Journal of Economics and Sustainable Development www.iiste.org
ISSN 2222-1700 (Paper) ISSN 2222-2855 (Online)
Vol.5, No.4, 2014

Modelling Residential Electricity Demand for Kenya

Geoffrey Aori Mabea
Postgraduate Energy Economics and Policy Student
Department of Economics, University of Surrey, Guildford, United Kingdom
Email: geoffrey.mabea@gmail.com;contact@iiste.org

Abstract
This paper investigatesthe relationship between Kenya electricity consumption, real disposable income and residential electricity prices. The research employs the Engle and Granger two-step procedure and ECM method to a time series data over the period from 1980 to 2009 to analyze the electricity demand. The model suggests a co-integration with long-run price and income elasticity of -0.095 and 0.1 respectively with 4% increase in consumption of other non-economic factors.It can therefore be concluded that the estimates of the analysis are indicative of a rising electricity requirements as Kenya achieves higher GDP growth rates.
Keywords: Electricity demand, Error correction Models, short-andlong-run elasticities

1. INTRODUCTION

Electricity demand is a derived demand; its consumption is used as an input in other processes giving utility. The demand for electricity just like any other good depends on income and price and other factors as well. The electricity demand analysis contributes significantly to policy implementation especially on energy planning. These decisions are key determinants in investments in the various infrastructural sectors, electricity tariff planning, marketing and manpower (Al-Alawi & Islam, 1996; Rhys, 1984). The electricity demand studies in Kenya have always been conducted by the government through a committee formed from the key players in the electricity sector. The first documented report on the electricity demand was developed by the Kenya Power and Lighting Company and thereafter a committee was formed to work together and look at the expansion plan and forecast the electricity demand.

Moreover, in recent time, some studies have been conducted concentrating on causality studies and energy reforms. Some notable studies include a research by Ngui, et al., (2011), that estimated price and fuel expenditure‘s elasticities of demand by applying the Linear approximate Almost Ideal Demand System(LA-AIDS) to 3,665 households sampled in Kenya. The study concluded that electricity prices are inelastic while the motor spirit premium (MSP), Automotive Gas Oil (AGO) and lubricants are elastic.

Kenya experienced a steady economic growth from around 2002 to 2007 but soon after, the economy took a downturn due to a difficult year characterized by global financial crisis and post-election violence. Later, the real GDP regained from as low as 1.6% experienced after the post-election violence in 2007 to 5.8% in 2010. This is as a result of implementing appropriate broad-based policies leading to high growth momentum. However, this growth momentum was not sustainable hence slowed down in 2011 to 4.4 % due to challenges related to high commodity prices and depreciating exchange rate. The country picked up in 2012 and has so far been increasing (MoE, 2013).

This research employs the Engle and Granger two-step procedure and ECM method to a times series of annual data over the period from 1980 to 2009 to analyze the electricity demand in Kenya. Co-integration methodology is one of the most popular approaches in demand modelling. In this study, this method is employed because it allows estimation of both long-run and short-run effects of explanatory variables on electricity demand.

The reminder of the paper is organized as follows. The next section provides a review of existing literature followed by a detailed theoretical overview of the methods employed for analysis in section three. Section four gives an overview of data used. Section five outlines the results that are discussed in section six. The final section concludes giving policy implications.

2. LITERATURE REVIEW

The studies into causal relationship between energy consumption and economic growth proliferated in early 1970's (Jamil & Ahmad, 2010). These studies soon split into two schools of thought; one arguing that energy is a core source of economic growth since it is complementary to other factors of production (for example Stern, 2000; Asafu-Adjaye, 2000) while the other argues that energy is neutral to economic growth (Soytas& Sari, 2003).The modelling of energy demand models sparked many studies but suffered from lack of appropriate time series data and the development of a definite method for analyzing it. The studies began with simple models which according to Ryan & Plourde (2009), lacked the dynamic structure in their specification, but now sophisticated models have been developed which included lagged dependent variables.

There are different methodologies that are applied in energy demand modelling; some of the notable method includes Engle-Granger (for example Hunt & Manning, 1989; Koli, et al., 2003,) and vector autoregressive

(VAR) which is capable of testing restrictions on the vectors using standard asymptotic inference. The VAR method has been applied in studies to analyze Danish residential energy demand for example Bentzen & Engsted, 1997 and a study byHunt & Witt (1995), to estimate the UK's aggregate energy demand model. Autoregressive distributed Lag Model (ARDL) which is deemed reliable among many methods has been applied by many researches for example a study by Narayan & Smyth (2005), which analyzed the residential demand for electricity in Australia. One other related study includes a comparative study on Danish residential energy consumption by Bentzen & Engsted (2001) using ARDL and ECM which found out that quantitatively and qualitatively the two methods give similar results. Beginning late 1980's, co-integration analysis has become widely used in most studies of energy demand. Various papers have been written in this area, amongst these include: (Engle, et al., 1989; Hunt & Lynk, 1992; Bentzen & Engsted,1993; Beenstock & Goldin, 1999).

Structural Time Series Model (STSM) later emerged as an alternative to the co-integration method. As suggested by Harvey (1997), this method is capable of applying stochastic time trends. This method has been employed by Hunt et al., (2000) in modelling technical progress on the United Kingdom energy demand by allowing the underlying energy demand trends (UEDT) to be stochastic. In general therefore, the econometric modelling of energy demand takes the form of three main econometric models namely, structural models, reduced form and decomposition models (Erdogdu, 2007). The reduced model employs a log linear model which assumes that energy demand is a direct linear function of energy price and real income (Kouris, 1981). The structural model is a disaggregated model based on the assumption that energy is a derived demand. This has been applied widely though it requires a large number of variables compared to the reduced model. The decomposition model was first applied by Wolffram (1971) in the analysis of the problem of supply versus price irreversibility. This method was based on the assumption that the response to price reductions would be less than that to price increase.

The decomposition method was later improved by Gately (1992), who introduced price decomposition to isolate the effects on demand of price decrease, price increase below and above historic maximum. This has been applied in various studies for example in Gately& Huntington (2002), a research that looked at the determination of commercial energy and oil demand for 96 of the world's largest countries. This study further examined the asymmetric effects on demand of increases and decreases in oil prices, in income and the speed of demand adjustment to changes in price and income. Other studies that have applied this method include (Adofe, et al., 2013; Adeyemi & Hunt, 2007; Griffin & Schulman, 2005).

Most of the methods applied in energy demand modelling have been used interchangeably to model electricity demand and subsequently using the elasticities obtained to forecast the electricity demand. As Hondroyiannis (2004) indicates, the empirical studies into residential electricity demand have developed recently. This has sparked demand analysis in developed countries (for example Garbacz, 1984; Clements &Madlener, 1999) and demand forecasting in emerging market (for example Tiwari, 2000).

3. THEORETICAL REVIEW

In order to run the long-run and short-run relationship of the electricity demand, the following model is adopted:

$e_t = f\,(p_t, z_t, y_t)$ (1)

Where$e_t$is the consumption for electricity at time t, $p_t$is the nominal price of aggregate electricity,y_t, the real income while $z_t$represents all exogenous non-economic factors that affect electricity demand such associal-economics factors. The non-economic factors play a critical role in energy modelling but according to Beenstock& Willcocks (1983) and Hunt, et al.(2003), it is sometimes difficult to quantify these factors. In addition, based on economic theory, effect of price is expected to be negative while the impact of income on demand of electricity is expected to be positive.

3.1. Unit root testing

Most econometric theories are grounded on the premise that the underpinning variables are stationary thus having constant means and variances over the period. However, it is understood that economics variable such as economic growth rate are not stable hence the assumption does not hold all the time. On the other hand the inclusion of non-stationary variable will definitely result into spurious regression. Similarly a statistical and distribution properties containing I(k) (integrated of order k, k>(0)) variables are different from the series comprising I(0) (integrated of order (0)) variables.

To test for stationarity, or non-stationarity, it is important to test for the presence of unit root. A time series y_t is integrated of order k, denoted I(k) , if $\Delta^d y_t$is stationary. The series y_t therefore said to have k unit roots.

If we consider the equation

$\Delta y_t = -\alpha y_{t-1} + b_t + c_t + u_t u_t \sim IID(0,\sigma^2)$ (2)

A unit root test is a test of the null hypothesis of

H_o: α=0 against H_1: α>0 in this equation.

However, the distribution of the parameter α in the equation is non-standard and we cannot use standard t-test to test the hypothesis that α=0. Instead, new test with non-standard distribution have been developed. Dickey and

Fuller (1979, 1981), proposes a test based on the t-ratio t(α) in the OLS regression. The distribution of this statistic is non-standard and depends on the presence of the nuisance parameter, b and c.

The Dickey-Fuller test is based on the assumption that $u_t$is 'white noise', that is, serially uncorrelated. If $u_t$is serially correlated then the serial correlation needs to be corrected before the unit root test is performed. The correction is attained through adding the p lagged terms Δy_{t-1}.......,Δy_{t-p} to the regression in equation (2) resulting to:

$$\Delta y_t = -\alpha y_{t-1} + b_t + c + \gamma_1 \Delta y_{t-1} + \ldots + \gamma_p \Delta y_{t-p} + u_t \ldots\ldots\ldots u_t \sim IID(0,\sigma^2)$$

The Schwarz information criterion is used in this study to determine the number of lags to use in the unit root test procedure. In addition, the Phillips-Perron (PP), an alternative to ADF test and the visual correlogram tests are also employed to test for stationarity.

3.2. Co-integration

Non-stationary variables are usually regressed to model the energy demand provided that they are *I*(1)and are also dependent. The indicators of spurious regression are low Durbin-Watson values and very high R^2 together. If *I*(1) variable are co-integrated, it means that although they are individually non-stationary, they are moving together so that there is a long run relationship between them. For example

$$e_t = \beta_0 + \beta_1 y_t + \beta_2 p_t + \beta_{3t} + u_t$$

If two or more economic variables, such as energy consumption (e_t), income (y_t) and electricity prices (p_t), are co-integrated, then there is a single value for the two or more parameters such that the linear combination et- β_0-$\beta_1 y_t$- $\beta_2 p_t$-β_{3t} isstationary. This provides parameters with weights (w_t) of a co-integrating vector and hence a valid econometric equation with stationary error term u_t.

This therefore represents the long-run equilibrium relationship between the variable and it can only exist when there is co-integration. Dickey-Fuller tests on the OLS residuals from a static regression provide away of testing co-integration. According to Engle and Granger (1987), the null hypothesis is the test that estimates $w_t \sim I(0)$, i.e. zero co-integrating vectors, against the alternative that estimates $w_t \sim I(1)$, i.e. one co-integrating vector. Critical values for the ADF test, based on fitting response surface to simulation results, are given in Mackinnon (1996).

3.3. Engle -Granger Error Correction Model (ECM)

The ECM represents an adjustment mechanism whereby deviations from the equilibrium relationship in the previous period lead to adjustment in the following period. It is basically a parameterisation of the general dynamic model. Once all the variables are co-integrated, the relationship among these variables can be represented by ECM. The framework includes lagged values of the residuals of the static model (the first step in the Engle and Granger procedure) which are considered as the deviation from the long-term equilibrium in the previous period and the error in the next period which should be corrected. In order to construct a short-run model, the estimated residuals from the static model are first tested to confirm that they are stationary, and then the next step is to lag and include them in the ECM equation. In this study, co-integration/ECM techniques; Engle and Granger's two step OLS method is employed because it allows estimation of both long-run and short-run effects of explanatory variable on electricity demand.

3.4. Modelling Procedure

Assuming that there exists for Kenya, a simple long-run equilibrium log-linear Electricity Price (P_t), GDP (y_t) and the Underlying Energy Demand Trend (T) given by:

$$e_t = \beta_0 + \beta_1 y_t + \beta_2 p_t + \beta_{3t} \quad (3)$$

Where e_t= natural logarithm of electricity demand measured in kWh;

y_t= natural logarithm of GDP at constant 2000 Local Currency units (LCU) prices in Kenya Shillings;

p_t= natural logarithm of average unit (per kWh) price of electricity at constant (LCU) 2000 prices in Kenya Shillings;

t = 1980 – 2009.

The time series properties of the variables are tested to determine whether they are stationary using the Augmented Dickey Fuller (ADF), the Philips-Perron (PP) unit root test and the visual correlogram. Equation (3) is then estimated by Ordinary Least Squares (OLS) and the residuals used via the ADF statistic to test for co-integration as explained by Engle et al. (1987).Various versions of this equation are then undertaken with and without time trend and with and without price variable to obtain the preferred relationship. Moreover, Johansen multivariate method is used to check that the assumption of one co-integrating vector is acceptable.After testing for co-integration, the residuals from the preferred co-integrating vector are then used as the Error correction (EC) term in the following short-run dynamic model.

$$\Delta e_t = \alpha_0 + \alpha_1 \Delta e_t + \alpha_2 \Delta e_{t-1} + \alpha_3 \Delta e_{t-2} + \alpha_4 \Delta y_t + \alpha_5 \Delta y_{t-1} + \alpha_6 \Delta y_{t-2} + \alpha_7 \Delta pt + \alpha_8 \Delta p_{t-1} + \alpha_9 \Delta p_{t-2} + \alpha_{10} rain_t + \alpha_{11} temp_t + \alpha_{12} EC_{t-1} \quad (4)$$

Where Δ is the difference operator-change in energy,

$\alpha_{12} EC_{t-1}$ is the speed of adjustment

$rain_t$= Annual rainfall at Nyeri District measured in millimetres,

$temp_t$= Annual average temperature data in Nyeri District in multiples of 10 degree Celsius.

This model contains rainfall data as a proxy for reservoir water level in the hydro power plants taken from a monitoring station closest to the plants. The Nyeri station is chosen because it has whole data for the period and is closest to the plants. In addition, the temperature for the same area was also taken. The preferred equation is then determined through selection of the restricted model by eliminating from the over-parameterised model in equation (4) that satisfies parameter restrictions without violating a range of diagnostic tests. This involves testing residuals from equation (4) for presence of non-normality, serial correlation and heteroscedasticity.

4. OVERVIEW OF DATA

The research employs annual time series data for a period of thirty years from 1980 to 2009. The data on electricity consumption for Kenya e_t , GDP for Kenya y_t was obtained from the World Development Indicators (World Bank, 2013), while the average annualized electricity price for Kenya $p_t$was obtained from the Kenya Power which is the onlyelectricity seller (KPLC, 2010). The electricity price was deflated using the GDP deflator also obtained from the World Bank Development Indicator.

The data on rainfall ($rain_t$) and temperature ($temp_t$) was obtained from the Meteorological Department of the Government of Kenya.The Average annual temperature and rainfall data is taken from the local area (Nyeri) as highlighted in the methodology section. The values for descriptive statistics is as indicated in *table 1.* The currency for the price of electricity is in Kenya Shillings (KES) which is the Local Currency Units (LCU). The transmission and distribution losses indicate an average of 17% with a maximum of 22% of total consumption.

Table 1: Summary of descriptive Statistics for Kenya's data

	Electricity consumption (kWh)	GDP deflator	GDP growth (annual %)	GDP (LCU)	Electricity Price(KES/kWh)	Rain(mm)	Temperature (degree Celsius)	Trans & distribution losses (% of output)
Mean	3462433333	65.1273	3.3684	6.97E+11	3.9872	79.9019	12.3398	16.6122
Standard Error	217557934	9.0469	0.4027	1.21E+11	0.6001	3.5802	0.0722	0.5064
Median	3423000000	50.0005	3.5323	4.33E+11	3.6955	80.5375	12.325	15.633
Mode	-	-	-	-	-	-	12.05	-
Standard Deviation	1191613878	49.5522	2.2055	6.65E+11	3.2869	19.61	0.3953	2.7739
Sample Variance	1.42E+18	2455.428	4.8642	4.42E+23	10.8038	384.5414	0.1563	7.6946
Kurtosis	-0.5607	-1.0545	-1.0231	0.1456	-0.293	0.707	-0.6847	-0.98
Skewness	0.456	0.4993	0.0145	1.0007	0.6731	0.5409	-0.0577	0.5719
Range	4106000000	159.953	7.9773	2.31E+12	12.1843	86.283	1.4661	8.797
Minimum	1707000000	9.836	-0.7992	5.39E+10	0.4	48.9	11.567	12.941
Maximum	5813000000	169.7892	7.178	2.37E+12	12.584	135.183	13.033	21.738

Data Source: World Bank, 2013. World Development Indicators. [Online]

5. RESULTS AND DISCUSSION

5.1. Stationarity test

The non-stationary properties of the time series data were analyzed and summary results of the test statistics (ADF & PP & correlogram) are as indicated in *table 2.*There was neither intercept nor trend included to the level and first difference equation of the ADF test for e_t. For p_t ,an intercept and trend was included at level but only intercept included at first difference. On the other hand, an intercept term was included to both level and first difference equation for y_t

Table 2: Analysis results for unit roots of the time series variables

Variable	ADF*	PP	Critical Values	Correlogram lags					Test
				1	2	3	4	5	
e_t	1.529	1.529	(-1.953)	0.883	0.769	0.649	0.528	0.420	*I*(0)
p_t	-1.856	-1.957	(-3.581)	0.889	0.799	0.695	0.620	0.541	*I*(0)
y_t	-1.047	-0.870	(-2.967)	0.906	0.812	0.718	0.624	0.531	*I*(0)
$Rain_t$	-5.777	-8.121	(-2.972)	-0.058	-0.420	-0.006	0.083	-0.074	*I*(0)
$Temp_t$	-4.532	-4.108	(-3.581)	0.386	0.109	0.264	0.410	0.131	*I*(0)
Δe_t	-4.742	-4.754	(-1.940)	-0.020	0.044	0.125	-0.205	0.020	*I*(1)
Δp_t	-5.066	-5.047	(-2.862)	-0.047	-0.113	-0.000	-0.011	-0.021	*I*(1)
Δy_t	-3.689	-3.790	(-2.862)	0.312	0.266	0.235	-0.080	-0.196	*I*(1)

*lag values for ADF statistics for all three variables are determined automatically based on SIC criteria. Absence of serial correlation was checked in ADF regression.
**All critical values are 5% level and are calculated based on table of MacKinnon (1996).

The ADF and PP values are larger than the critical values from the MacKinnon (1996) for all e_t, p_t and y_t. Therefore the null hypothesis of unit root cannot be rejected for these three variables at 5% level as a result of t-statistics. However, on examining the first differences, it is concluded that first differences of the three variables are stationary suggesting that e_t, $p_t$and y_t are*I*(1). In addition to the ADF tests, the lag values of the first order autocorrelation are inspected. It is found out that the values of e_t, p_t and y_t are close to unit even after the fifth lag. However, the values at first difference show a small value and becoming insignificant as the number of lags increase. These tests (ADF, PP & Correlogram) therefore agree that the three variables are stationary at*I*(1). The rain and temperature variables were added since they were found to be stationary at level.

5.2. Analysis of co-integration by Engle & Granger two-step

5.2.1. Co-integration and long-run Estimation

Following a conclusion that e_t, p_t, y_t are all of order *I*(1), the research further sort to confirm a linear stationary relationship among the *I*(1) variables. This was to analyze whether there is co-integration among this variables in order to build a long-run relationship. Having run the simple OLS of equation (3) in Engle and Granger's method as highlighted in the methodology section, the residuals were obtained and tested in terms of stationary using ADF, PP test statistics and visual correlogram. The results are as indicated in *table 3*.

Table 3: Regression results for Long run relationship among variables

Variable	Coefficient		Unit root test results						
constant	18.789			Test statistics	Critical value				
p_t	-0.095		ADF*	-2.297	-1.953				
y_t	0.100		PP*	-2.343	-1.953				
T	0.037		Correlogram	lags	1	2	3	4	5
					0.727	0.583	0.398	0.016	-0.056

*lag values for ADF statistics for all three variables are determined automatically based on SIC criteria. Absence of serial correlation was checked in ADF regression.
**All critical values are 5% level and are calculated based on table of MacKinnon (1996).

Several versions of equation (3) were estimated and with and without time trend as well as with and without price variable and ended up with the following preferred relationship:e_t= 18.78892+ 0.099868y_t-0.094620p_t+ 0.037206$_t$ *t=1980-2009 ADF= -2.30*

This model shows co-integration given that the ADF and PP statistic is greater in absolute terms than 5% critical value of -1.953. Moreover the correlogram lags test indicates a decreasing trend with very low lags in the fifth year, indicating a co-integration and thus having a long-run relationship. It is therefore found out that the long-run income elasticity is 0.1 while the long-run price elasticity is -0.095. In other words, if price decreases by 1 per cent, demand decreases by 0.1 per cent. Similarly, if income increased by 1 per cent, the demand will increase by 0.1 per cent too. These results are in line with the economic theory.This equation further suggests that the underlying energy demand trend is increasing at about 4 per cent per annum. This would be attributed to some exogenous effects leading to electricity consumption(Amarawickrama & Hunt, 2005). It is also evident that consumer's response to income change raises the overall electricity consumption in the long-run. Furthermore, the signs of the electricity price elasticity and income elasticity in short-run and long-run are in line with economic theory.

The trend is also supported by the ambitious program in Kenya to move towards middle industrialized nation in the next 17 years and the huge amount of flagship projects on-going requiring electricity.

5.2.2. Johansen co-integration test

Johansen test is mostly used to test for the order of co-integration of the series. Therefore this test was conducted to ensure that there is only one co-integrating vector. The results of the test are as indicated in *table 4*. Both trace and maximum-Eigen statistic suggest that there is only one co-integrating vector

Table 4: Co-integration test results for the variables with lag 2

Unrestricted co-integration test				
No of CE*	Trace statistic	critical value**	Maximum-Eigen statistic	critical value**
0	36.539	0.007	23.902	21.132
At most 1	**12.637**	**15.495**	**11.088**	**14.265**
At most 2	0.056	1.549	1.549	3.842

*lag values for ADF statistics for all three variables are determined automatically based on SIC criteria. Absence of serial correlation was checked in ADF regression.
**All critical values are 5% level and are calculated based on table of MacKinnon (1996).

5.2.3. ECM and Short-Run Estimation

This is the second step of the Engle-Granger method in which the short run dynamic model was estimated, or the ECM of elasticity of demand. The test employs a general model of equation (4) and through series of testing for significance, the final preferred equation is found to be:$\Delta e_t = \alpha_0 + \alpha_4 \Delta y_t + \alpha_{12} EC_{t-1}$

Having identified the preferred model, various tests were applied to the restricted model and diagnostic tests as well to find out the suitability of the model. These include heteroscedasticity, serial correlation, model misspecification test, stability and normality. The model passes the entire diagnostic test indicating that there is no heteroscedasticity and no serial correlation and the model is well specified. In addition, the recursive tests such as Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) were conducted to fortify the stability test. These tests indicated that the estimated parameters of the preferred model are stable over period despite the short-run disturbances. This is clearly demonstrated in *figure 1 and 2;* where the structural stability of the estimated model as used for the analysis of the ECM is valid. The validity is attested by the confinement of the CUSUM and CUSUMSQ statistics within 5% critical bound of parameter stability.

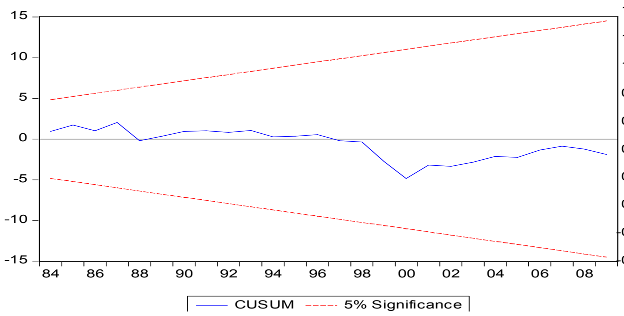
Kenya was hit by ever worst drought in 37years thus creating a dramatic decrease in electric production and resulting to increase in general electricity price as the oil substituted the hydro power plant. The Chow test is therefore applied to test whether the 2000 energy crisis had a contagion effect thus affecting the model. There is no evidence of breakdown in the model identified. On the other hand, a re-estimate of the model for the period 2000-2009 is applied with no signs of predictive failure in this period. The results are summarized in *table 5*.

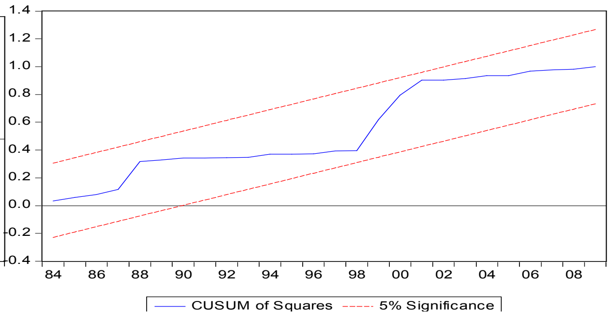
Table 5: Test results for the preferred ECM model

Test		F- Statistics	Critical Values*	R-squared	DW
Heteroskedasticity	White test	0.812	2.64 :F(5,23)	0.15	1.58
	ARCH	2.468	4.22 :F(1,26)	0.09	1.87
	Breusch-Pagan-Godfrey Test	1.154	3.37 :F(2,26)	0.08	1.57
Serial Correlation	Breusch-Godfrey LM Test	0.135	3.40 :F(2,24)	0.01	2.00
Model misspecification	Ramsey RESET Test	1.970	4.24 :F(1,25)	0.27	1.85
Stability test	Chow Break point test for 2000	0.324	3.03 :F(3,23)		
	Chow Forecast Test for 2000-2009	0.984	2.49 :F(10,16)	0.20	1.75
Normality	Jarque-Bera	1.704	3.841 :χ^2(1 df)		

*All critical values are 5% level

Figure 2: Representation of CUSUMFigure 3: Representation of CUSUMSQ test for ECM





The short-run equation is given by: $\Delta e_t = 0.013205 + 0.221915\Delta y_t - 0.341372EC_{t-1}$

Table 6: ECM regression results for short run relationship among variables

Explanatory variable	Coefficient	t-statistics	Probability
constant	0.013	0.796	0.433
Dy_t	0.222	1.891	0.070
EC_{t-1}	-0.341	-2.614	0.015
R-squared	0.217		
Durbin-Watson	1.813		

The coefficients of the variable are statistically significant a 10 per cent level. The error correction terms simply indicate deviations in electricity consumption from its mean in the long-run. The error is significant and of the right sign and magnitude implying 34 per cent of any disequilibrium is adjusted for each year. In this equation, the rain and the temperature variables proved insignificant hence eliminated.The results are as indicated in *table 6.*

6. CONCLUSION AND POLICY IMPLICATION

The aim of this study was to analyze the electricity demand in Kenya. Specifically, the research aimed at answering the following research questions: the short-run and Long-run elasticities of price and income and the implications of these elasticities. This is expected to contribute significantly to the otherwise limited literature in electricity modelling in Kenya and provide insight into energy policy planning.

The two-step Engel and Granger co-integration and ECM is applied using the annual data over the period 1980 to 2009.The method suggested that there is a unique co-integration relationship among the variable, with income elasticity having a significant effect on electricity demand. The Long-run income elasticity is found to be 0.1 whereas the Long-run price elasticity of demand being -0.095. The large effect of the income elasticity is attributed to the fact that Kenya, an emerging market is among the fastest growing economies thus income continues to be the main driver of the electricity demand of Kenya.It can therefore be inferred that the estimates of the analysis are indicative of a rising electricity requirements as Kenya achieves higher GDP growth rates. The time trend of 4 per cent per annum indicates the non-economic factors that is, even if income and price were to be held constant, there would be 4 per cent annual increase in electricity demand. It is therefore imperative to note how the non-economics factors contribute greatly to the Kenyan electricity demand modelling.

REFERENCES

1. Adeyemi, O. I. & Hunt, L. C., 2007. Modelling OECD Industrial EnergyDemand: Asymmetric Price Responses and Energy – Saving Technical Change. *Energy Economics,* 29(4), pp. 693-709.
2. Adofo,C.Y.O., Evans,J. & Lester, H., 2013 How sensitive to time period sampling is the asymmetric price response specification in energy demand modelling? *Energy economics, Volume 40, pp.90-109*
3. Al-Alawi, S. M. & Islam, S. M., 1996. Principles of electricity demand forecasting I. Methodoligies. *Power engineering journal,* 10(3), pp. 139-143.
4. Amarawickrama, H. & Hunt, L., 2005. Sri lanka Electricity Supply Industry: Acritique of the Proposed reforms. *Journal of Energy and Development,* 30(2), pp. 239-278.
5. Asafu-Adjaye, J., 2000. The relationship between energy consumption, energy prices and economic growth: time series evidence from Asian developing countries. *Energy Economics ,* Volume 22, pp. 615-625.
6. Beenstock, M. & Goldin, E., 1999. The demand for electricity in Israel.. *Energy Economics,* 21(2), pp. 168-183.
7. Beenstock, M. & Willcocks, 1983. Energy and Economics activity: a reply to Kouris. *Energy Economics,* 5(3), p. 212.
8. Bentzen, J. & Engsted, T., 1993. Short-and long-run elasticities in enrgy demand: a cointegration approach.

Energy Economics, 15(1), pp. 9-16.
9. Bentzen, J. & Engsted, T., 1997. Dynamic modelling of energy demand: a guide tour through the jungle of unit roots and cointegration. *OPEC Review*, December, pp. 261-293.
10. Bentzen, J. & Engsted, T., 2001. A revival of the autoregressive distributed lag model in estimating energy demand relationship. *Energy,* 26(1), pp. 45-55.
11. Clements, M. P. & Madlener, R., 1999. Seasonality, Cointegration,and Forecasting UK Residential Energy Demand. *Scottish Journal of Political Economy,* 46(2).
12. Dickey, D. & Fuller, W., 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association,* Volume 74, pp. 427-431.
13. Dickey, D. & Fuller, W., 1981. Likelihood ratio statisitcs for autoregressive time series with a unit root. *Econometrica,* Volume 49, pp. 1057-1072.
14. Engle,R.&Granger, C., 1987. Cointegration and error correction: representation,estimation and testing. *Econometrica,* Volume 55, pp. 251-276.
15. Engle, R., Granger, C. & Hallman, J., 1989. Merging short-and long-run forecasts:an application of seasonal cointegration to monthly electricity sales forecasts. *Journal of Econometrics,* 40(1), pp. 45-62.
16. Erdogdu, E., 2007. Electricity demand analysis using cointegration and ARIMA modelling: A case study of Turkey. *Energy Policy ,* Volume 35 , pp. 1129–1146.
17. Garbacz, C., 1984. A National Micro-Data Based Model of ResidentiaEl lectricitDye mand: New Evidence on Seasonal Variation. *Southern Economic Journal,* 51(1), pp. 235-249.
18. Gately, D., 1992. Gately, D., 1992. Imperfect price-reversibility of US gasoline demand:asymmetric responses to price increases and declines. *Energy Journal,* 13 (4), pp. 179–207.
19. Gately, D. & Huntington, H. G., 2002. The asymmetric effects of changes in price and income on energy and oil demand. *The energy Journal,* 23(1).
20. Griffin, J. M. & Schulman, C. T., 2005. Price asymmetry in energy demand models: A proxy for energy-saving technical change?. *The Energy Journal,* 26(2), pp. 1-21.
21. Harvey, A., 1997. Trends, cycles and autoregressions. *The Economic Journal,* 107(440), pp. 192-201.
22. Hondroyiannis, G., 2004. Estimating residential demand for electricity in Greece. *Energy Economics ,* Volume 26, pp. 319-334.
23. Hunt.L.C., Judge, G. & Ninomiya, Y., 2000. *Modelling Technical Progress: An Application of the Stochastic Tren Model to UK Energy Demand,* Guildford Surrey, UK:Surrey Energy Economics Discussion paper,No.99: Department of Economics, University of Surrey.
24. Hunt, L., Guy, J. & Ninomiya, Y., 2003. Modelling underlying energy demand trends. In: C. L. Hunt, ed. *Energy in a competitive Market: Essays in Honour of Colin Robinson.* Chelternham: Edward Elgar Publishin Limited, pp. 140-175.
25. Hunt, L. & Lynk, E., 1992. *Industrial energy demand in the UK: A cointegration approach. In: David, Hawdon(Ed.), Energy Demand: Evidence and Expectations.* Guildford: Surrey Univeristy.
26. Hunt, L. & Manning, N., 1989. Energy price and income-Elasticities of Demand: some estimates for the UK using the cointegration procedure. *Scottish Journal of political economy,* 36(2), pp. 183-193.
27. Jamil,F.& Ahmad, E., 2010. The relationship between electricity consumption,electricity prices and GDP in Pakistan. *Energy Policy,* Volume 38, pp. 6016-6025.
28. Koli, F., Les, O. & Frank, G. S., 2003. Modelling and Forecasting the Demand for Electricity in New Zealand: Acomparison of alternative Approaches. *The Energy Journal,* 24(1), pp. 75-102.
29. Kouris, G., 1981. Elasticities - science or fiction?. *Energy Economics,* 3(2), pp. 66-70.
30. MacKinnon, J.,1996'Critical values for cointegration tests', Queen's Economics Department Working Paper, No. 1227
31. MoE, 2013. *Updated Least Cost Power Development Plan Study Period 2013-2033,* Nairobi: Ministry of Energy.
32. Narayan, P. & Smyth, R., 2005. The residential demand for electricity in Australia: an application of the bound testing approach to cointegration. *Energy policy,* 33(4), pp. 467-474.
33. Ngui, D., Mutua, J., Osiolo, H. & Aligula, E., 2011. Household energ ydemand in Kenya: Anapplication of the linear approximate almos tidea ldemand system (LA-AIDS). *Energy Policy,* Volume 39, pp. 7084-7094.
34. Rhys, J. M. W., 1984. Techniques for Forecasting Electricity Demand. *Journal of the Royal Statistical Society,* 33(1), pp. 23-33.
35. Ryan, D. L. & Plourde, A., 2009. Empirical modelling of energy demand. In: J. Evans & L. C. Hunt, eds. *International Handbook on the Economics of Energy.* Cheltenham: Edward Elger Publishing Limited, pp. 112-143.
36. Soytas, U. & Sari, R., 2003. Energy consumption and GDP: causality relationship in G-7 countries and emerging markets. *Energy Economics,* Volume 25, pp. 33-37.
37. Stern, D., 2000. Amultivariate cointegration analysis of the role of energy in the the US Macroeconomy.

Energy Economics, Volume 22, pp. 267-283.
38. Wolffram, R., 1971. Positivistic Measures of Aggregate Supply Elasticities: Some New Approaches: Some Critical notes. *American Journal of Agricultural Economics,* Volume 53, pp. 356-359.
39. WorldBank,2013.*World Development Indicators.* [Online] Available at: http://databank.worldbank.org/data/views/variableselection/selectvariables.aspx?source=world-development-indicators#
[Accessed 19 June 2013].

The author is a Chevening Scholar currently working as Chief Engineer Energy Projects Performance in Geothermal Development Company of the Republic of Kenya. The present article is a part of the dissertation submitted by the author in fulfilment of the requirements for the award of the degree “MSc in Energy Economics and Policy”. In September 2013, the author is awarded an “MSc with distinction” by the Department of Economics, University of Surrey (UK).