.087	0.092	34.248	0.002
		19	0.114	-0.066	35.325	0.002
		20	-0.054	-0.189	35.576	0.003