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Research Article

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Statistical Intervention Modelling of Nigerian Monthly Household Kerosene Distribution

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Abstract Monthly distribution of household kerosene (HHK) in Nigeria from January 2009 to December 2015 experienced a sudden jump as from January 2013. It is believed that this increase was caused by the deregulation of the downstream sector of the petroleum industry of Nigeria in January 2012. This is an intervention case with January 2013 as the point of intervention. It is being speculated that what is responsible for this is the deregulation of the downstream sector of the petroleum industry. The pre-intervention distribution is adjudged stationary and follows an ARMA(1,1) model. Post-intervention forecasts based on this model are computed and the difference between these forecasts and their corresponding actual observations is modelled to obtain the intervention transfer function. The overall intervention model is observed to generate forecasts that agree closely with the original data. Intervention measures may therefore be based on this model.

Keywords Household kerosene, intervention analysis, distribution, arima modelling

Introduction

In developed countries the use of household kerosene (HHK) for lighting, heating and cooking has reduced because of preference for electricity. However in developing countries like Nigeria where electricity is costly and unsteady, its use is still widespread. It is otherwise called paraffin and is seen as a cleaner and better alternative to solid fuels, biomass and coal for cooking, lighting and heating [1].

The distribution of HHK in Nigeria by the Nigerian National Petroleum Corporation (NNPC) is the subject of this research work. It has been observed to encounter an intervention as from January 2013. It is believed that this intervention is the deregulation of the downstream sector of the Nigerian petroleum industry in January 2012 by the Goodluck Ebele Jonathan-led administration. It means that the impact happened a year later. The aim of this work is to determine an intervention model for this time series.

The technique based on autoregressive integrated moving average (ARIMA) modelling proposed by Box and Tiao [2] is to be adopted for this work. The pioneers used it to explain the change in the Los Angeles Oxidant data due to the 1960 opening of the Golden State Freeway and the promulgation of a new law. Ever since its introduction it has found application in various contexts. For example, Tagaris *et al.*, [3] used the technique to study the effect of brain activation on functional magnetic resonance imaging. Collier *et al.,* [4] observed that 1997-1998 El Nino severe flooding in North Peru increased problem loans from a microfinance institution and estimated the extent of this effect. The effects of the 9-21 earthquake in 1999 and the severe acute respiratory syndrome of 2003 have been shown to be significant on inbound tourism demand in Japan by Min [5]. Anderson *et al.* [6] used this Box-Tiao approach to model the effect of programmed audio and environmental/physiological cues on cow heart rate. Sabiruzzaman and Razzaque [7] have demonstrated the supremacy of the intervention technique over the pure ARIMA approach. Etuk and Eleki [8] have fitted an intervention model to daily Yuan/ Naira exchange rates. Etuk *et al.* [9] have conducted an intervention analysis on prime motor spirit distribution in Nigeria. Amadi and Etuk [10] have proposed an ARIMA based interrupted time series model to daily amounts of Naira per Euro, to mention only a few cases.

Materials and Methods

Data

The data analyzed in this work are monthly HHK distribution in thousands of litres from January 2009 to December 2015 the website of the Nigerian National Petroleum Corporation (NNPC) http://nnpcgroup.com/. A list of the data has been provided in the Appendix.

Statistical Intervention Modelling

A time series $\{X_t\}$ is said to experience an intervention at time t=T if an event changes the course of the time series at that time. The event is called an intervention. The pre-intervention data may be modelled by an ARIMA model (Box and Tiao, 1975). Suppose this is an ARIMA(p, d, q) model. That means that

$$\nabla^d X_t = \alpha_1 \nabla^d X_{t-1} + \alpha_2 \nabla^d X_{t-2} + ... + \alpha_p \nabla^d X_{t-p} + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + ... + \beta_q \varepsilon_{t-q} \quad (1)$$

Or

$$A(L)\nabla^d X_t = B(L)\varepsilon_t \quad (2)$$

where $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - ... - \alpha_p L^p$; $B(L) = 1 + \beta_1 L + \beta_2 L^2 + ... + \beta_q L^q$; $L^k X_t = X_{t-k}$ and $\nabla = 1 - L$.

Therefore from (2)

$$X_t = \frac{B(L)\varepsilon_t}{A(L)\nabla^d} \quad (3)$$

On the basis of model (3) forecasts are obtained for the post-intervention period. Suppose these are denoted by F_t, t > T-1. The difference between these forecasts and the original post-intervention observations, $Z_t = X_t - F_t$, may be modelled as

$$Z_t = \frac{c(1)*(1-c(2)^{(t-T+1)})}{(1-c(2))} \quad (4)$$

for the intervention transfer function [11]. The final intervention model is obtained by a combination of the noise component (3) and the transfer function (4) to give

$$Y_t = \frac{B(L)\varepsilon_t}{A(L)\nabla^d} + I_t \frac{c(1)*(1-c(2)^{(t-T+1)})}{(1-c(2))} \quad (5)$$

where I_t is an indicator variable such that I_t =0, t<T and I_t = 1, otherwise.

In practice the difference order d is obtained sequentially with d=0 initially. If the realization of the time series $\{X_t\}$ to be analyzed is certified stationary, by for example the Augmented Dickey Fuller (ADF) Test, then d=0. Otherwise first order differencing of the realization is done. If the differences are declared stationary, then d=1. Otherwise, the process continues until stationarity is achieved. Next are the autoregressive (AR) and the moving average (MA) orders p and q respectively. They are estimated as the cut-off lags, if any, of the partial autocorrelation function (PACF) and the autocorrelation function (ACF) respectively. Then the least squares procedure is used to estimate the α's and the β's so that model (1) is both stationary and invertible. Eviews 7 was used for all computations in this research work.

Results and Discussion

The time plot of the realization in Figure 1 clearly shows the time series as having encountered an intervention in January 2013, at which point there is a sharp increase in the distribution of the commodity. It is believed that the intervention is the deregulation policy of the Nigerian in the downstream sector of the petroleum industry in January 2012. Pre-intervention data have a fairly horizontal trend (See Figure 2) and, with a test statistic value of -4.54 and the 1%, 5% and 10% critical values of -3.58, -2.93 and -2.60 respectively, are adjudged by the ADF test as stationary. Their autocorrelation structure displayed in Figure 3 suggests an ARMA(1,1) fit. Estimation of this model as summarized in Table 1 yields

$$X_t = 0.9820X_{t-1} - 0.5869\varepsilon_{t-1} + \varepsilon_t \quad (6)$$

Hence the noise component of the intervention model is

$$X_t = \frac{(1-0,5869L)\varepsilon_t}{1-0.9820L} \quad (7)$$

Model (6) is adequate; the residuals are uncorrelated (See Figure 4) and are normally distributed (See the Jarque-Bera test in Figure 5).

Forecasts F_t are made in the post-intervention period based on model (6). The difference of the post-intervention observations and the corresponding forecasts $Z_t = X_t - F_t$ are modelled using equation (4). As summarized in Table 2, c(1) = 149877.1 and c(2) = 0.184743. By (5), the overall intervention model is therefore given by

$$Y_t = \frac{(1-0.5869L)\varepsilon_t}{1-0.9820L} + I_t * \frac{149877.1*(1-0.184743^{t-48})}{0.815257} \quad (8)$$

Forecasts on the basis of model (8) agree closely with the post-intervention observations as evident from Figure 6, showing that the model is adequate.

Conclusion

It may be concluded that model (8) is the intervention model for monthly HHK distribution in Nigeria. Clearly there is significant positive impact of the deregulation policy on the distribution. This result may be the basis for a management of the distribution of this commodity.

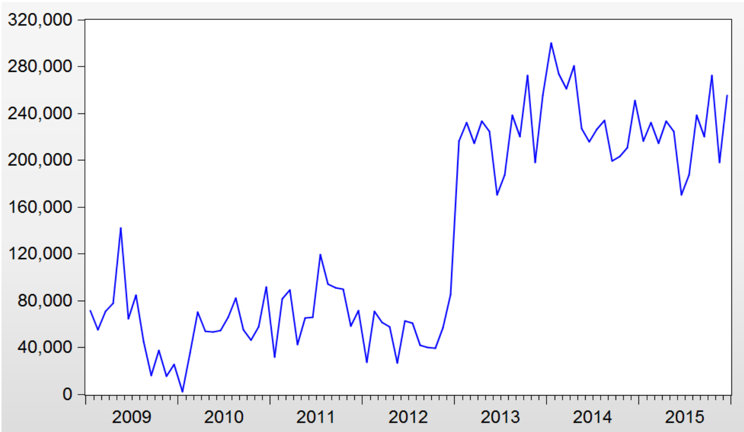

Figure 1: Nigerian Monthly HHK Distribution

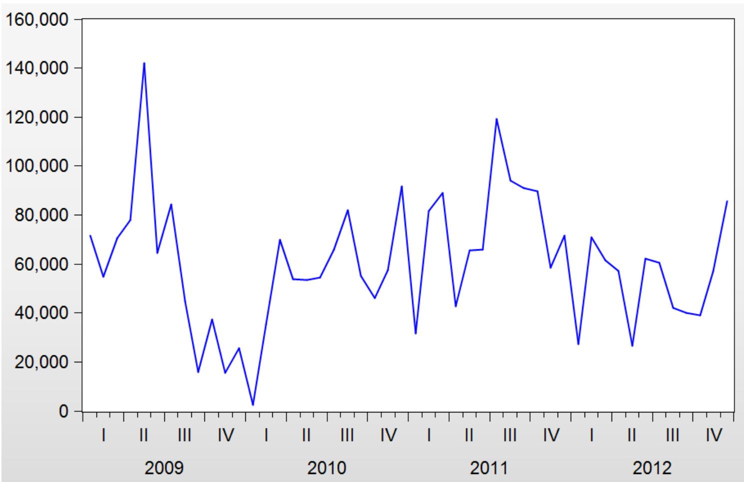

Figure 2: Pre-intervention Monthly HHK Distribution

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.363	0.363	6.7247	0.010
		2	0.306	0.201	11.626	0.003
		3	0.147	-0.018	12.771	0.005
		4	0.070	-0.036	13.035	0.011
		5	0.002	-0.041	13.035	0.023
		6	-0.231	-0.270	16.085	0.013
		7	-0.104	0.054	16.724	0.019
		8	-0.210	-0.091	19.360	0.013
		9	-0.112	0.020	20.135	0.017
		10	-0.145	-0.046	21.461	0.018
		11	-0.130	-0.054	22.559	0.020
		12	0.002	0.055	22.559	0.032
		13	-0.160	-0.179	24.318	0.028
		14	-0.081	-0.073	24.782	0.037
		15	-0.058	0.052	25.027	0.050
		16	0.027	0.036	25.083	0.068
		17	-0.105	-0.188	25.943	0.076
		18	-0.219	-0.205	29.774	0.040
		19	-0.034	0.065	29.867	0.054
		20	-0.250	-0.276	35.215	0.019

Figure 3: The ACF and the PACF of Pre-intervention HHK distribution

Table 1: Estimation of the Pre-intervention ARMA(1,1) Model

Dependent Variable: HHKD
Method: Least Squares
Date: 08/26/17 Time: 12:23
Sample (adjusted): 2009M02 2012M12
Included observations: 47 after adjustments
Convergence achieved after 10 iterations
MA Backcast: 2009M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.981981	0.027178	36.13147	0.0000
MA(1)	-0.586874	0.128993	-4.549669	0.0000

R-squared	0.052298	Mean dependent var	60302.97
Adjusted R-squared	0.031238	S.D. dependent var	26716.35
S.E. of regression	26295.76	Akaike info criterion	23.23382
Sum squared resid	3.11E+10	Schwarz criterion	23.31255
Log likelihood	-543.9949	Hannan-Quinn criter.	23.26345
Durbin-Watson stat	1.905580		

Inverted AR Roots	.98
Inverted MA Roots	.59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.014	0.014	0.0093	
		2	0.054	0.054	0.1574	
		3	-0.068	-0.069	0.3980	0.528
		4	-0.050	-0.051	0.5310	0.767
		5	0.005	0.014	0.5322	0.912
		6	-0.277	-0.279	4.8372	0.304
		7	0.013	0.015	4.8463	0.435
		8	-0.140	-0.125	6.0073	0.422
		9	0.017	-0.024	6.0241	0.537
		10	-0.043	-0.063	6.1369	0.632
		11	-0.041	-0.062	6.2462	0.715
		12	0.153	0.076	7.7926	0.649
		13	-0.137	-0.159	9.0641	0.616
		14	-0.017	-0.114	9.0834	0.696
		15	0.023	0.052	9.1223	0.764
		16	0.171	0.125	11.305	0.662
		17	-0.021	-0.094	11.338	0.728
		18	-0.179	-0.167	13.873	0.608
		19	0.144	0.118	15.569	0.555
		20	-0.201	-0.242	19.014	0.391

Figure 4: The ACF and PACF of Residuals ot The Pre-intervetion ARMA(1,1) Model

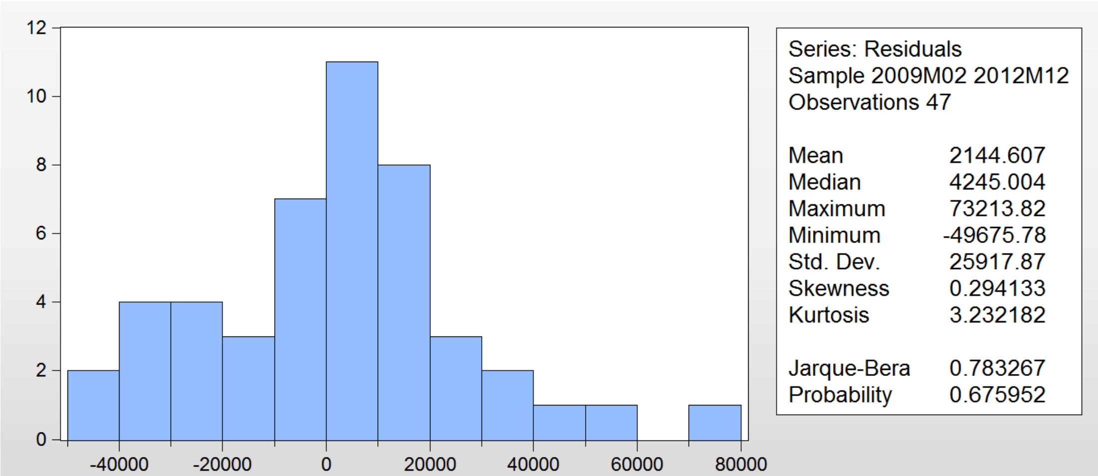

Figure 5: Histogram of the Residuals of the Pre-Intervention ARMA(1,1) Model

Table 2: Estimation of the Intervention Transfer Function

Dependent Variable: Z1
Method: Least Squares
Date: 08/26/17 Time: 15:12
Sample: 2013M01 2015M12
Included observations: 36
Convergence achieved after 29 iterations
Z1=C(1)*(1-C(2)^(T-48))/(1-C(2))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	149877.1	29241.97	5.125410	0.0000
C(2)	0.184743	0.162209	1.138913	0.2627

R-squared	0.027104	Mean dependent var	182699.7
Adjusted R-squared	-0.001511	S.D. dependent var	31248.35
S.E. of regression	31271.94	Akaike info criterion	23.59278
Sum squared resid	3.32E+10	Schwarz criterion	23.68076
Log likelihood	-422.6701	Hannan-Quinn criter.	23.62349
Durbin-Watson stat	1.439258		

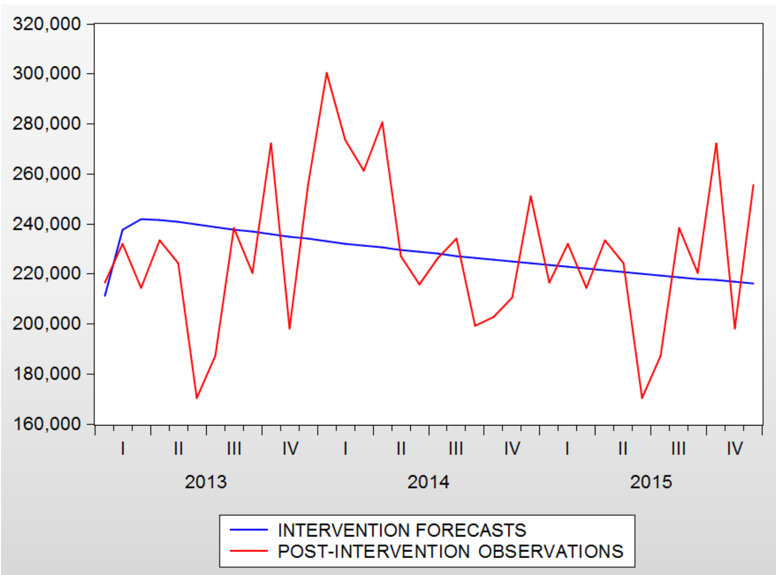

Figure 6: Comparison of Intervention Forecasts and Post-intervention Data

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APPENDIX:

DATA: Monthly House Hold Kerosene Distribution in Nigeria

Year	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Month							
January	71630.95	2496.40	31807.75	27304.88	216521.66	300414.64	216,521.66
February	54862.00	35297.09	81598.08	71096.29	232002.78	273825.89	232002.78
March	70621.16	70078.58	89157.70	61696.92	214392.85	261376.00	214392.85
April	78035.39	53788.25	42777.76	57329.91	233346.86	280844.94	233346.86
May	142184.12	53373.91	65511.35	26588.62	224417.92	227056.77	224417.92
June	64649.90	54652.85	65784.41	62378.04	170517.55	215750.75	170517.55
July	84459.41	65973.57	119354.27	60513.04	187245.52	226521.15	187245.52
August	44886.46	82179.37	93960.11	42037.73	238548.04	234127.97	238548.04
September	15978.26	55335.15	91009.48	40102.04	220314.66	199406.33	220314.66
October	37246.01	46063.75	89780.29	39155.04	272360.99	202885.78	272360.99
November	15587.44	57629.48	58473.41	57176.11	198385.56	210648.24	198385.56
December	25514.71	91679.69	71495.37	85578.19	255565.10	251263.68	255565.10

Source: http://nnpcgroup.com/