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Shocks affecting electricity prices in Kenya, a fractional integration study

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ABSTRACT

We conduct a fractional integration and cointegration study of several Kenyan electricity price series in order to determine whether signs of persistence or mean reversion can eventually be discovered. Such features can be considered as relevant when considering the possibilities of shocks affecting the energy market of Kenya, which has recently been subjected to major debate. We conclude that electricity prices in Kenya contain unit roots, implying permanent shocks lasting forever. Among the factors affecting electricity prices, we find oil prices and interest rates have significant positive effects on electricity, and based on the fact that all the series are I(1), long run relationships are examined by means of fractional cointegration. The recently introduced FCVAR model is implemented, with results showing that the series under study are fractionally cointegrated, with oil price shocks affecting electricity prices.

1. Introduction

A critical issue in energy policy in Kenya is ensuring that electricity prices are affordable but at the same time ensure fair returns to investors [39]. Consumer electricity bills have been an issue of great concern in Kenya for several years now. This preoccupation has continued into the present when it is thought that middle-class households and industrial consumers will bear the highest burden when electricity distributor Kenya Power brings the new tariffs into force, raising their monthly bills by at least 10%. This escalation in billings is linked to the planned increase in the fixed charge and the energy charge, which account for half of the monthly power costs. The new tariffs will remain in place until July 2017 when the energy charge is expected to drop marginally for the various categories of consumers. Fixed charges will either remain unchanged or rise further for industrial firms. Costly electricity means inflationary pressure which rose to 7.3% in 2015 will escalate, diminishing the consumer purchasing power as prices of goods and services produced by expensive power increase.

Electricity prices in Kenya have historically been influenced by both demand and supply side shocks. Demand side shocks arise from high demand for electricity in years of higher production associated with higher growth rates of critical sectors such as manufacturing that rely heavily on electricity as an input into the production process. They also arise from higher consumer demand associated with an increasing population. Supply side shocks arise from Kenya's heavy reliance on hydroelectric power which is in turn influenced by unpredictable annual rainfall patterns. Major attempts are currently underway to diversify Kenya's sources of electricity especially towards wind and geothermal sources which are expected to provide as much as 45% of electricity supply by 2022. The proportion of hydroelectric power is expected to fall to 20% by 2022 so as to potentially make Kenya's supply of electricity much less vulnerable to hydroelectric power during drought years. Inadequate and unreliable supply of electricity in several areas of Kenya necessitating periodic power rationing therefore compounds the problem of high electricity prices. Market structure also plays a role since there is currently also limited competition in supply of electricity to end-users. The electricity sector in Kenya also has a commercial orientation and the government currently has a policy

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of full cost recovery tariffs. Electricity prices in Kenya are however regulated by the Energy Regulatory Commission and an energy tribunal also exists to settle disputes [39].

It is within this context that we have decided to carry out a time series analysis of historical electricity cost for Kenya, with the aim of determining the size of the risks that shocks may have in this sector and in general on the Kenyan economy. We believe that the examination of the statistical properties of energy is important on several fronts. First, if energy consumption or its associated prices are stationary in levels, shocks to the series will have only transitory effects. On the other hand, if the energy series have unit roots, requiring first-differencing to render stationarity, shocks will have permanent effects. Second, the distinction between the transitory or permanent nature of shocks has implications for the transmission of shocks from energy to other sectors of the economy. Indeed, if shocks to energy are persistent such shocks may be transmitted to other sectors of the economy with inflationary consequences. We present for the first time in this kind of studies the recently introduced FCVAR model by Johansen and Nielsen [20]; which can serve as a basis for policy makers interested in energy related issues in Eastern Africa.

The paper is structured as follows; Section 2 describes the literature review on the issue of electricity prices focusing on the case of Kenya. Section 3 presents the methodology used. Section 4 presents the data. Section 5 displays the empirical results while Section 6 concludes the paper.

2. Literature review

Research by Chen and Lee [5]; Narayan and Smyth [31]; Hsu et al. [15]; and Mishra et al. [29] has focused on the stationarity of aggregate energy consumption across panels of countries using standard unit root procedures. This short communication parallels the recent work by Lean and Song [23] which dealt with the long memory processes for U.S. petroleum consumption by sector. Specifically, this study emphasizes the long memory properties in the consumption of various energy sources by the U.S. electric power sector: coal, natural gas, petroleum, hydroelectric, nuclear, total fossil fuel, total renewable energy, and total primary energy. In this work we use fractional integration methodologies that permit us to study the standard cases of stationarity ($d = 0$) and unit roots ($d = 1$) as particular cases of interest. Moreover, allowing the order of integration to be a real value we allow for a richer degree of flexibility in the dynamic specification of the series, and, depending on the value of d we can determine if the series is I(0) stationary ($d = 0$); stationary with long memory ($0 < d < 0.5$); nonstationary but mean reverting ($0.5 < d < 1$); or nonstationary and non-mean reverting ($d > 1$). In this work we introduce for the first time in the energy field the implementation of the FCVAR model, which was recently introduced by Johansen and Nielsen [20]; which extends the more traditional CVAR model to the fractional long memory case.

Several studies exist on various aspects of electricity prices in the Kenyan context. Wasseja and Mwenda [38] analyze the monthly costs of electricity using Autoregressive Integrated Moving Average Models (ARIMA) so as to determine the most efficient and adequate model for analyzing the volatility of the electricity cost in Kenya. The fitted ARIMA model is used to do an out-of-sample forecasting for electricity cost for September 2013 to August 2016. The forecasting values obtained indicated that the costs will rise initially but later adapt a decreasing trend. The authors argue that a better understanding of the electricity cost trend in the small commercial sector will enhance the ability of producers to make better decisions about their products since electricity is a major input in the sector. Mabea [27] investigates the relationship between Kenya electricity consumption, real disposable income and residential electricity prices. The research employs the Engle and Granger [11] two-step procedure and error correction model to a time series from the period 1980 to 2009 to analyze electricity demand. The model suggests a cointegration with long run price and income elasticity of -0.095 and 0.1 respectively with a 4% increase in consumption of other non-economic factors. The results of the analysis are indicative of rising electricity requirements as Kenya achieves higher GDP growth rates. This has a potential implication for electricity prices.

Mumo et al. [30] seek to determine the best tariff model that can be used in Kenya to improve on the electricity consumption and their study explores all the factors which affect the costing of electrical energy. The tariff model is developed considering fuel prices, the economic factors such as inflation and the purchasing power of the consumers, and the other factors associated with system costs such as capital costs and running costs. In addition, the study also considers some recent developments and significant trends in distribution and pricing of the electrical energy such as pre-paid metering. It is expected that this will help Kenya to develop better tariff structures and more reasonable charging rates. The research uses the data provided by the KPLC to analyze the consumer purchasing trends and uses the current tariff system as a reference to see how best the power company can supply the energy to the country at a balanced cost which encourages industrial development. The study develops a tariff model which is gradual in nature and one which excludes the fixed changes but where the consumers are charged on a gradual basis such that the price increases with the increases of the Kilow at thours consumed.

The Kenyan Institute for Public Policy Research and Analysis [22] has also conducted an analysis of energy consumption patterns in Kenya which in turn affect electricity prices. With regard to the electricity sub-sector the study finds that costs should be reduced and electricity tariff setting harmonized to minimize costs transfer to low income households with regard to fuel and exchange rate adjustment costs which have remained high due to over reliance of thermal electricity generation. It is argued that increasing funding and resources to the electricity sector to increase clean electricity generation from wind energy and solar energy will not only put more electricity on the national grid, but also ensure improved access and reduction in the cost of power as well as protect the environment from carbon dioxide emissions. It is also argued that there is a need to ensure that universal access to electricity in the rural areas for the majority of citizens is adhered to so as to increase access. Thus, from this literature review, it can be seen that most studies in Kenyan electricity prices have focused on standard methods of unit roots and cointegration, and no existing study in the Kenyan context however examines the long memory properties of electricity prices and whether the effects of shocks on electricity prices are transitory or permanent using this approach.

3. Methodology

It is quite common in macroeconomics to find nonstationarity in the time series to be analyzed and many attempts have been proposed in the literature to remove it.[1] The two standard approaches are i) the Trend Stationarity (TS) that basically assumes that the series is stationary I(0) once the trend (or other deterministic

[1] Nonstationarity means that the series fails to achieve any of the following three properties that must be satisfied for a time series to be considered (covariance) stationary: a) the mean should be constant across time; b) the variance should also be constant across time; and c) the covariance between any two observations does not depend on the specific location on time but simply on the distance between the observations. Stationarity is in fact a minimal requirement in time series to make statistical inference.

terms) have been removed, and ii) the Stochastic Difference (SD) that assumes first differences on the original data. The latter approach has received a lot of recognition during the last decades especially after the paper by Nelson and Plosser [32] and with the development of powerful unit root tests. However, the I(1) model[2] can be taken as a particular case within a more general framework based on the I(d) class where d can be any real number. This type of processes belongs to a broader class denominated long memory, which is characterized because the infinite sum of the autocovariances is infinite, or alternatively because the spectral density function is unbounded at the zero frequency [28].[3]

The I(d) model can be expressed as:

$$(1-L)^d x_t = u_t, \quad t = 0, \ \pm 1, \ldots, \tag{1}$$

with $x_t = 0$ for $t \leq 0$, and where d can be any real value, L is the backshift-operator ($Lx_t = x_{t-1}$) and u_t is I(0), defined for our purposes as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Using the Binomial expansion we can expressed the polynomial in the left hand side in (1) as

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j$$
$$= 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots,$$

for all real d, and thus

$$(1-L)^d x_t = x_t - d x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \ldots$$

In this context, *d* plays a crucial role since it indicates the degree of dependence of the time series: the higher the value of *d* is, the higher the level of association will be between the observations. Special cases of interest are the following: i) d = 0: Clearly then $x_t = u_t$, and x_t is said to be "short memory" or I(0). In this case, "weakly autocorrelation" is permitted if the values decay at an exponential rate. ii) d > 0: Then, x_t is "long memory", given the strong association between observations far distant in time. Here, we can distinguish several cases: iii) if $0 < d < 0.5$ the process is covariance stationary, while iv) $d \geq 0.5$ implies nonstationarity. Finally, if $d < 1$, the series is mean reverting in the sense that the effect of the shocks will tend to disappears in the long run, while if $d \geq 1$ shocks will persist forever.

Among the different existing methods of estimating and testing the differencing parameter d, we have selected for this paper two parametric and a semiparametric one. The different between them is that in the parametric methods we fully specify the functional form of the model, while in the semiparametric one the I(0) disturbances are not defined. The three methods employed are based on the Whittle function in the frequency domain[4]: Dahlhaus [7] uses the whole Whittle function in estimating the parameter d; Robinson [36] is a Lagrange Multiplier (LM) test that might be preferred in some cases since it does not require the estimation of d, and we also employ a semiparametric "local" Whittle method that uses a band of frequencies degenerating to zero.

In the second part of the empirical application we consider a standard linear regression model of form:

$$y_t = \beta^T z_t + x_t, \quad t = 1, 2, \ldots. \tag{2}$$

where y_t is the dependent variable under examination (in our case, the energy price) and z_t is a vector of exogenous regressors formed by economic macro fundamentals such as oil prices or interest rates, and to allow for a certain degree of generality, we suppose x_t is I(d) of the same form as in equation (1). Note that the estimation of the β-coefficients can be seriously biased if standard Ordinary Least Squares (OLS) methods are employed under the assumption of I(0) errors and they are in fact I(d) with $d \neq 0$. We will test the null hypothesis

$$H_o : d = d_o, \tag{3}$$

for any real value d_o, in the model given by (1) and (2). Thus, under H_o (3), the model becomes:

$$\tilde{y}_t = \beta^T z_t + u_t, \quad t = 1, 2, \ldots \tag{4}$$

where

$$\tilde{y}_t = (1-L)^{d_o} y_t, \quad \text{and} \quad \tilde{z}_t = (1-L)^{d_o} z_t,$$

and based on the I(0) assumption on the error term u_t in (4), standard OLS methods can be used.

In the following section, we jointly estimate the vector parameter β along with the fractional differencing parameter d in the model given by (1) and (2) by means of using a Whittle function in the frequency domain [7]; in addition, we test the null hypothesis (3) using the parametric Lagrange Multiplier (LM) tests of Robinson [36]. (See, e.g., [13] for an empirical application of this approach).

Since we are working with series that present fractional integration features, we also decided to carry out a fractional cointegration analysis. Additionally, fractionally cointegrated techniques will also be investigated. The Fractionally Cointegrated Vector-AutoRegressive (FCVAR) model was introduced by Johansen [18] and further explained by Johansen and Nielsen [19,20]. The model is a generalization of Johansen [16] cointegrated vector autoregressive (CVAR) model which allowed for fractional processes of order d that cointegrate to order d-b. In order to introduce the FCVAR model we can refer first to the well-known, non-fractional, CVAR model. Let $Y_t, t = 1, \ldots T$ be a p-dimensional I(1) time series. Then the CVAR model is

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \varepsilon_t, \tag{5}$$

The simplest way to derive the FCVAR model is to replace the difference and lag operators Δ and L in (13) by their fractional counterparts, Δ^b and $L_b = 1 - \Delta^b$, respectively.

We then obtain

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t, \tag{6}$$

which is applied to $Y_t = \Delta^{d-b} X_t$ such that

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t, \tag{7}$$

where ε_t is p-dimensional independent and identically distributed

[2] Note that a time series $\{x_t, t = 1, 2, \ldots\}$ is I(1) if it requires first differences, i.e. $(1 - L)x_t$ or $x_t - x_{t-1}$ to become I(0). In a similar way a time series is I(d) if it requires d differences to become I(0).

[3] The spectral density function is the counterpart of the autocovariance function in the frequency domain. It corresponds in fact to the Fourier transformation of the autocovariances.

[4] The Whittle function is an approximation to the likelihood function.

with mean zero and covariance matrix Ω.

The parameters have the usual interpretations known from the CVAR model. In particular, α and β are $p \times r$ matrices, where $0 \le r \le p$. The columns of β are the cointegrating relationships in the system, that is to say the long-run equilibria. The parameters Γ_i dominate the short-run behavior of the variables and the coefficients in α represent the velocity of adjustment towards equilibrium for each of the variables. Thus, the FCVAR model permits simultaneous modelling of the long-run equilibria, the adjustment responses to deviations from the equilibria and the short-run dynamics of the system. As an intermediate step towards the final model, we consider a version of model (7) with d = b and a constant mean term for the cointegration relations. That is to say,

$$\Delta^d X_t = \alpha\left(\beta^{'} L_d X_t + \rho^{'}\right) + \sum_{i=1}^{k} \Gamma_i \Delta^d L_d^i X_t + \varepsilon_t. \quad (8)$$

In Johansen and Nielsen [20] and Nielsen and Morin [34] one can find estimation and inference for the model, and the latter provides the Matlab computer programs for the calculation of the estimators and the test statistics.

4. Data

We use monthly data of electricity costs in Kenya (January 2008–December 2015) that were obtained from Stima website (https://stima.regulusweb.com/historic). The data is provided by Regulus, a web technology consultancy firm based in Kenya. Each of the series corresponds to a concrete tariff, which differs between the users of Kenyan electricity. This difference is however proportional, being this the reason why estimation of long memory properties are finally very similar for all the cases presented. Consumer Price Index data was obtained from the Kenya National Bureau of Statistics, and the interest rates are those established by the Central Bank of Kenya. The oil prices were obtained from the World Bank historical data on commodity prices.

Fig. 1 displays the time series plots for all the electricity price series. As it can be observed, they are all proportional, meaning that every time there is a change in electricity price in Kenya this will have a similar impact in all different types of industries and clients of such energetic sources. Fig. 2 presents the graphical representation of the other three variables under study.

5. Empirical results

We firstly conducted standard ADF [9] unit root tests, and the results can be found in the Appendix. The p-values of all the series reveal that we cannot reject the null hypothesis of a unit root. Therefore we would need to difference the series in order to make them stationary. Nevertheless, we should take into account that these unit root tests might have very low power when directed against specific alternatives such as trend-stationary I(0) models [8], the presence of potential structural breaks [3], or regime-switching [33], or fractionally integration I(d) models [10,14,24]. In this paper we focus on the latter type of alternatives, noting that fractional integration includes the classic unit root models as particular cases of interest.

Based on the I(d) approaches, we estimate the following model,

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, \ldots, \quad (9)$$

where y_t is the observed time series (in our case each of the energy price series); β_0 and β_1 are the coefficients corresponding to the intercept and the linear time trend respectively, and u_t is I(0) described for the purpose of the present work as a simple white noise disturbance term. Table 1 displays the Whittle estimates of d along with the 95% confidence interval of the non-rejection values of d using the Robinson [36] parametric approach, using the original data; Table 2 focuses on the log-transformed data, while Table 3 displays the estimates for the squared returns, which are used as a proxy for the volatility process.[5]

We present the estimates of d for the three standard cases that have been examined in the unit roots literature, i.e., i) the case of no deterministic terms in the undifferenced regression (i.e., $\beta_0 = \beta_1 = 0$ in (9)), ii) the case including only a constant (β_0 unknown and $\beta_1 = 0$), and finally iii) a model with a constant and a linear time trend (β_0 and β_1 unknown). We marked in bold across the tables the significant cases according to the deterministic terms (in all cases, the series seem to require an intercept but not a time trend). Since the series are proportional to each other, the results obtained are very similar and hence the fractional integration undertaken for one of the series can be considered as applicable to the whole Kenyan electricity market.

Starting with the original data (in Table 1) the first thing we observe is that the unit root null hypothesis (i.e. d = 1) cannot be rejected in any of the cases presented, neither for the uncorrelated nor for the autocorrelated cases. If the disturbances are white noise this value is slightly above 1 (1.04, 1.05), and if they are autocorrelated, the estimates of d are substantially smaller (around 0.6, 0.7) though the unit root null hypothesis cannot be rejected in neither of the two approaches. Very similar results are obtained in Table 2 (for the log-transformed data) though the estimates are slightly higher. In any case as just mentioned the unit root is never rejected implying that shocks are highly persistent with shocks having permanent effects on the series. Table 3 refers to the volatility measured in terms of the squared returns. Here, the most notorious feature is that, though the estimates of d are slightly negative, the I(0) hypothesis cannot be rejected in any single case.

Tables 4–6 display the estimates of d using the Robinson's semiparametric method [37]; again for the three cases corresponding to the original data, log-transformed data and squared returns. We marked here in bold the cases where the unit root hypothesis cannot be rejected. Once more, this hypothesis cannot be rejected in the majority of the cases for the original (Table 4) and log-transformed (Table 5) data. However, for the squared returns (Table 6) it is the I(0) hypothesis the one that cannot be rejected (see Table 7).

Next we move to the multivariate analysis, and the first thing we do is to consider the following regression model,

$$y_t = \alpha + \sum_{i=1}^{3} \beta_i^T z_{it} + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, \ldots \quad 10$$

where y_t refers to the electricity prices (measured now exclusively in terms of C1) and z_t refers to the variables that may affect the prices; in particular, we use Consumer Price Index (CPI) denoted by z_{1t}; oil prices (z_{2t}), and interest rates (z_{3t}). All series are log-transformed except the interest rates. We reported the estimates of the coefficients in (10) for the three types of disturbances (white noise, AR(1) and Bloomfield) and we observe that the β-coefficients are positive and statistically significant across all the cases presented, though the estimates of d substantially change from one case to another. Choosing the model of Bloomfield (which seems realistic based on its non-parametric nature) the estimated value of d is 0.57 and the unit root null cannot be rejected. Focusing on the

[5] The returns are obtained as the first differences of the log-prices. Squared returns are used as proxies for the volatility in a number of papers including Lobato and Savin [25]; Gil-Alana [12]; Cavalcante and Assaf [4] and Cotter [6].

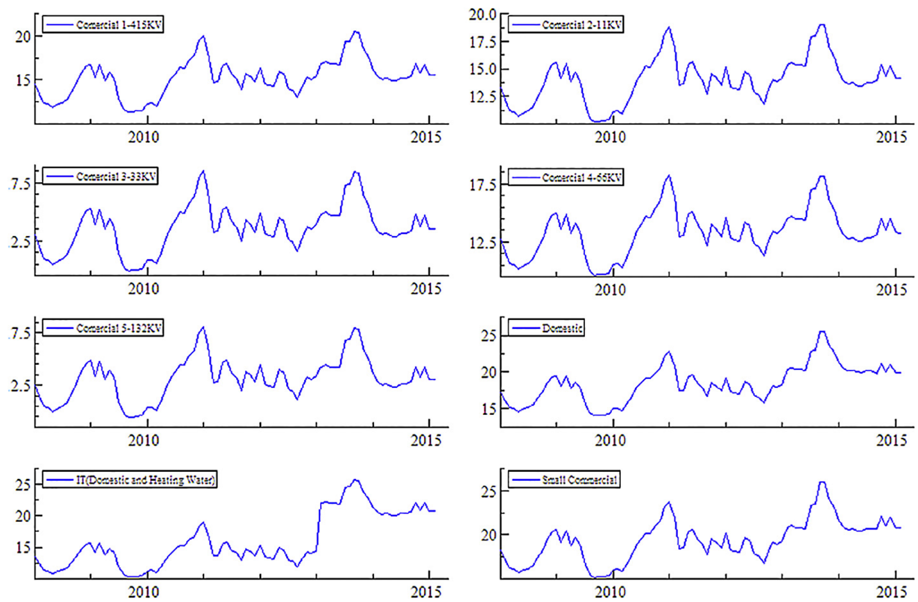

Fig. 1. Electricity price series graphical representation.

regressors, the highest impact corresponds to CPI (0.3074), followed by oil prices (0.2607) and the interest rates (0.0155).

In Table 8 we look at the univariate statistical properties of the three variables that may affect electricity prices in Kenya. Using once more I(d) techniques and employing the autocorrelated model of Bloomfield [2] we see that the unit root null cannot be rejected in any single case, suggesting that the four variables (that is, including the electricity prices) may be related in the long run throughout a cointegrating relationship.

When working with the Fractional Cointegrated VAR (FCVAR) methodology, the first step is to select the lag augmentation, k, for which we apply a general-to-specific testing strategy. Starting with a generous lag order, we test in each step for significance of the coefficient of the highest order lag by an LR test. We selected a lag order of 2.

After establishing the appropriate lag length we need to determine the rank of the system, that is to say the number of cointegrating relations which are stationary after counting for fractional integration. Following standard practice in the cointegration literature we selected the rank based on a series of LR tests, whose asymptotic distributions are non-standard and derived in Johansen and Nielsen [20]. For all cases the appropriate rank order turned out to be 2. We also performed the most standard and frequently used Johansen CVAR [17] tests, whose results are presented in Table 9. While these results conducted us to rejecting any cointegrating possibility, when applying the FCVAR model, a cointegrating rank of 2 could not be rejected, as presented in Table 10.

After having selected the lag length and the cointegration rank, we obtained the FCVAR results. For this work we need to take into account that the fractional differencing parameter d has been set equal to the fractional cointegrating parameter b in order to make sure that the resulting cointegrating system is stationary I(0). We have the following two cointegrating possibilities which provide a cointegrating system that can explain the relationship between Kenya electricity prices and the other three variables, namely oil prices, interest rates and Kenya Consumer Price Index,

$$\Delta^d\left(\begin{bmatrix} CPI \\ Electricity\_Price \\ Interest\_Rate \\ Oil\_Price \end{bmatrix} - \begin{bmatrix} 14.588 \\ 103.928 \\ 8.145 \\ 51.275 \end{bmatrix}\right) = L_d \begin{bmatrix} 45395.032 \\ 8653.604 \\ 51496.232 \\ -1214950.98 \end{bmatrix} v_t + \sum_{i=1}^{2} \Gamma_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t, \tag{11}$$

and

$$\Delta^d\left(\begin{bmatrix} CPI \\ Electricity\_Price \\ Interest\_Rate \\ Oil\_Price \end{bmatrix} - \left[\begin{bmatrix} 14.588 \\ 103.928 \\ 8.145 \\ 51.275 \end{bmatrix}\right]\right) = L_d \begin{bmatrix} 1503.406 \\ 36127.405 \\ -42956.787 \\ 41861.078 \end{bmatrix} v_t + \sum_{i=1}^{2} \Gamma_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t, \tag{12}$$

In equations (11) and (12) we present the fractional cointegration systems which determine an equilibrating system between the variables under study in which we take into account the fractional integration characteristics that we had previously perceived. The cointegration relationship presented in (11) comes to tell us that oil prices penalize the whole system, in the sense that its decreases will be counteracted by increases in the other variables. This, however, could be well affected by the current and constant decreases in the oil prices all over the world. Hence the cointegrating system presented in (12) could be a more reliable equation to describe the relationship between the four variables. A forecasting graphical representation of this system is shown in Fig. 3. Given the fact that oil prices in Kenya, following possibly global trends, have recently been falling, it could be argued that the Consumer Price Index may decrease. Indeed, the latest data released by the Kenya National Bureau of Statistics indicates that the Consumer Price Index decreased by 0.42% from 165.37 in January 2016 to 164.67 in February 2016. The overall inflation rate stood at 6.84% in February 2016. As a consequence, the cointegrating system predicts a slight

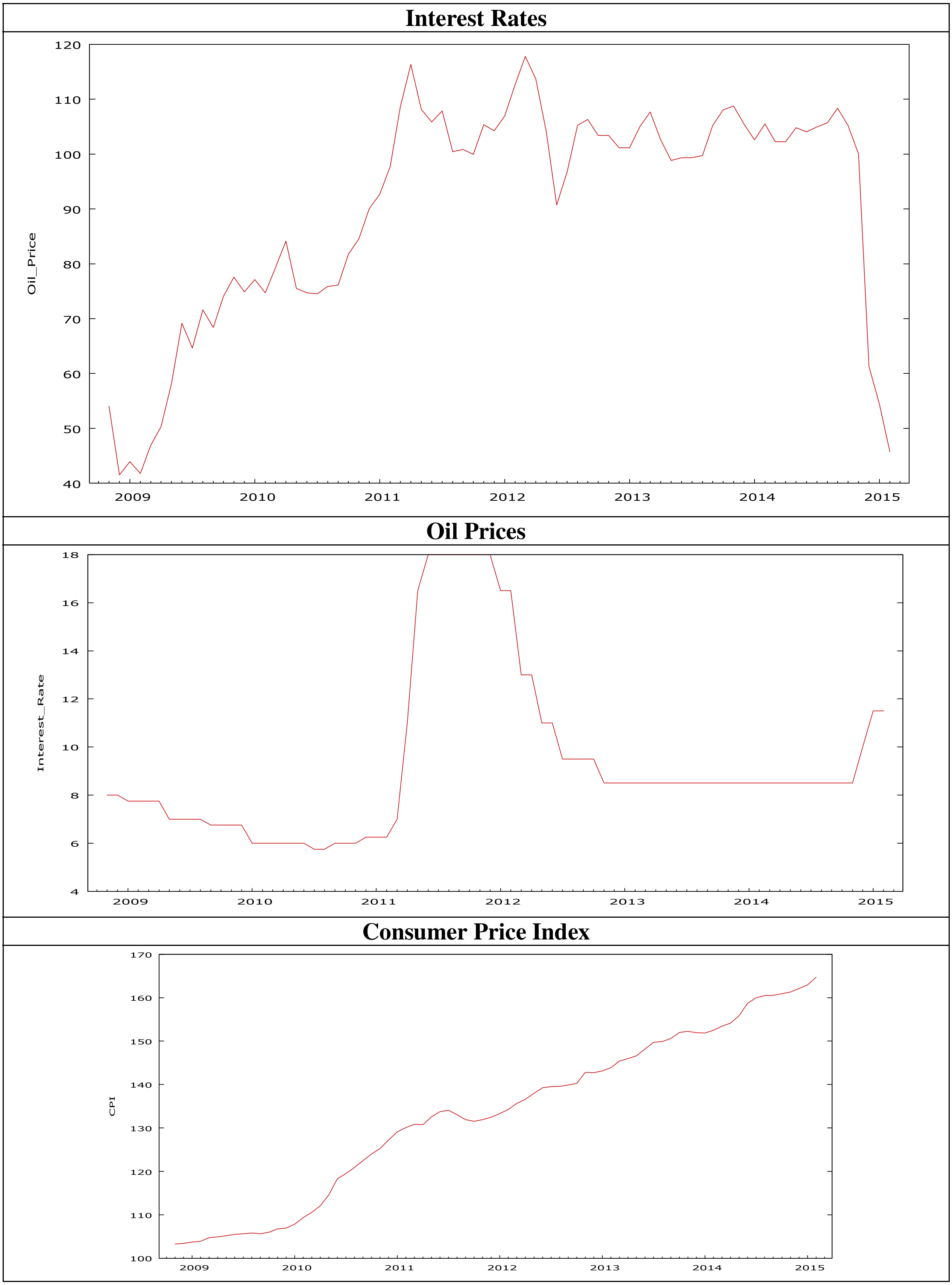

Fig. 2. Kenyan interest rates, oil and prices and CPI.

increase for the coming periods in both the interest rates set up by the Kenyan Central Bank and the electricity prices. Oil shocks may eventually result in changes in both electricity prices and interest rates.

Table 1
Estimates of d based on the original data.

	No regressors	An intercept	A linear time trend
i) Uncorrelated (shite noise) disturbances			
C1	0.90 (0.76, 1.09)	**1.05 (0.85, 1.32)**	1.05 (0.85, 1.32)
C2	0.90 (0.75, 1.09)	**1.05 (0.85, 1.32)**	1.05 (0.85, 1.32)
C3	0.90 (0.75, 1.09)	**1.04 (0.84, 1.31)**	1.04 (0.84, 1.31)
C4	0.90 (0.75, 1.09)	**1.04 (0.84, 1.32)**	1.04 (0.84, 1.32)
C5	0.90 (0.75, 1.09)	**1.04 (0.85, 1.32)**	1.04 (0.85, 1.32)
DC	0.89 (0.74, 1.09)	**1.04 (0.85, 1.30)**	1.04 (0.84, 1.30)
IT	0.91 (0.76, 1.11)	**1.04 (0.87, 1.27)**	1.04 (0.87, 1.27)
SC	0.89 (0.75, 1.09)	**1.04 (0.84, 1.31)**	1.04 (0.84, 1.31)
ii) Autocorrelated (Bloomfield) disturbances			
C1	0.82 (0.46, 1.20)	**0.63 (0.29, 1.09)**	0.60 (0.15, 1.09)
C2	0.81 (0.44, 1.19)	**0.61 (0.28, 1.10)**	0.60 (0.16, 1.10)
C3	0.81 (0.44, 1.19)	**0.60 (0.24, 1.10)**	0.61 (0.18, 1.10)
C4	0.81 (0.44, 1.20)	**0.59 (0.25, 1.10)**	0.61 (0.18, 1.10)
C5	0.80 (0.43, 1.19)	**0.61 (0.27, 1.10)**	0.61 (0.19, 1.10)
DC	0.80 (0.50, 1.16)	**0.70 (0.39, 1.15)**	0.67 (0.20, 1.15)
IT	0.80 (0.48, 1.19)	**0.79 (0.53, 1.18)**	0.77 (0.43, 1.18)
SC	0.83 (0.53, 1.18)	**0.62 (0.35, 1.15)**	0.63 (0.18, 1.14)

In bold the statistically significant cases.

Table 2
Estimates of d based on the log-transformed data.

	No regressors	An intercept	A linear time trend
i) Uncorrelated (shite noise) disturbances			
Log C1	0.92 (0.79, 1.11)	**1.07 (0.87, 1.33)**	1.07 (0.87, 1.33)
Log C2	0.92 (0.79, 1.10)	**1.07 (0.87, 1.33)**	1.07 (0.87, 1.33)
Log C3	0.91 (0.78, 1.10)	**1.07 (0.87, 1.34)**	1.07 (0.87, 1.34)
Log C4	0.92 (0.79, 1.10)	**1.07 (0.87, 1.34)**	1.07 (0.87, 1.34)
Log C5	0.92 (0.78, 1.10)	**1.07 (0.87, 1.34)**	1.07 (0.87, 1.34)
Log DC	0.92 (0.79, 1.11)	**1.05 (0.86, 1.31)**	1.05 (0.86, 1.31)
Log IT	0.91 (0.78, 1.10)	**1.05 (0.88, 1.28)**	1.05 (0.87, 1.29)
Log SC	0.93 (0.80, 1.11)	**1.05 (0.86, 1.32)**	1.05 (0.85, 1.32)
ii) Autocorrelated (Bloomfield) disturbances			
Log C1	0.87 (0.63, 1.22)	**0.65 (0.31, 1.17)**	0.66 (0.17, 1.17)
Log C2	0.89 (0.61, 1.19)	**0.66 (0.30, 1.16)**	0.66 (0.16, 1.16)
Log C3	0.88 (0.61, 1.20)	**0.67 (0.29, 1.18)**	0.67 (0.18, 1.18)
Log C4	0.88 (0.61, 1.21)	**0.67 (0.30, 1.17)**	0.67 (0.18, 1.17)
Log C5	0.87 (0.60, 1.20)	**0.67 (0.29, 1.17)**	0.67 (0.19, 1.17)
Log DC	0.87 (0.61, 1.20)	**0.72 (0.40, 1.18)**	0.68 (0.19, 1.18)
Log IT	0.84 (0.57, 1.20)	**0.77 (0.51, 1.20)**	0.75 (0.37, 1.20)
Log SC	0.86 (0.64, 1.22)	**0.66 (0.37, 1.15)**	0.65 (0.19, 1.15)

In bold the selected models according to the deterministic terms.

6. Concluding comments

In this paper we have examined the electricity prices in Kenya by using fractional integration and cointegration techniques. The results indicate that the series examined present a high degree of persistence, and though fractional degrees of integration are found in all cases, the unit root null hypotheses cannot be rejected in any of the series examined. This result is robust to the differencing methods examined based on both parametric and semiparametric techniques. This implies that strong policy action should be taken whenever major shocks to electricity prices occur as they do not exhibit a tendency to mean reversion. In Kenya, such action would have to be taken by the Regulator, the Energy Regulatory Commission, and would be critical since electricity is a critical input in both consumption and production. Next we also examine which factors might be behind the electricity price movements and we find that CPI, oil prices and interest rate all have positive and significant effects on the electricity prices. Moreover, based on the fact that all the series display I(d) behavior, fractional cointegration techniques are also taken into account.

The primary causality is that of CPI being dependent on electricity prices. Individual elements of the CPI such as the price of fuel, however, impact the price of electricity but this impact should be analyzed individually rather than though the overall impact of the CPI. In the current CPI in Kenya housing, water, electricity, gas and other fuel prices are classified together and given a combined weight of 18.3% in the CPI. For example, over the period between November and December 2016 the housing, water, electricity, gas and other fuels index increased by 0.41%. This was partly attributed to increases in electricity, house rents and kerosene which outweighed price decreases in the cost of cooking gas. Electricity prices rose because of fuel adjustment charges that increased from Ksh 2.34 per KWh in November 2016 to Ksh 2.85 per KWh in December 2016. Thus individual components such as fuel adjustment can be said to affect electricity prices directly as they contribute to making up the electricity tariff [21].

The results here indicate that a fractional cointegrating equilibrium can be achieved between the series under study. The corresponding results have been presented and a graphical representation of the forecasting results has been provided. We can conclude that given the fractionally integrated nature of the series that we have worked with, employing a fractional cointegration framework such as the FCVAR by Nielsen and Johansen (2012) results in an appropriate decision. We conclude that oil price shocks eventually affect the oil prices, which co-move with the Central Bank interest rates. This is because oil prices are a critical component of the Consumer Price Index in Kenya, especially given that Kenya is a net importer of oil whose prices are denominated in US dollars. Shocks to oil prices therefore often result in the Central Bank changing its policy rate, the Central Bank Rate. Changes in oil

Table 3
Estimates of d based on the squared return data.

	No regressors	An intercept	A linear time trend
i) Uncorrelated (white noise) disturbances			
Sq. Rtn. C1	−0.01 (−0.12, 0.17)	**−0.01 (−0.14, 0.17)**	−0.02 (−0.15, 0.16)
Sq. Rtn.Log C2	−0.01 (−0.12, 0.18)	**−0.01 (−0.14, 0.17)**	−0.02 (−0.15, 0.17)
Sq. Rtn.Log C3	−0.01 (−0.12, 0.18)	**−0.01 (−0.14, 0.17)**	−0.02 (−0.16, 0.17)
Sq. Rtn.Log C4	−0.01 (−0.12, 0.18)	**−0.01 (−0.14, 0.17)**	−0.02 (−0.16, 0.17)
Sq. Rtn.Log C5	−0.01 (−0.13, 0.18)	**−0.02 (−0.15, 0.17)**	−0.03 (−0.16, 0.16)
Sq. Rtn.Log DC	−0.03 (−0.12, 0.14)	**−0.03 (−0.16, 0.14)**	−0.03 (−0.17, 0.14)
Sq. Rtn.Log IT	−0.08 (−0.17, 0.10)	**−0.09 (−0.23, 0.10)**	−0.11 (−0.26, 0.10)
Sq. Rtn.Log SC	−0.01 (−0.12, 0.16)	**−0.02 (−0.15, 0.16)**	−0.02 (−0.15, 0.16)
ii) Autocorrelated (Bloomfield) disturbances			
Sq. Rtn. C1	−0.04 (−0.19, 0.33)	**−0.05 (−0.28, 0.31)**	−0.06 (−0.29, 0.27)
Sq. Rtn.Log C2	−0.04 (−0.19, 0.31)	**−0.05 (−0.28, 0.29)**	−0.06 (−0.31, 0.29)
Sq. Rtn.Log C3	−0.04 (−0.20, 0.34)	**−0.05 (−0.29, 0.28)**	−0.06 (−0.33, 0.27)
Sq. Rtn.Log C4	−0.04 (−0.19, 0.34)	**−0.06 (−0.29, 0.29)**	−0.07 (−0.33, 0.27)
Sq. Rtn.Log C5	−0.05 (−0.20, 0.33)	**−0.06 (−0.29, 0.27)**	−0.08 (−0.31, 0.27)
Sq. Rtn.Log DC	−0.01 (−0.14, 0.38)	**−0.01 (−0.26, 0.36)**	−0.02 (−0.29, 0.36)
Sq. Rtn.Log IT	−0.12 (−0.26, 0.12)	**−0.19 (−0.40, 0.16)**	−0.25 (−0.61, 0.15)
Sq. Rtn.Log SC	0.01 (−0.14, 0.43)	**0.03 (−0.27, 0.41)**	0.03 (−0.26, 0.40)

In bold the selected models according to the deterministic terms.

Table 4
Semiparametric estimates based on the original data.

m	C1	C2	C3	C4	C5	DC	IT	SC	Low	Upper
8	0.530	0.517	0.504	0.506	0.504	0.690	**0.997**	0.550	0.709	1.290
9	0.712	0.699	0.682	0.685	0.682	**0.792**	**1.031**	0.690	0.725	1.274
10	**0.839**	**0.823**	**0.802**	**0.805**	**0.802**	**0.875**	**1.160**	0.796	0.739	1.260
11	**0.951**	**0.935**	**0.914**	**0.917**	**0.914**	**0.966**	**1.215**	0.901	0.752	1.247
12	**1.033**	**1.022**	**1.008**	**1.011**	**1.010**	**1.008**	**1.138**	0.964	0.762	1.237
13	**0.886**	**0.879**	**0.870**	**0.871**	**0.871**	**0.913**	**1.006**	0.873	0.771	1.228
15	**0.804**	**0.795**	0.785	0.766	**0.786**	**0.830**	**0.993**	0.786	0.787	1.212
20	**0.875**	**0.873**	**0.871**	**0.871**	**0.872**	**0.899**	**0.928**	0.881	0.816	1.184
25	**1.044**	**1.044**	**1.043**	**1.043**	**1.042**	**1.043**	**1.043**	1.041	0.835	1.164
30	**1.100**	**1.099**	**1.097**	**1.098**	**1.098**	**1.108**	**1.079**	1.105	0.849	1.150

In bold, evidence of unit roots at the 5% level.

Table 5
Semiparametric estimates based on the log-transformed data.

m	C1	C2	C3	C4	C5	DC	IT	SC	Low	Upper
8	0.544	0.534	0.524	0.525	0.524	0.698	**0.896**	0.570	0.709	1.290
9	**0.732**	0.720	0.706	0.708	0.706	**0.822**	**0.951**	**0.726**	0.725	1.274
10	**0.904**	**0.892**	**0.872**	**0.874**	**0.872**	**0.957**	**1.148**	**0.874**	0.739	1.260
11	**0.999**	**0.984**	**0.964**	**0.967**	**0.964**	**1.036**	**1.217**	**0.968**	0.752	1.247
12	**1.119**	**1.111**	**1.098**	**1.099**	**1.098**	**1.114**	**1.215**	**1.061**	0.762	1.237
13	**0.948**	**0.945**	**0.940**	**0.940**	**0.940**	**0.974**	**1.046**	**0.934**	0.771	1.228
15	**0.841**	**0.836**	**0.828**	**0.831**	**0.831**	**0.864**	**0.994**	**0.822**	0.787	1.212
20	**0.911**	**0.914**	**0.916**	**0.917**	**0.918**	**0.921**	**0.931**	**0.907**	0.816	1.184
25	**1.073**	**1.077**	**1.079**	**1.080**	**1.061**	**1.051**	**1.061**	**1.061**	0.835	1.164
30	**1.117**	**1.120**	**1.121**	**1.122**	**1.123**	**1.114**	**1.081**	**1.114**	0.849	1.150

In bold, evidence of unit roots at the 5% level.

Table 6
Semiparametric estimates based on the squared return data.

SR	C1	C2	C3	C4	C5	DC	IT	SC	Low	Upper
8	0.019	0.015	0.007	0.006	0.002	−0.048	−0.068	−0.049	−0.290	0.290
9	−0.068	−0.080	−0.094	−0.094	−0.100	−0.062	−0.001	−0.075	−0.274	0.274
10	0.008	−0.002	−0.017	−0.017	−0.024	0.016	−0.014	0.010	−0.260	0.260
11	0.058	0.051	0.042	0.039	0.035	0.025	−0.047	0.036	−0.247	0.247
12	0.077	0.068	0.055	0.054	0.050	0.071	−0.019	0.079	−0.237	0.237
13	0.126	0.114	0.100	0.099	0.095	0.124	0.135	0.135	−0.228	0.228
15	0.130	0.127	0.122	0.121	0.118	0.124	0.161	0.161	−0.212	0.212
20	0.061	0.059	0.061	0.059	0.056	0.091	0.121	0.121	−0.184	0.184
25	0.017	0.018	0.019	0.019	0.017	0.016	0.046	0.046	−0.164	0.164
30	0.026	0.025	0.024	0.024	0.020	0.042	−0.038	0.060	−0.150	0.150

Table 7
Regression coefficient estimates in the multiple regression model.

	d	β_1 (CPI)	β_2 (Oil prices)	β_3 (Int. rate)
White noise	0.94 (0.74, 1.25)	0.3333 (4.33)	0.2564 (3.03)	0.0123 (1.68)
AR (1)	0.14 (−0.08, 0.96)	0.3822 (6.58)	0.1617 (2.51)	0.0134 (3.21)
Bloomfield type	**0.57 (0.21, 1.04)**	**0.3074 (4.75)**	**0.2607 (3.62)**	**0.0155 (2.80)**

In bold the selected models according to the deterministic terms.

Table 9
Cointegration VAR ranking tests [17].

Rank	Eigenvalue	Trace Test	p-value	Lmax test	p-value
0	0.1971	33.526	0.5323	16.251	0.6509
1	0.1286	17.276	0.6284	10.189	0.7306
2	0.0913	7.0864	0.5739	7.0851	0.4877
3	0	0.0012	0.9715	0.0012	0.9517

prices can also sometimes exacerbate exchange rate movements in Kenya further impacting inflation in the country. Despite the current turbulent situation of the oil price markets it is our belief that using this methodology can provide reliable forecasts of electricity prices in Kenya. Since electricity prices are a critical input for both production and consumption in Kenya, this methodology can potentially lead to better planning at consumer and firm level which would have a positive effect on economic activity through the reduction of uncertainty of electricity prices. It is important to distinguish between the impact of better prediction on domestic and industrial consumers. If electricity prices are well predicted electricity consumers would be able to plan better. Electricity prices make up an important input for production for domestic producers and challenges in predicting them also complicate production

Table 8
Estimates of d for the individual series using the model of Bloomfield.

	No regressors	An intercept	A linear time trend
Log CPI	0.86 (0.60, 1.22)	1.17 (0.88, 1.58)	1.14 (0.83, 1.51)
Log OIL prices	0.80 (0.56, 1.08)	1.31 (0.93, 1.76)	1.29 (0.93, 1.86)
Interest rates	1.21 (0.84, 1.69)	1.23 (0.90, 1.68)	1.23 (0.91, 1.68)
Log C1	0.87 (0.63, 1.22)	0.65 (0.31, 1.17)	0.66 (0.17, 1.17)

Table 10
Fractional cointegration VAR ranking tests (Nielsen & Johansen, 2012).

Rank	d	Log-Likelihood	LR statistic	p-values
0	**0.294**	**−516.845**	**74.905**	**0.000**
1	**0.057**	**−499.500**	**40.215**	**0.000**
2	0.01	−480.546	2.307	0.679
3	0.01	−479.393	0.311	0.577

In bold the selected models according to the deterministic terms.

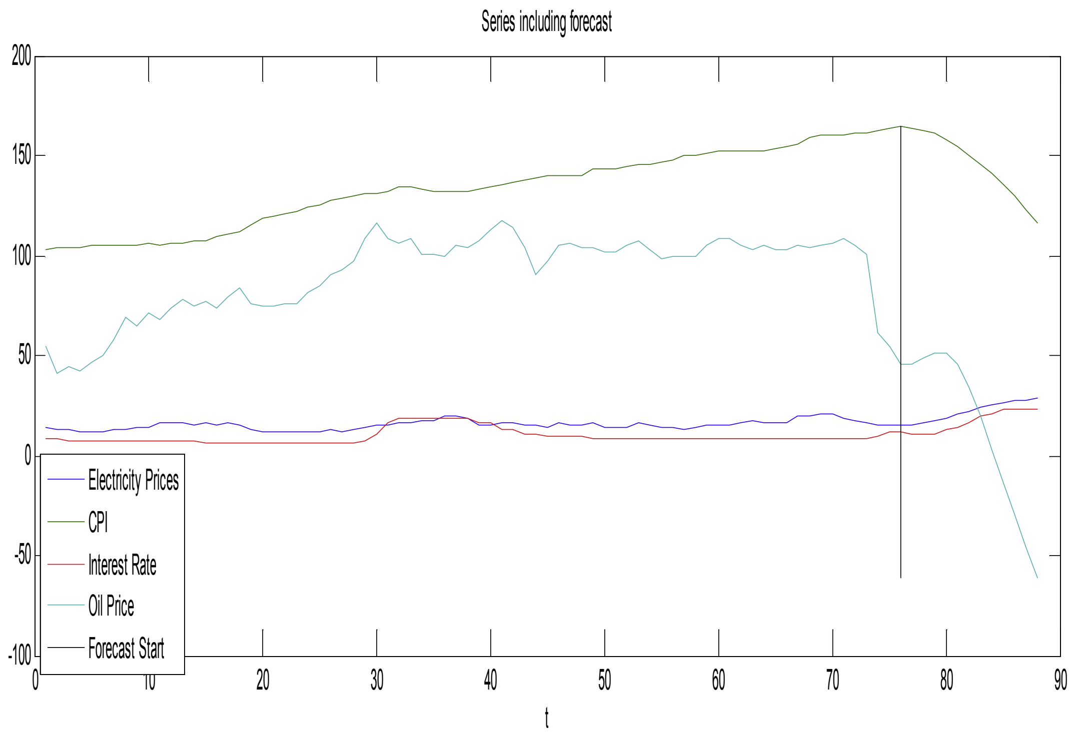

Fig. 3. FCVAR forecasts.

planning for firms. This will in turn affect product pricing which would have an effect on consumers depending on the price elasticity of demand for the product produced. As for domestic consumers, greater predictability would enable better financial planning facilitating both better budgeting for electricity and also other key consumer goods. This impact is likely to be important especially given the trend of rising electricity demand in Kenya in the long run associated particularly with demographic factors. If more renewable energy is implemented, as is currently the focus of the Kenyan government, electricity prices are predicted to fall in the long-term owing to lower production costs. Even potentially higher oil prices would be to some extent offset by this predicted long-term fall in production costs due to greater use of renewable energy sources. This trend of falling electricity production costs would also potentially partly offset potential increases in electricity costs arising from higher interest rates. Thus lower long-term production costs arising from greater reliance on renewable energy would mitígate the adverse effects of shocks arising from oil price and interest rates shocks.

It would also be beneficial to policy makers who attempt to make forecasts of inflation of which electricity prices are an important component. More accurate forecasts of inflation are critical in the inflation targeting approach currently used by the Central Bank of Kenya. Supply-side drivers of inflation have presented a particular challenge to the monetary authorities in Kenya over the last few decades and more accurate forecasts of inflation generated through better forecasts of electricity prices would be invaluable to policy makers. Information about persistence of electricity price shocks also reinforces the need for policy makers to take strong policy action to address such shocks. Specifically, strong policy intervention will be required by the Energy Regulatory Commission whenever there are significant shocks to electricity prices. If this action is not taken, then an increase in electricity prices will have a major and long lasting impact on inflation in the Kenyan economy, especially given the current weight of electricity prices in the CPI in Kenya. Given the prevalence of the use of electricity by both industrial and domestic consumers, and the interdependence of different sectors of the Kenyan economy, these high price shocks would be transmitted to other segments of the economy. This will in turn maintain the focus of the Central Bank on addressing inflationary stability giving them less of a possibility to focus on issues of economic growth. However, electricity prices need to be distinguished from the cost of electricity since the electricity tariff is made up different cost elements such as the fuel levy. Strong policy interventions will result in electricity prices not reflecting costs for certain categories of consumers. This would affect the sustainability of electricity production in Kenya in the future. A long-term approach to making strong policy intervention in electricity markets less necessary and distortionary is the current approach being pursued by the Kenyan government of relying less on hydroelectric power sources by 2022 and more other sources such as wind and solar sources as these are less susceptible to supply side shocks. Initial challenges in the use of renewable sources will, however, include high capital investment for generation equipment, weak enforcement of standards and lack of adequate awareness on the potential benefits of these alternative energy sources among the broader public [35].

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Appendix. ADF unit root tests

	No regressors	With Intercept	Intercept and Trend
Comercial 1-415 V	−0.2039	−2.7836	−3.0465
Comercial 2-11 KV	−0.2559	−2.8437	−3.0491
Comercial 3-33 KV	−0.2975	−2.9083***	−3.044
Comercial 4-66 KV	−0.3004	−2.9006***	−3.0453
Comercial 5-132 KV	−0.3125	−2.9116***	−3.0422
Domestic	−0.0115	−1.9765	−2.9577
IT(Domestic and Water Heating)	0.2481	−1.2873	−2.3780
Small Comercial	−0.0015	−2.4560	−3.0758

With *** the cases in which the null hypothesis of a unit root can be rejected, implying stationarity.

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