The electricity-growth nexus in South Africa: Evidence from asymmetric co-integration and co-feature analysis

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THE ELECTRICITY-GROWTH NEXUS IN SOUTH AFRICA: EVIDENCE FROM ASYMMETRIC COINTEGRATION AND CO-FEATURE ANALYSIS

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ABSTRACT: This study undertakes an examination of asymmetric adjustment effects between electricity consumption and economic growth in South Africa using quarterly data collected from 1983Q1 to 2013:Q4. In our study, we employ a momentum-threshold cointegration method to examine the long-run equilibrium relationship between electricity consumption and economic growth. Our empirical results reveal significant nonlinear cointegration behaviour between the time series variables with uni-directional causality running from electricity consumption to economic growth and no causal effects in the short-run. This implies that energy authorities in South Africa should avoid implementing conservative electricity policies as this may hamper long-run economic growth. We further extend our empirical analysis by decomposing the time series into their trend and cyclical components and our estimations also depict stronger nonlinear behaviour among the de-trended components with bi-directional causality existing between the variables in both the short and long-run. Generally, our study highlights that cointegration and causal effects between electricity usage and output growth is related with the business cycle. Therefore, ignoring the cyclical components of the variables could prove to be quite costly for South African policymakers.

Keywords: Electricity consumption; Economic growth; Threshold co-integration; Nonlinear granger causality; South Africa.

JEL Classification Code: C32, C51, Q43.

1 *INTRODUCTION*

The empirical investigation into the effects of electricity consumption on economic growth is a fairly novel field of exploration, having its roots entrenched in the pioneering works of Kraft and Kraft (1978) and has, of recent, attracted increasing attention within the academic paradigm. Pragmatically, the economic effects between electricity consumption and economic growth are well documented by a plethora of research academics and are thus not difficult to pinpoint within the literature. Take for instance, Jumbe (2004) who argues that energy plays a significant role in economic development, not only because it enhances the productivity of capital, labour and other factors of production but also because increased consumption of energy signifies the prestigious developmental status of a country. Similarly, Ouedraogo (2010) advocates that the modernization of traditional economic sectors and the continuous expansion of secondary and tertiary sectors create new energy needs that increase the national consumption of electricity. Economic units such as companies, households, governmental structures as well as the general economy as a whole tend to exhibit a demand for electricity which is driven by factors such as industrialization, extensive urbanization, population growth and a rise in the standard of living (Gurgul and Lach, 2012). Therefore, it is rational to assume that the quality and quantity of electricity supply plays a vital role in both the production and consumption of goods and services. Also worth noting are the fundamental differences in the development role of electricity consumption between developed economies, on one hand, and industrialized economies, on the other hand. In substantiating these differences, Wolde-Rafael (2006) advocate that the supply of electricity in developing economies is a necessary requirement for improvement in health, educational standards and overall welfare of households whereas in industrialized economies, electricity is more significant for urbanization and advances made in technological progress. Generally the process of economic development will necessarily involve a transition from low levels to higher levels of energy usage in which the linkages among energy, other factor inputs and economic activity significantly changes as an economy moves through different stages of development (Toman and Jemelkkova, 2003). Therefore, the supply and consumption of electricity is deemed to be so heavily intertwined with economical, societal and environmental spheres such that it would be irrational to envisage human, social and economic development without reliance upon modern energy supply, and in particular electricity usage (Ouedraogo, 2013).

Within the existing academic literature, two contemporary issues lie at the heart of empirical investigation when determining the extent to which electricity consumption and economic growth are correlated. The first issue concerns of the sign of the relationship, of which there exists overwhelming support in favour of a significant positive co-integration between the two time series variables (see Payne (2010) for an extensive and comprehensive review of the existing literature). The second issue concerns the identification of granger causal effects existing between electricity consumption and economic growth. Seeing that the literature appears to depict more discrepancy or ambiguity towards the latter aspect of empirical investigation; casual effects among the variables incidentally presents a central area of contention within the electricity-growth debate. Take for example the works of Yuan et. al. (2007), Kouakou (2010) and Wolde-Rufel (2011) which apply granger causal tests to establish uni-directional causality which runs from energy consumption to economic growth for the cases of China, Ivory Coast and India, respectively. This evidence of uni-directional causality from electricity consumption to economic growth, which is popularly branded as the conservation hypothesis, signifies that an economy is dependent upon energy such that economic growth can be adversely affected through a reduction in energy consumption (Squalli, 2007). Conversely, there also exist separate case studies which contend for causality running from economic growth to energy consumption as is reported in the studies of Jumbe (2004) for Malawi as well as that of Mozumder and Marathe (2007) for Bangladesh. Under such a scenario, also known as growth hypothesis, economic activity is deemed as being less dependent upon energy such that environmental policies directed at energy conservation would have little or no impact on economic growth. Furthermore, other researchers have found simultaneous evidences of both types of causal effects, commonly referred to as feedback causality, in which electricity consumption and economic growth are jointly determined and affected at the same time (examples include Morimoto and Hope (2004) for Sri Lanka; Odhiambo (2009) for South Africa and Ouedraogo (2010) for Burkina Faso) whereas yet another cluster of researchers can be identified who find the absence of causal relations (i.e. neutrality hypothesis), thereby deeming that neither conservative nor expansive policies in relation to electricity consumption have any effect on economic growth (see Wolde-Rufeal (2007) for 17 African countries).

From an empirical perspective, different studies have focused on different economies using different spans of time periods and have obtained various and, at often times, conflicting evidence on the precise relationship existing between electricity consumption and economic growth. Chen et. al. (2007) attribute this observation to differences in country-specific characteristics such as different indigenous energy supplies, different political and economic histories, different political arrangements, different cultures, different energy policies etc. Notwithstanding these factors, recent research has further suggested that the traditionally presumption that the electricity-growth relationship can be well approximated by a simple linear functional form is misleading and that, in fact, a range of nonlinearities exist in the relationship (Shahiduzzaman and Alam, 2012). For instance, Hu and Lin (2013) contend that, in the real world, energy markets often exert complex relationships within economic systems and, hence, researchers are cautioned against ignoring asymmetric factors which could impact the electricity-growth correlation. Extending upon this line of reasoning, Chiou et. al. (2008) point out particular economic events which may realistically induce regime switching behaviour and these are inclusive of changes in the economic environment, changes in energy policy and fluctuations in energy prices. Such structural changes provide incentive to speculate that the pattern of energy consumption and economic growth possibly evolves as a nonlinear process over a given period of time. Therefore, failure to account for existing asymmetric relations between electricity consumption and economic growth may produce misleading inferences concerning the actual relationship between electricity consumption and output growth.

In a majority of empirical case studies, examing cointegration relations between electricity consumption and economic growth is achieved by making use of Engle and Granger's (1989) two-step estimation procedure. Conventional linear unit root testing procedures and symmetric cointegration techniques would normally suffice for testing the order of integration of the time series variables under the strict assumption of a linear cointegration framework. However, when the true data generating process (DGP) of a series is indeed found to be nonlinear, conventional unit root tests as well as symmetric cointegration procedures suffer from important power distortions. Therefore, bearing this argument in mind as well as making use of recent advances made in econometric modelling of time series variables, our study hereafter, contributes to the existing literature by re-examining the correlation between electricity consumption and economic growth in South Africa from an asymmetric perspective. To this end, this study makes use of the Kapetanois and Shin (2006) nonlinear unit root tests as well as the momentum threshold autoregressive error correction (MTAR-TEC) model as first implemented by Enders and Granger (1998). The empirical composition of our study can generally be described as being two-fold in nature. Firstly, this study examines possible asymmetric integration, cointegration and threshold error correction effects between electricity consumption and economic growth and then in view of significant asymmetric cointegration effects, the paper proceeds to the second objective of devising granger causal testing procedures within the econometric framework. Taking South Africa as a contextual reference, we consider such an empirical undertaking as being worthwhile, since up-to-date and to the best of our knowledge, no empirical studies have investigated possible asymmetric causal effects between electricity consumption and economic growth for the country. In adding to the novelty of our study, we further extend our empirical analysis by decomposing the observed time series variables into their trend and variable components. This allows us to examine the extent to which electricity consumption and economic growth are cointegrated with the business cycle.

Having provided the backdrop to our case study, we structure the rest of the paper as follows. In the following section, we provide an overview of electricity usage in South Africa and in the third section of the paper; we review the development phases of the associated literature. In section four, we provide a description of the utilised data as well as their transformations and then we also outline the nonlinear unit root testing procedures as well as the asymmetric cointegration and error correction models to be employed in our empirical analysis. Section five presents the empirical results of our study, whilst the paper is concluded in section six in the form of policy implications and possible future research avenues.

2 *ELECTRICITY USAGE IN SOUTH AFRICA*

South Africa is frequently hailed as being amongst the leading powerhouses in terms of electricity provision, not only within the Southern African region, but also on a global platform. Boasting one of the largest dry-cooled power stations in the world (i.e. Matimba power station) as well as operating the only official nuclear power station in Africa (i.e. Koeberg nuclear plant); South Africa is ranked amongst the top seven in terms of capacity generation and is also highly recognized as being one of the four cheapest producers of electricity worldwide. According to the Department of Energy (DoE) and other local editorial statements, an estimated 92 percent of South Africa's electricity is generated by coal-fired power stations; another 7 percent is generated by nuclear stations; whereas the remaining 1 percent or so is provided by hydroelectric and pumped storage schemes. It also worth noting that South Africa's electricity supplying activities are not domestically constrained, as the economy is also responsible for supplying approximately two-thirds of Africa's electricity. Within the Southern African Development Community (SADC) region, South Africa supplies electricity to other neighbouring countries such as Lesotho, Swaziland, Botswana, Namibia, Mozambique and Zimbabwe which roughly accounts for about 2 percent of total net energy produced nationally. Furthermore, it is well-acknowledged that South Africa supplements its sources of energy by occasionally importing electricity directly from Mozambique, Zimbabwe, Zambia and the Democratic of Congo (DRC).

Electricity generation in South Africa is dominated by the Electricity Supply Commission (ESKOM), the state-owned, partially-monopolistic company, which supplies approximately 95 percent of the country's electricity. ESKOM operates within an integrated national high-voltage transmission system which is responsible for supplying nearly 60 percent of its produced electricity directly to commercial farmers, mining companies, mineral beneficiaries and other large institutions; whereas the remaining 40 percent is indirectly allocated to residential consumers. In allocating electricity to residential sectors, ESKOM carries out its activities through the Integrated National Electrification Programme (INEP) in which ESKOM sells bulk to amalgamate municipal distributors who repackage and then resell compatible units to consumers within their designated jurisdictions. In referring to domestic electricity consumption, it is estimated that over 75 percent of South Africa's population have access to electricity, which is a figure well above the SADC average of less than 25 percent. In fact, over the last decade or so, there have been a number of reports which have emerged, claiming that the economy as a whole has increased its electricity consumption at rate which marginally exceeds that of its production counterpart. This is evident from the 2008 power crisis which saw ESKOM fail to supply enough electricity in response to escalating electricity demand which resulted in a nation-wide load shedding scheme. Odhiambo (2010) describes this load-shedding strategy as "...a last resort [used by ESKOM] to prevent a system wide blackout [in order to enable] ESKOM to bring the demand for electricity slightly closer to its supply, while at the same time maintaining a reasonable reserve margin...".

Subsequently to the 2008 electricity crisis, a number of initiatives have been proposed as a means of improving the overall effectiveness as well as facilitating efficient electricity supply within the South African economy. So far, it is well-acknowledged that a vast majority of South Africa’s energy woes are attributed to the country’s historical energy structure which is characterized by an energy-intensive sector built almost exclusively upon coal-based power generating schemes. Apart from placing unwarranted pressure on the mining of new coal deposits, heavy reliance upon the coal-based scheme has adversely resulted in extremely high levels of carbon emissions; of which ESKOM is currently ranked as the second largest power utility emitter of CO_2 globally. Therefore, particular emphasis on the future development of power generating schemes is currently being directed towards increasing reliance upon alternative power sources which are capable of producing electricity with environmental benefits. The key challenge for South African energy authorities is to move to a cleaner, more efficient use of energy supply, while extending affordable access to modern energy services (Winkler, 2005). Presently, the South African government is embarking on both medium and long-term programmes, which are meant to enable the country to efficiently cope with the future demand for electricity (Odhiambo, 2009). On the forefront of these programmes, the Department of Energy has formulated an Integrated Resource Plan (IRP) which outlines a mix of energy sources aimed at obtaining the most energy efficiency trade-off between least investment cost, climate change, mitigation, diversity of supply localization and regional development (Roula, 2010). The particular IRP energy mix consists of a target of 48 percent coal; 13.4 percent nuclear energy; 6.5 percent hydro; 14.5 percent other renewable energy; and 11 percent peaking open cycle gas turbine; which are targets set to be achieved by 2030. However, prior to the success of energy authorities in ushering these future prospects, it is quite essential for energy authorities to acquire a growing understanding of the evolving empirical interrelations between electricity consumption and economic growth within the economy.

3 LITERATURE REVIEW

In order to understand the chronological evolution of the associated literature, it is necessary to probe into the empirical developments as made possible by various innovations and advancements linked to econometric modelling techniques. During the early development of the literature, academics relied on the novel contribution of Clive Granger (1969) and his seminal work on causality analysis which allowed econometricians to determine whether one time series can significantly predict another series. Prominent examples from the early literature which made use of Granger's (1969) causality tests include Kraft and Kraft (1978); Akarca and Long (1980); Proops (1984); Yu and Hwang (1984); Yu and Choi (1985); as well as Erol and Yu (1987) and yet, as previously mentioned, the aforementioned studies provide a variety of conflicting empirical evidences. At this juncture, it is also worth noting that even though electricity consumption was not directly used as a regressive variable against economic growth, each of these early energy studies acknowledged electricity consumption as being the greatest component of total energy consumption. The next development in the initial literature saw empirical economists turn to the 'Nobel prizing-winning' cointegration theorem as introduced by Robert Engle and Clive Granger (1987). Accordingly, the Engle-Granger (1987) two-stage cointegration procedure presented a new dimension towards empirically diagnosing the electricity consumption-economic growth nexus, in the sense of eradicating possible spurious correlations estimated between the nonstationary variables. Moreover, the cointegration framework permits the investigation of causal effects via an associated error correction model of the regression residuals. The Engle-Granger contribution has assumed a paramount position in the development of the literature, due to the fact that some early empirical studies which had investigated causal effects between energy consumption and economic growth; were later on discovered to have employed variables that were indeed not cointegrated. A conspicuous illustration of this is provided by Thoma (2004) who finds no cointegration relations between the series for the US economy, therefore invalidating the early results obtained by Kraft and Kraft (1978) as well as Yu and Hwang (1984), who both established causal effects running from economic growth to electricity consumption for corresponding US data.

Soren Johansen (1988, 1991) as well as Soren Johansen and Katarina Juselius (1990) developed on Engle and Granger (1987) by allowing for multivariate cointegration analysis among a set of time series variables. In differing from Engle and Granger (1987), the authors devised cointegration tests for vector error correction models (VECMs) based on vector autoregressive (VAR) structures as introduced by Sims (1980). The studies of Shiu and Lam (2004); Lee and Chang (2005); Yoo (2005); and Mozumder and Marathe (2007) all successfully apply the log-likelihood cointegration tests of Johansen and Juselius (1990) for the cases of China, Taiwan, Korea and Bangladesh, respectively. Also closely aligned with the contributions of Johansen (1988, 1991) and Johansen and Juselius (1990), a number researchers began to pounder on the idea of basing their empirical analysis on panel data studies which commonly make use of the panel data estimation models of Pedroni (1999, 2004); Pesaran et al. (2001) and Westerlund (2006). Inclusive of this group of studies in the electricity-growth nexus are the popular works of Chen et. al. (2007) for Asian countries, Ciarreta and Zarraga (2010) for European countries, and Narayan et. al. (2010) for seven panel datasets comprising of West European, Asian, Latin American, African, Middle East and G7 countries. Nonetheless, there appears to a exist a mutual consensus within the literature suggesting that single country analysis provides a better method of empirical investigation over panel data studies which are criticized for generalizing their results over entire populations with various economic disparities. As a result, a number of studies have, more recently, sought to improve the standard of panel data analysis by investigating the correlation between electricity consumption and economic growth for a number of countries using single country analysis for each observed economy. This latter group of studies includes, amongst a host of many others, Wolde-Rufael (2006) for African countries; Yoo (2006) for ASEAN countries; Squali (2007) for OPEC countries; Narayan and Prasad (2008) for OECD countries; as well as Yoo and Kwak (2010) for South American countries.

Notwithstanding the ever-increasing contributions witnessed in the developmental phases of econometric modelling techniques, the literature has nevertheless failed to reach a unanimous conclusion regarding the precise co-relationship between electricity consumption and economic growth. As a means of further pursuing reconciliation of the discrepancies identified in the literature, researchers and academic connoisseurs alike are increasingly considering the possibility of the underlying relationship between electricity consumption and economic growth being asymmetric. This assumption of asymmetric behaviour among the time series, has probed economists to apply nonlinear estimation techniques in their data analysis. The idea behind the use of nonlinear econometric models is that the data generating process (DGP) of a set of time series variables can be captured through different regimes which are segregated by unique threshold variable points. Above and below the identified threshold points, the autoregressive (AR) properties of the observed time series variables are deemed to differ in statistical composition (Phiri, 2012). Chief among the developers of the sophisticated theories of threshold modelling procedures is Bruce Hansen (1996, 1997, 1999, 2000), who in a series of interrelated publications devised estimation techniques for abrupt, regime-switching threshold autoregressive (TAR). Others, such as Luukkonen et. al. (1988), Teravirsta (1994) and Van Dijk et. al. (2002); have followed in pursuit by developing estimation procedures within the context of smooth transition regression (STR) models whereas Hamilton (1989) developed the Markov-switching (MS) framework which is more suited for capturing regime-switches behaviour which are triggered by sudden shocks to the economy. In a continuous fashion, Hansen and Seo (2002) as well as Seo (2006) have further extended the statistical foundations of the TAR model to the case of an error correction framework i.e. threshold vector error correction (TVEC) model. Furthermore; Kapetanois et. al. (2006) extended the STR framework into a smooth transition vector error correction model (STVEC) model; whilst Psaradakis et. al. (2004) have developed an error correction model based on a Markov switching mechanism (i.e. MSECM). It is also worth noting that granger causality tests can be facilitated through the use of the aforementioned nonlinear error correction models, even though a number of statisticians have directly devised nonparametric nonlinear granger causal tests which can directly be applied to the observed time series variables e.g. Baek and Brock (1992) and Diks and Panchenko (2006). The above-described threshold models have been extensively used in the electricity consumption-economic growth literature, of which the available literature is summarized below in Table 1.

{INSERT TABLE 1 HERE}

4 *DATA AND EMPIRICAL FRAMEWORK*

4.1 *EMPIRICAL DATA*

As a means of ensuring consistency of data collection, all data used in our empirical study is retrieved from the Statistics South Africa (STATSSA) database. Our dataset consists of electricity consumption and gross domestic product (GDP) and is collected over a sample period of 20 years covering January 1983 – December 2013. Ideally our study would employ monthly data, but bearing in mind that electricity consumption can only be collected on a monthly basis and GDP is only available on a quarterly basis, we opt to convert the monthly electricity consumption series into quarterly data via cubic spline interpolation. Thus for each time series, we are able to extract 84 observations available for empirical use. Furthermore, we take into consideration the empirical works of Yuan et. al. (2007) and Akinlo (2009), who employ the Hodrick-Prescott (HP) filter as a means of decomposing the trend and cyclical component of the observed time series. In doing so, we are enabled to investigate whether the series are of co-integration and co-feature, which is an analytically superior testing strategy in comparison to the empirical approach of solely investigating cointegration effects.

Pragmatically, the HP filter provides an estimate of the unobserved variable (trend) as the solution to the following minimization problem:

$$\min_{T_{Yt}} : \sum_{i=1}^{T} (Y - T_{Yt})^2 + \lambda\, (\Delta^2 T_{Yt})^2 \quad (1)$$

Where y is the observed time series variables, T_{Yt} is the unobserved variable, σ_c^2 is the variance of the cyclical component; $Y - T_{Yt}$, and σ_T^2 is the variance of the growth rate of the trend component; and $= \sigma_T^2/\sigma_c^2$is the smoothing components. The first part of the filter measures the fitness of the extracted data, whereas the second is a measure of its smoothness. The parameter λ is the signal-to-noise ratio and weights the relative importance of the two conflicting goals in the loss function. Thus when λ= 0, the filter produces the original series; whereas when λ approaches infinity, the HP filter collapses to a linear trend. Accordingly we employ a value of λ= 1600 for our quarterly dataset. In extracting the trend component from the HP filter, we then derive the cyclical component as follows:

$$C_{y_t} = y_t - T_{yt} \quad (2)$$

Having decomposed the time series into its trend and cyclical components it is possible to thereafter analyse cointegration and the causality among the trend and cyclical components of the original series. This involves separately testing for cointegration effects among the original series, on one hand, and its cyclical components, on the other hand. If the original series are found to be cointegration whereas the cyclical components are not, we then conclude cointegration effects among the original series with no co-featuring effects. Conversely, if cointegration is found for the cyclical components but not for the original series, we can only conclude co-featuring among the variables. However, it would be most ideal to achieve both cointegration and co-featuring, that is, to obtain simultaneous evidence of cointegration among the original series and its cyclical components. Such simultaneous evidence of cointegration and co-featuring allows for the inherent relationship found between the series to be integrated with the business cycle.

4.2 *UNIT ROOT TESTS*

Typically, the literature depicts that both electricity consumption and economic growth variables evolve as linear I(1) process, with South Africa bearing no exception to this rule (see Odhiambo (2009, 2010) and Kahsai et. al. (2012)). However, as previously discussed, a growing consensus within the literature suggests that both electricity consumption and economic growth evolve as nonlinear processes over time. Surprisingly, the electricity-growth literature is, thus so far, devoid of analysing possible nonlinear integration properties of the time series, of which the confirmation of nonlinear unit root processes could strengthen the case for asymmetric cointegration among the time series variables. Moreover, the literature on time series modelling is filled in abundance with a variety of applications of asymmetric unit root tests to macroeconomic variables such as exchange rates, interest rates and inflation rates. A popular implemented model, in this regard, is one developed in Caner and Hansen (2001) which describes asymmetric unit root testing procedures for univariate time series variables under the context of a two-regime TAR model. However, as cautiously advised by Kapetanois and Shin (2006) such nonlinear unit root testing procedures "...would be useful in certain univariate contexts..." but may ultimately prove to be of "...reduced interest for analyzing the long-run economic relationship in the context of threshold cointegration...". Therefore, as a means of circumventing this issue, we follow in pursuit of Kapetanois and Shin (2006) by implementing unit root testing procedures for threshold cointegration based upon the following three-regime threshold autoregressive (TAR) model specification:

$$y_t = \begin{cases} \alpha_1 y_{t-1} + \mu_t, \; if \; y_{t-1} \leq \gamma_1 \\ \alpha_0 y_{t-1} + \mu_t, \; if \; \gamma_1 < y_{t-1} \leq \gamma_2 \\ \alpha_2 y_{t-1} + \mu_t, \; if \; y_{t-1} > \gamma_2 \end{cases} \tag{3}$$

For t= 1,2, ... , T, where the error tem, μ_t, is assumed to follow an iid sequence N(0,σ^2) and γ_1 and γ_2 are the threshold parameters with $\gamma_1 < \gamma_2$ and (γ_1, γ_2) $\epsilon\Gamma=[\gamma_{min}, \gamma_{max}]$ where/with γ_{min} and γ_{max} are picked such that Pr($y_{t-1} < \gamma_{min}$)=π_1>0 and Pr($y_{t-1} < \gamma_{min}$)=π_2<0. Unit root testing is facilitated by imposing the condition α_0=1 in equation (3), thus allowing y_t to follow a random walk process in the corridor regime. Thereafter, the unit root testing procedures are therefore derived from the following compact threshold regression equation:

$$\Delta y_t = \beta_1 y_{t-1} I_{\cdot(y_{t-1} \leq \gamma_1)} + \beta_2 y_{t-1} I_{\cdot(y_{t-1} > \gamma_2)} + \epsilon_t \tag{4}$$

Where $\beta_1 = \alpha_1 - 1$, $\beta_2 = \alpha_2 - 1$ and the indicator functions $y_{t-1} I_{\cdot(y_{t-1} \leq \gamma_1)}$ and $y_{t-1} I_{\cdot(y_{t-1} > \gamma_2)}$ govern the behaviour of the time series in the first and last regimes of the SETAR process, respectively. From equation (2), the joint null hypothesis of a unit root can be tested as:

$$H_0: \beta_1 = \beta_2 = 0 \tag{5}$$

Whereas the alternative hypothesis of threshold stationarity is tested as:

$$H_1: \beta_1, \beta_2 < 0 \tag{6}$$

An appropriate test of the joint null hypothesis of a unit root against the alternative of threshold stationary process can be tested through the computation of a standard Wald statistic. By denoting $\hat{\beta}' = [\hat{\beta}_1, \hat{\beta}_2]$ as the OLS estimator of $\beta = [\beta_1, \beta_2]$, X=$\begin{bmatrix} y_0 I_{\cdot(y_0 \leq \gamma_1)} & y_0 I_{\cdot(y_0 > \gamma_1)} \\ y_1 I_{\cdot(y_1 \leq \gamma_1)} & y_1 I_{\cdot(y_1 > \gamma_1)} \\ \vdots & \vdots \\ y_{T-1} I_{\cdot(y_{T-1} \leq \gamma_1)} & y_{T-1} I_{\cdot(y_{T-1} > \gamma_1)} \end{bmatrix}$, $\hat{\sigma}^2 = \frac{1}{T-2} \sum_{i=1}^{T} \hat{\mu}_t^2$ and $\hat{\mu}_t^2$ as the regression residuals obtained from (2); the Wald test statistic can be computed as:

$$W_{[\gamma_1, \gamma_2]} = \hat{\beta}' [Var(\beta)]^{-1} \hat{\beta} = \frac{\hat{\beta}'(X'X)\hat{\beta}}{\hat{\sigma}^2} \tag{7}$$

However, due to inference complexities associated with the unidentified threshold parameters under the null hypothesis, Kapetanois and Shin (2006) opt to derive asymptotically valid distributions from Supremum, average and exponential average-based versions of the Wald statistics. These statistics can, respectively, be computed as follows:

$$W_{sup} = \sup_{i \in \Gamma} W_{\gamma_1, \gamma_2}^{(i)}, W_{avg} = \frac{1}{\#\Gamma} \sum_{i=1}^{\#\Gamma} W_{\gamma_1, \gamma_2}^{(i)}, \; W_{avg} = \frac{1}{\#\Gamma} \sum_{i=1}^{\#\Gamma} \exp\left(\frac{W_{\gamma_1, \gamma_2}^{(i)}}{2}\right) \tag{8}$$

The optimal threshold estimates are then obtained by maximizing the above Wald statistics over a search grid and then constructing summary statistics for the obtained threshold estimates. In the spirit of Kapetanois and Shin (2006) we employ the nonlinear unit root testing procedures to three empirical settings, namely; (i) the case of a zero mean process

(ii) the case of a process containing a non-zero mean; and (iii) the case of a process containing both a non-zero mean and underlying trend. The associated asymptotic distributions are therefore computed using a de-meaned and the de-trended standard Brownian motion in the construction of the associated Wald statistics.

4.3 *MTAR-TEC MODEL*

The baseline cointegration regression equation can be specified as:

$$y_t = \gamma_0 + \gamma_1 x_t + \varepsilon_t \tag{9}$$

Where $\gamma_0$and $\gamma_1$are the estimated parameters and ε_t is a disturbance term. For the simple fact that the actual causal relationship between electricity and economic growth cannot be assumed a-prior, we estimate two long run cointegration regressions, by placing lgY as the dependent variable in the first regression and placing electricity consumption lgEC as the dependent variable in the second regression. The lgY and lgEC variables represent the natural logarithm of electricity consumption and real gross domestic product, respectively. Thereafter, possible cointegration effects between the time series $y_t$and x_t is examined via the order of integration of the residuals from using a Dickey Fuller test:

$$\Delta\hat{\varepsilon}_t = \rho\hat{\varepsilon}_{t-1} + \mathrm{v} \tag{10}$$

However, in alignment with Enders and Silkos (2001), we introduce asymmetric adjustment by allowing the residual deviations from the long-run equilibrium to behave as a threshold process. In particular, we choose to specify four variations of threshold cointegration models namely (1) the threshold autoregressive (TAR) model with a zero threshold (2) the c-TAR model with a consistent threshold estimate (3) the MTAR model with a zero threshold estimate; and (4) the c-MTAR with a consistent threshold estimate. These systems of threshold cointegration models are respectively formulated as:

$$\Delta\hat{\varepsilon}_{t1} = \rho_{11}\hat{\varepsilon}_{t-1}I_t.(\hat{\varepsilon}_{t-1} < 0) + \rho_{21}\hat{\varepsilon}_{t-1}I_t.(\hat{\varepsilon}_{t-1} \geq 0) + \textstyle\sum_{i=1}^{k}\beta_i\,\Delta\hat{\varepsilon}_{t-1} + \zeta_t \tag{11.1}$$

$$\Delta\hat{\varepsilon}_{t2} = \rho_{12}\hat{\varepsilon}_{t-1}I_t.(\hat{\varepsilon}_{t-1} < \tau) + \rho_{22}\hat{\varepsilon}_{t-1}I_t.(\hat{\varepsilon}_{t-1} \geq \tau) + \textstyle\sum_{i=1}^{k}\beta_i\,\Delta\hat{\varepsilon}_{t-1} + \zeta_t \tag{11.2}$$

$$\Delta\hat{\varepsilon}_{t3} = \rho_{13}\hat{\varepsilon}_{t-1}I_t.(\Delta\hat{\varepsilon}_{t-1} < 0) + \rho_{23}\hat{\varepsilon}_{t-1}I_t.(\Delta\hat{\varepsilon}_{t-1} \geq 0) + \textstyle\sum_{i=1}^{k}\beta_i\,\Delta\hat{\varepsilon}_{t-1} + \zeta_t \tag{11.3}$$

$$\Delta\hat{\varepsilon}_{t4} = \rho_{14}\hat{\varepsilon}_{t-1}I_t.(\Delta\hat{\varepsilon}_{t-1} < \tau) + \rho_{24}\hat{\varepsilon}_{t-1}I_t.(\Delta\hat{\varepsilon}_{t-1} \geq \tau) + \sum_{i=1}^{k}\beta_i\,\Delta\hat{\varepsilon}_{t-1} + \zeta_t \qquad (11.4)$$

Where ρ_1, ρ_2 and β_i are associated coefficients of the threshold cointegration models; ζ_t is a white noise disturbance term, k is the number of lags. The indicator functions, I_t, govern the regime switching behaviour of the equilibrium errors and are responsible for distinguishing between the working mechanism of the threshold cointegration models (11.1) – (11.4). Specifically, the TAR cointegration models (i.e. equations 11.1 and 11.2) are designed to capture potential asymmetric deep movements in the residuals if, for example, positive deviations are more prolonged than negative deviations. On the other hand, the MTAR model specifications (i.e. equations 11.3 and 11.4) allows the $\{\Delta\hat{\varepsilon}_t\}$ series to exhibit more momentum in one direction than the other and allows the variable of interest to display various amounts of autoregressive decays depending on whether the series is increasing or decreasing (Hu and Lin, 2013). By design, the TAR model is used for capturing the "depth" of the swings in equilibrium relationships by allowing decay in the relationship to be captured by $\hat{\varepsilon}_{t-1}$ whereas the MTAR model can capture spiky adjustments in the equilibrium relationship by permitting the decay in the relationship to be captured by $\Delta\hat{\varepsilon}_{t-1}$ instead of $\hat{\varepsilon}_{t-1}$.

Since the threshold variable under the c-TAR and c-MTAR models, are unknown a prior, the threshold co-integration regression (12) is estimated by ordering the threshold variable, τ, in ascending order such that $\tau_0 < \tau_1 < \cdots < \tau_T$,where T is the number of observations used after truncating the upper and lower 15 percent of the observations. In accordance with Hansen (2000), the estimated threshold yielding the lowest residual sum of squares is considered to be the appropriate estimate of the threshold variable. Furthermore, for each of the threshold cointegration regressions from (9.1) – (9.4), a battery of cointegration tests are applied to the observed data as a means of verifying threshold cointegration effects among the time series variables. These cointegration tests consists of testing for the (i) stationarity of the equilibrium error term (i.e. $H_0^{(1)}: \rho_1, \rho_2 < 0$) (ii) null hypothesis of no cointegration against an alternative of significant cointegration effects (i.e. $H_0^{(2)}: \rho_1 = \rho_2 = 0$); and (iii) null hypothesis of linear cointegration against an alternative of asymmetric cointegration effects (i.e. $H_0^{(3)}: \rho_1 = \rho_2$). Each of aforementioned cointegration tests are evaluated using a standard F-test. Once the observed series successfully 'pass' through these battery of tests, a threshold error correction model (TECM) can be introduced as a means of supplementing the threshold cointegration regressions (9.1) – (9.4). In accordance with the granger representation theorem, the functional specification of the TECM models can be respectively specified as:

$$\Delta x_t = \Lambda_i^- X_{t-1}(\beta)(\hat{\varepsilon}_{t-1} < 0) + \Lambda_i^+ X_{t-1}(\beta)(\hat{\varepsilon}_{t-1} \geq 0) + \mu \tag{12.1}$$

$$\Delta x_t = \Lambda_i^- X_{t-1}(\beta)(\hat{\varepsilon}_{t-1} < \tau) + \Lambda_i^+ X_{t-1}(\beta)(\hat{\varepsilon}_{t-1} \geq \tau) + \mu \tag{12.2}$$

$$\Delta x_t = \Lambda_i^- X_{t-1}(\beta)(\Delta\hat{\varepsilon}_{t-1} < 0) + \Lambda_i^+ X_{t-1}(\beta)(\Delta\hat{\varepsilon}_{t-1} \geq 0) + \mu \tag{12.3}$$

$$\Delta x_t = \Lambda_i^- X_{t-1}(\beta)(\Delta\hat{\varepsilon}_{t-1} < \tau) + \Lambda_i^+ X_{t-1}(\beta)(\Delta\hat{\varepsilon}_{t-1} \geq \tau) + \mu \tag{12.4}$$

Where:

$$x_t = \begin{pmatrix} lgec_t \\ lgY_t \end{pmatrix},\ X_{t-1}(\beta) = \begin{pmatrix} 1 \\ \Delta\xi_{t-1}(\beta) \\ \Delta x_{t-1} \\ \Delta x_{t-2} \\ \vdots \\ \Delta x_{t-j} \end{pmatrix},\ \Lambda_i^- = \begin{pmatrix} a_{i0}^- & 0 & 0 & 0 & \cdots & 0 \\ 0 & \lambda^- & 0 & 0 & \cdots & 0 \\ 0 & 0 & a_{i1}^- & 0 & \cdots & 0 \\ 0 & 0 & 0 & a_{i2}^- & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & \cdots & a_{ij}^- \end{pmatrix}, and\ \Lambda_i^+ = \begin{pmatrix} a_{i0}^+ & 0 & 0 & 0 & \cdots & 0 \\ 0 & \lambda^+ & 0 & 0 & \cdots & 0 \\ 0 & 0 & a_{i1}^+ & 0 & \cdots & 0 \\ 0 & 0 & 0 & a_{i2}^+ & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & \cdots & a_{ij}^+ \end{pmatrix}.$$

With respect to the equations (12.1) to (12.4), long-run adjustment is determined by the parameters λ^- and λ^+, whereas the short-run adjustment is governed by the parameter coefficients a_i^- and a_i^+, for k = 1,2,...,p. Based on the above-described TECM representations, the presence of asymmetries between the variables could be formally tested by examining the signs on the coefficients of the error correction terms. This involves a joint significance F-test for the null hypothesis of no threshold error correction mechanism (i.e. $H_0^{(4)}: \lambda^+ \xi_{t-1}^+ = \lambda^- \xi_{t-1}^-$) against the alternative hypothesis of threshold error correction effects (i.e. $H_0^{(4)}: \lambda^+ \xi_{t-1}^+ \neq \lambda^- \xi_{t-1}^-$). If the computed F-statistic is greater than the critical values tabulated in Granger and Silkos (2001), we reject the null hypothesis of no threshold error correction effects. Similarly, we can test for both short-run and long-run causal effects among the time series variables by examining whether the short-run adjustment coefficients and the long-run adjustment coefficients, respectively, are significantly different from zero. Both short-run and long-run causal tests are evaluated through the use of a standard F-statistic.

5 *EMPIRICAL RESULTS ANS DISCUSSIONS*

5.1 *RESULTS FROM UNFILTERED DATA*

As a preliminary step to evaluating cointegration effects among the filtered data, we conduct Kapetanois and Shin (2006) unit root tests on the original time series variables as means of evaluating the stationarity status of the data used. The order of the unit root tests is determined in the conventional manner of making use of the model selection criterion. The results of the unit root test, as reported in Table 2, confirm that the all observed time series are stationary in their logarithm levels. Generally, our results are in alignment with the Engle and Granger (1987) precondition of a pair of time series variables needing to be integrated of similar order I(0) or I(1) in order to produce a stationary cointegration vector. Indeed, the gist of the matter is that since both electricity consumption as well as economic growth are found to be mutually integrated of order I(0), we are able to pre-assume that the observed time series variables nonlinearly move more or less together over time. However, this pre-assumption that needs to be proved via formal cointegration analysis.

Table 2: Kapetanois and Shin (2006) Unit Test Results: Unfiltered data

		test statistics									threshold values	
		$\mathcal{W}_{sup}$			$\mathcal{W}_{ave}$			$\mathcal{W}_{exp}$				
		None	constant	trend	none	constant	trend	None	constant	trend	γ_1	γ_2
lgEC		14.89	32.75	16.70	4.25	8.25	3.46	38.21	250.8	61.54	5.416	5.558
lgY		20.55	6.99	11.82	6.03	4.66	7.96	294.05	12.05	73.01	11.11	12.93
critical values	10%	6.01	7.29	10.35	6.01	7.29	10.35	7.49	38.28	176.80		
	5%	7.49	9.04	12.16	7.49	9.04	12.16	20.18	91.83	437.03		
	1%	10.49	12.64	16.28	10.49	12.64	16.28	237.46	555.57	3428.9		

Significance Level Codes:"***", "**" and '*' denote the 1%, 5% and 10% significance levels respectively.

We begin our analysis by modelling TAR-TEC, c-TAR-TEC, MTAR-TEC and c-MTAR-TEC estimation specifications for the unfiltered time series and then we apply the four generic tests of cointegration and threshold effects to the data. The selected lag length of each the estimation regressions is chosen such that the AIC is minimized. Our obtained results are reported below in Table 3 and can be summarized in the form of two key observations. Firstly, we observe that none of the cointegration regressions fails to reject the null hypotheses of no cointegration effects at a 1 percent significance level. We treat this evidence as a mere confirmation of existing cointegration relations effects amongst the time series variables. Secondly, we find that all regressions fail to reject at least one of the remaining null hypotheses of no threshold cointegration and/or no asymmetric error correction effects; that is, with the exception of the c-MTAR-TEC model with electricity consumption placed as the 'driving' variable. This second result signifies a plausible nonlinear cointegration and error correction effects between electricity consumption and economic growth for the c-MTAR model with electricity consumption placed as a dependent variable. Having verified at least one asymmetric cointegration relationship between electricity consumption and economic growth, we, therefore, proceed to estimate the coefficients of adjustment and then examine how they vary across negative and positive error deviations. We also investigate causality effects between the time series variables for the c-MTAR-TEC model specification.

Table 3: Co-integration and error correction tests: Unfiltered data

y_t	x_t	TAR-TEC				MTAR-TEC			
		$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$	$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$
lggdp	*lgec*	reject	19.70	2.18	1.32	reject	19.59	2.01	0.02
			(0.00)***	(0.14)	(0.25)		(0.00)***	(0.15)	(0.90)
lgec	*lggdp*	reject	20.71	0.17	0.93	reject	22.09	2.18	3.26
			(0.00)***	(0.68)	(0.34)		(0.00)***	(0.14)	(0.07)*
		c-TAR-TEC				c-MTAR-TEC			
		$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$	$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$
lggdp	*lgec*	reject	21.38	4.71	1.61	reject	21.92	5.51	0.26
			(0.00)***	(0.03)*	(0.21)		(0.00)***	(0.02)*	(0.61)
lgec	*lggdp*	reject	21.61	1.49	3.75	reject	24.67	5.95	3.69
			(0.00)***	(0.23)	(0.06)*		(0.00)***	(0.02)*	(0.06)*

Notes: The numbers in parentheses are the t-ratios. The symbols *, ** and *** denote the significance at the 10, 5 and 1 percent levels, respectively.

In estimating the c-MTAR-TEC model, the key findings of our empirical exercise are summarized in Table 4 below. As is reported in Table 4, our results reveal a consistent threshold estimate value of -0.022, which is an encouraging result seeing that this value is relatively close to zero. In turning our attention to the coefficient estimates of the long-run regression, we find a positive and significant income elasticity of electricity consumption of 0.21 for our estimated model. Notably the sign and significance of this relationship is consistent with existing theory; and in our case, the coefficient on the economic growth variable indicates that a 1 percent increase in economic growth generates a 0.21 percent increase in electricity usage. Furthermore, we observe larger absolute values of ρ_1 in comparison to those obtained for the ρ_2 coefficient counterparts, a result which implies that positive deviations from the long run equilibrium are eliminated quicker than negative deviations. In particular, we find that negative deviations are eliminated at a rate of 30 percent per quarter whereas 71 percent of positive deviations are eliminated during the same time frame.

The lower half of Tale 4 presents the corresponding threshold error correction models for the c-MTAR specification. The long-run adjustment measures the percentage of deviations from the long-run equilibrium that are corrected in each time period and is determined by the estimates of λ^{-} below the threshold level and by λ^{+} above the threshold estimate. While the adjustment speed on the exceeding or underlying threshold values in all estimated regression equations is in the right direction by acting to eliminate deviations from the long-run equilibrium; only the error correction terms in the upper regimes (i.e. $\Delta\hat{\varepsilon}_{t-1} \geq$ -0.022) are found to be statistically significant. In particular, we find that shocks to economic growth result in approximately 70 percent of deviations from the steady-state equilibrium being corrected in the upper regime, whereas shocks to electricity consumption are corrected by only 13 percent above the threshold level. We therefore conclude that shocks to economic growth are absorbed at a much higher rate than shocks to electricity consumption for the unfiltered data.

Also reported in the last few rows of Table 4, are the results of the diagnostic tests performed on the selected c-MTAR-TECM regressions estimates as a means of ensuring the validity of our obtained empirical results. At a 10% significance level, all diagnostic tests do not display any evidence of violation of the classical linear regression assumptions. Specifically, the Jarque-Bera (J-B) normality test cannot reject the null hypothesis of the estimation residuals being normally distributed (i.e. iid~N(0,1)) and the Ramsey regression equation specification error test (RESET) test statistics indicate that none of the estimated regressions is mis-specified. Moreover, the standard statistical inferences of the estimated regressions (t-statistic, F-statistic and R^2) are valid. At the same level of significance, both the Ljung-Box (LB) test statistic and the ARCH-LM test consistently reveal that the residuals are not serially correlated and neither are they prone to the problem of heteroskadasticity.

Table 4: TAR-TEC and MTAR-TEC Model Estimates: Unfiltered data

model type	c-MTAR-TEC lgY	lgEC
γ_0		2.97
		(0.00)***
γ_1		0.21
		(0.00)***
τ		-0.022
ρ_{0i}^{-}		-0.30
		(0.06)*
ρ_{1i}^{+}		-0.72
		(0.00)***
β_i		0.21
		(0.03)*
ΔlgY^{-}	-0.81	-1.66
	(0.20)	(0.00)***
ΔlgY^{+}	-0.16	-0.23
	(0.41)	(0.00)***
$\Delta lgEC^{-}$	0.49	0.56
	(0.03)*	(0.00)***
$\Delta lgEC^{+}$	0.12	0.26
	(0.58)	(0.02)*
λ^{-}	-0.30	-0.03
	(0.10)	(0.76)
λ^{+}	-0.70	-0.13
	(0.00)***	(0.04)*
R^2	0.53	0.35
J-B	3.41	3.06
Dw	1.78	1.82
p-value	0.270	0.366
LB[1]	0.00	0.00
ARCH-LM[1]	0.00	0.00
RESET[1]	0.00	0.00

Notes: The numbers in the parentheses () are the t-ratios and the parentheses [] is the order of the diagnostic tests. The symbols *, ** and *** denote the significance at the 10, 5 and 1 percent levels, respectively.

Having ensured validity of the estimated c-MTAR-TECM model, we now turn our attention towards testing for causal effects between electricity consumption and economic growth. As previously discussed, we evaluate short-run causal effects by testing the significance of the sum of lagged terms for each explanatory variable whereas long-term causal effects are evaluated by significance of the long-run equilibrium adjustment coefficient. Both causality tests are evaluated through F-test statistics and our estimation results are reported below in Table 5. As is evident for the short-run, we find that both the null hypothesis of electricity consumption not leading economic growth as well as that of economic growth not granger causing electricity consumption are rejected at all significance levels. However, concerning the long-run, the null hypothesis that electricity consumption does not lead to economic growth is rejected at a 1 percent significant level whilst the null hypothesis of economic growth not causing electricity consumption cannot be rejected. Our results, therefore, advocate for causality running from electricity consumption to economic growth in the long-run whereas we report of no causal effects existing in the short-run.

Table 5: Granger Causal Tests: Unfiltered data

	Model	y	x	y granger causes x F-stat	x granger causes y F-stat	Decision
short-run causality	c-MTAR-TEC	*lgEC*	*lgY*	0.92 (0.34)	0.84 (0.36)	no causality
long-run causality	c-MTAR-TEC	*lgEC*	*lgY*	4.91 (0.00)***	1.58 (0.21)	lgec granger causes lggdp

Notes: The numbers in parentheses are the t-ratios. The symbols *, ** and *** denote the significance at the 10, 5 and 1 percent levels, respectively.

5.2 *Results From Filtered Data*

Subsequent to analyzing the results of the unfiltered data, we extract the trend and cyclical components of the two series by the HP filter. Similar to the empirical strategy employed in the previous section, we begin our analysis by checking for the stationary of the filtered data a la Kapetanois and Shin (2006) unit root tests. The lag length of the unit root tests are such that the AIC is minimized. As is evident from the results reported in Table 6 below, we find that both the trend and cyclical components of the series are nonlinearly integrated of order I(1); and this result bears similarity to those obtained for the unfiltered data.

Table 6: Kapetanois and Shin (2006) Unit Test Results: Filtered data

		test statistics									threshold values	
		$\mathcal{W}_{sup}$			$\mathcal{W}_{ave}$			$\mathcal{W}_{exp}$				
	none	intercept	trend	none	intercept	trend	none	intercept	trend	γ_1	γ_2
lgY^{trend}		11.00	9.95	11.82	4.20	6.94	7.96	15.00	38.70	73.01	10.45	10.54
$lgEC^{trend}$		17.99	4.24	13.71	4.85	2.02	4.02	176.99	2.94	17.90	5.137	5.194
lgY^{cycle}		16.27	16.27	16.27	2.99	2.99	2.99	47.94	47.94	47.94	0.005	0.011
$lgEC^{cycle}$		38.78	38.78	38.78	9.45	9.45	9.45	178.13	178.13	178.13	-0.003	0.037
critical	10%	6.01	7.29	10.35	6.01	7.29	10.35	7.49	38.28	176.80		
values	5%	7.49	9.04	12.16	7.49	9.04	12.16	20.18	91.83	437.03		
	1%	10.49	12.64	16.28	10.49	12.64	16.28	237.46	555.57	3428.9		

Note: Significance Level Codes:"***", "**' and '*' denote the 1%, 5% and 10% significance levels respectively.

At this stage it would appear as if our results indicate possible asymmetric cointegration effects between electricity consumption and economic growth, but it remains yet to be proven whether this assumption is true. We, therefore, model relevant threshold cointegration and error correction for both the trend and cyclical components of the time series and then apply the four cointegration and error correction tests to the data. The results of these empirical tests are summarized below in Table 7. Similar to the results obtained for the unfiltered data, we find that all regressions reject the first two null hypotheses of nonstationary error terms and no cointegration effects at a 1 percent significance level, respectively. However, when testing for threshold cointegration and asymmetric error correction effects, we find a wider variety of significant asymmetries for the de-trended variables. Specifically, for the case of trend variables we find that the c-TAR-TEC model with electricity consumption as a dependent variable and the c-MTAR-TEC specification with economic growth as the dependent variable, are able to reject the null hypotheses of all the tests. On the other hand, only the c-TAR-TEC specifications, with both electricity growth and electricity consumption placed as the driving variables, reject all null hypotheses for the cyclical components of the time series variables. We therefore proceed to estimate the threshold cointegration and error correction specifications.

Table 7: Co-integration and error correction tests: Filtered data

y_t	x_t	TAR-TEC				MTAR-TEC			
		$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$	$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$
lgY^{trend}	$lgEC^{trend}$	reject	1.28	0.06	0.55	reject	2.80	3.04	1.57
			(0.28)	(0.81)	(0.46)		(0.08)*	(0.08)*	(0.21)
$lgEC^{trend}$	lgY^{trend}	reject	16.03	0.33	0.72	reject	17.27	2.26	2.43
			(0.00)***	(0.57)	(0.40)		(0.00)***	(0.14)	(0..12)*
lgY^{cycle}	$lgEC^{cycle}$	reject	69.34	0.46	7.55	reject	70.60	1.56	5.64
			(0.00)***	(0.50)	(0.00)***		(0.00)***	(0.21)	(0.02)**
$lgEC^{cycle}$	lgY^{cycle}	reject	121.59	1.65	6.32	reject	119.86	0.55	2.38
			(0.00)***	(0.20)	(0.01)**		(0.00)***	(0.46)	(0.12)*
		c-TAR-TEC				c-MTAR-TEC			
		$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$	$H_0^{(1)}$	$H_0^{(2)}$	$H_0^{(3)}$	$H_0^{(4)}$
lgY^{trend}	$lgEC^{trend}$	reject	2.49	2.42	2.30	reject	3.88	5.14	6.41
			(0.09)*	(0.12)	(0.13)*		(0.02)*	(0.02)*	(0.01)**
$lgEC^{trend}$	lgY^{trend}	reject	17.79	3.07	3.97	reject	18.61	4.34	0.82
			(0.00)***	(0.08)*	(0.05)**		(0.00)***	(0.04)*	(0.37)
lgY^{cycle}	$lgEC^{cycle}$	reject	72.61	3.36	6.64	reject	70.52	1.50	9.19
			(0.00)***	(0.07)*	(0.01)**		(0.00)***	(0.22)	(0.00)***
$lgEC^{cycle}$	lgY^{cycle}	reject	125.26	3.99	4.59	reject	120.11	0.71	1.29
			(0.00)***	(0.05)*	(0.03)**		(0.00)***	(0.4)	(0.30)

Notes: The numbers in parentheses are the t-statistics. The symbols *, ** and *** denote the significance at the 10, 5 and 1 percent levels, respectively.

From our estimation results reported in Table 8, three striking results emerge. Firstly, we obtain fairly robust results for the on the impact of electricity consumption on economic growth and all estimators reveal that both the trend and cyclical components of electricity consumption and economic growth are positively correlated with each other. These results are statistically significant to at least a 1 percent significance level. The magnitude of these relationships tends to vary quite significantly between various threshold cointegration models; ranging from 0.27 to 0.32 when electricity consumption is the driving variable of the system and slightly higher values varying between 0.73 and 1.08 when economic growth is the dependent variable. This implies greater absolute sensitivity between the time series variables when economic growth is the driving variable in the system. Secondly, our results highlight differences in the speed of adjustment of positive discrepancies in comparison to negative ones. In particular, we note that for the trend components, the speed of conversion towards steady-state equilibrium is more rapid for positive discrepancies when economic growth is the driving variable in the system and is more rapid for negative discrepancies when electricity consumption is the driving force in the system. Conversely, for the case of the cyclical components, we observe quicker conversion of positive deviations of the error terms regardless of whether economic growth or electricity consumption is used as the driving variable in the system. It is also worth noting that all threshold estimates, as obtained through the CLS estimates, are encouragingly close to zero.

Lastly, in turning to our TECM estimates, we note that for trend variables, significant elimination of shocks to economic growth only occur in the upper regimes of both c-TAR-TECM and c-MTAR-TECM models; whereas shocks to electricity consumption are significantly eliminated in the lower regime of the c-TAR-TECM specifications. Notably, for all estimated models, a higher percentage of deviations are corrected for shocks to electricity usage in comparison to economic growth for the trend variables. Conversely, for the case of cyclical variables, we observe that when economic growth is the driving variable, shocks to economic growth are significantly corrected in both regimes of the system; whereas shocks to electricity usage are only corrected in the upper regime of the system. However, when electricity consumption is the driving variable in the system of cyclical components, only shocks to electricity consumption are corrected for in each period. Overall, all cyclical components display a higher percentage of corrected deviations in the upper regime in comparison to those of negative deviations. Furthermore the estimated threshold cointegration regressions display reasonable goodness of fit based on the R^2 and the F-statistics; and the regressions passed the diagnostic tests including the Durbin-Watson (DW) test for serial correlation, the Engle test for first-order autoregressive heteroscedasticity (ARCH(1)), the Jarque-Bera (JB) test for normality and the Ramsey (RESET) test for model specification.

Table 8: TAR-TEC and MTAR-TEC Model Estimates: Filtered Data

	trend components				cyclical components			
model type	c-TAR-TEC		c-MTAR-TEC		c-TAR-TEC		c-TAR-TEC	
	lgY	lgEC	lgY	lgEC	lgY	lgEC	lgY	lgEC
γ_0		2.28	6.73		0.00			0.00
		(0.00)***	(0.00)***		(0.99)			(0.99)
γ_1		0.27	0.73		0. 32			1.08
		(0.00)***	(0.00)***		(0.00)***			(0.00)***
τ		0.043	-0.022		0.012			0.021
ρ_{0i}^{-}		-0.62	-0.01		-0.54			-0.65
		(0.00)***	(0.94)		(0.00)***			(0.00)***
ρ_{1i}^{+}		-0.35	-0.17		-0.86			-0.96
		(0.00)***	(0.01)**		(0.00)***			(0.00)***
β_i		0.19	-0.361		0.29			0.53
		(0.05)*	(0.00)***		(0.01)**			(0.00)***
ΔlgY^{-}	-0.99	-0.88	-1.14	-1.42	-0.06	-0.77	-0.34	-1.32
	(0.00)***	(0.01)**	(0.00)***	(0.00)***	(0.63)	(0.07)*	(0.02)*	(0.00)***
ΔlgY^{+}	-0.03	0.01	0.08	0.26	0.43	0.84	-0.89	-0.89
	(0.78)	(0.99)	(0.52)	(0.37)	(0.00)***	(0.04)*	(0.00)***	(0.00)***
$\Delta lgEC^{-}$	0.61	0.62	0.25	0.36	0.11	-0.04	0.56	1.21
	(0.00)***	(0.01)**	(0.02)*	(0.09)*	(0.12)	(0.88)	(0.00)***	(0.00)***
$\Delta lgEC^{+}$	0.33	0.06	0.57	-0.03	0.18	-0.44	0.29	1.26
	(0.01)**	(0.80)	(0.00)**	(0.91)	(0.04)*	(0.14)	(0.03)*	(0.00)***
λ^{-}	-0.17	0.64	-0.08	0.13	-1.46	-0.61	-1.11	-1.90
	(0.01)*	(0.00)***	(0.07)*	(0.19)	(0.00)***	(0.33)	(0.43)	(0.00)***
λ^{+}	-0.05	-0.26	0.05	0.06	-1.97	-1.49	0.04	-2.52
	(0.40)	(0.05)*	(0.07)*	(0.33)	(0.00)***	(0.03)*	(0.81)	(0.00)***
R^2	0.58	0.38	0.58	0.22	0.80	0.23	0.61	0.68
J-B	3.26	3.59	2.58	2.74	2.98	2.85	3.02	3.11
Dw	1.94	2.05	1.94	2.37	2.07	2.43	2.13	2.07
p-value	0.71	0.80	0.67	0.032	0.628	0.032	0.45	0.61
LB[1]	0.001	0.00	0.001	0.00	0.00	0.00	0.00	0.00
ARCH-LM [1]	0.001	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RESET [1]	0.003	0.00	0.003	0.00	0.00	0.00	0.00	0.00

Notes: The numbers in the parentheses () are the t-ratios and the parentheses [] is the order of the diagnostic tests. The symbols *, ** and *** denote the significance at the 10, 5 and 1 percent levels, respectively.

The existence of a cointegration relationship among the filtered data implies that there must be at least granger causality in one direction between both the trend and cyclical components of the electricity consumption and economic growth variables. The results of the conducted causality tests are presented in Table 9. In screening though these results, we generally find that for all filtered data (i.e. both trend and cyclical components); bivariate causality exists between electricity consumption and economic growth in both the short and long-run. An exception is warranted for the short-run causality between the cyclical components electricity consumption and economic growth under the c-TAR-TEC model with electricity consumption being the driving variable, in which no causality effects are found, but this specific finding proves to be an exception rather than the underlying norm/rule of the reported results.

Table 9: Granger Causal Tests: Filtered Data

	Model	y	x	y granger causes x F-stat	x granger causes y F-stat	decision
short-run causality	c-TAR-TEC	$lgEC^{trend}$	lgY^{trend}	2.41 (0.06)*	3.67 (0.12)*	bi-directional causality
		lgY^{cycle}	$lgEC^{cycle}$	11.98 (0.00)***	5.84 (0.02)**	bi-directional causality
		$lgEC^{cycle}$	lgY^{cycle}	0.04 (0.85)	1.68 (0.19)	No causality
	c-MTAR-TEC	lgY^{trend}	$lgEC^{trend}$	3.28 (0.07)*	35.42 (0.00)***	bi-directional causality
long-run causality	c-TAR-TEC	$lgEC^{trend}$	lgY^{trend}	8.07 (0.00)***	4.75 (0.01)**	bi-directional causality
		lgY^{cycle}	$lgEC^{cycle}$	7.96 (0.00)***	2.94 (0.06)*	bi-directional causality
		$lgEC^{cycle}$	lgY^{cycle}	48.26 (0.00)***	40.27 (0.00)***	bi-directional causality
	c-MTAR-TEC	lgY^{trend}	$lgEC^{trend}$	36.95 (0.00)***	48.81 (0.00)***	bi-directional causality

Notes: The numbers in parentheses are the t-ratios. The symbols *, ** and *** denote the significance at the 10, 5 and 1 percent levels, respectively.

6 *POLICY IMPLICATIONS AND CONCLUDING REMARKS*

Having investigated possible asymmetric behaviour between electricity consumption and economic growth for South Africa, there are a number of relevant policy implications which can be inferred from our empirical analysis. First and foremost, our study reveals that there exists not only co-trend but also a co-feature relationship between electricity consumption and economic growth for the South African economy. We consider this finding as being of particular importance since it allows us to distinguish between the correlation of electricity consumption and economic growth, on one hand, and the cyclical components of the variables, on the other hand. For instance, based on the finding of a long-run uni-directional causality found from electricity consumption to economic growth for the unfiltered data; we conclude that restrictions on electricity consumption may adversely affect economic growth within the economy. In other words, conservative policies, such as power shedding and other demand-suppressing strategies, will constrain the normal pace of economic growth over the long run. We further attribute the finding of unidirectional causality from electricity usage to economic growth as signifying the increased role played by urbanization within the development of the South African economy. Similarly, we find the absence of a causal relationship from economic growth to electricity consumption as being plausible, taking into consideration that South Africa has one of the most developed energy infrastructures in Africa. Generally, we would expect causality running from economic growth to electricity consumption for a fairly underdeveloped economy, whose population is generally denied access to electricity and lacks the necessary energy infrastructure to increase its electricity supply. However, given the accelerated development of the energy sector over the last decade or so, it is thus intuitionistic to comprehend as to why electricity usage would lead to economic growth for the South African economy.

Another crucial inference drawn from our study concerns the existence of both long-run and short-run bi-directional causality found between the de-trended components of the observed time series. This result, by implication, means that there exists a non-restricting relationship between fluctuations in both electricity consumption and economic growth over the business cycle. Notably, this has far-reaching policy implications for the South African economy as it primarily suggests that the energy authorities must prioritize their efforts towards implementing policies which will stabilize both long-run and short-run fluctuations in electricity consumption and economic growth. Bearing in mind the proposed future developments of the electricity sector in South Africa, our results specifically indicate that proposed improvements to the energy sector must be effective at smoothing out fluctuations in electricity usage over the business cycle. Therefore, environmental friendly policies and other demand-side efficiency measures, which aim to reduce the wastage of electricity, may prove to be of little value in the long-run, if the inherent electricity structures and devised policies are unable to account for both long-run and short-run fluctuations in both time series. Our supplementary findings of strong nonlinear cointegration effects essentially suggest that energy authorities must be increasingly attentive towards factors causing nonlinear behaviour when devising policies directed at smoothing fluctuations in both electricity usage and output growth. Policymakers and other research enthusiasts are thus encouraged to incorporate the asymmetric adjustment behaviour of the electricity-growth nexus when building estimation and prediction models of the business cycle for the South African economy.

In a nutshell, our results emphasize the importance of, not only implementing expansionary energy policies as a means of stimulating economic growth, but our analysis also highlights the importance of further developing the necessary infrastructures as well as implementing policies which are capable of managing fluctuations of electricity consumption over the business cycle. So even though the adequate provision of electricity may not be an overall panacea to South Africa's developmental problems, our study acknowledges that positive developments in the electricity sector would significantly contribute towards the improvement of output produced within the economy. Currently, the IRP mandate is founded on the aspiration of attaining an economic growth rate of 5.4 percent, which is believed to correspond with an annual electricity demand of 2.7 percent. However, a number of observers and other commentators believe that both figures may be quite optimistic, taking into consideration that current economic growth is within the 2 percent region; whilst present electricity consumption has fallen to levels last experienced about a decade ago. Therefore, a legitimate case can be put forward for higher levels of investment in energy infrastructure as a means of alleviating production spillages and demand suppression. Our study affirms that such infrastructural developments could ultimately lead to accelerated economic growth in the long-run.

Even though our empirical results appear to be rather optimistic at first glance, we interpret our results with caution due to the slow adjustment mechanism of shocks to the electricity consumption variables as obtained for all error correction estimates. In other words, policy-induced shocks to electricity usage will result in a slow reversion or response of economic growth as the cointegrated variables deviate from the long-run steady-state equilibrium. We believe that the relatively slow adjustment mechanism may be slightly indicative of our regression estimates suffering from the omitted variables pandemic. Therefore we recommend that future research look into the possibility of identifying other transmission mechanisms through which cyclical electricity efficiency could lead to improved productivity growth along an equilibrium steady-state path. Such efforts may assist in providing supplementary policy advice on how future developments within the energy sector could catalyse economic growth and boost development in South Africa.

REFERENCES

Akarca A. and Long T. (1980), “On the relationship between energy and GDP: a re-examination”, *Journal of Energy Development*, 5, 326-331.

Akinlo A. (2009), “Electricity consumption and economic growth in Nigeria: Evidence from cointegration and co-feature analysis”, *Journal of Policy Modeling*, 31, 681-693.

Baek E. and Brock W. (1992), “A general test for nonlinear granger causality: Bivariate model”, Working Paper, Iowa State University and University of Wisconsin, Madison, WI.

Bildiric M. (2013), “Economic growth and electricity consumption: MS-VAR and MS-granger causality”, *OPEC Energy Review*, 37(4), 447-476.

Binh P. (2011), “Energy consumption and economic growth in Vietnam: Threshold cointegration and causality analysis”, *International Journal of Energy Economics and Policy*, 1(1), 1-17.

Caner M. and Hansen B. (2001), “Threshold autoregression with a unit root”, *Econometrica*, 69, 1555-1596.

Chen S., Kuo H and Chen C. (2007), “The relationship between GDP and electricity consumption in 10 Asian countries”, *Energy Policy*, 35, 2611-2621.

Cheng-Lang Y., Lin H. and Chang C. (2010), “Linear and nonlinear causality between sectoral electricity consumption and economic growth”, *Energy Economics*, 6570-6573.

Chiou-Wei S., Chen C. and Zhu Z. (2008), “Economic growth and energy consumption revisited-Evidence from linear and nonlinear granger causality”, *Energy Economics*, 30, 3063-3076.

Ciarreta A. and Zarraga A. (2010), “Economic growth-electricity consumption causality in 12 European countries: a dynamic panel data approach”, *Energy Policy*, 38, 3790-3796.

Diks C. and Panchenko V. (2006), “A new statistic and practical guidelines for nonparametric granger causality testing”, *Journal of Economic Dynamics and Control*, 30, 1647-1669.

Enders W. and Granger C. (1998), "Unit root tests and asymmetric adjustment with an example using the term structure of interest rates", *Journal of Business and Economic Statistics*, 16, 304-311.

Enders W. and Silkos P. (2001), "Cointegration and threshold adjustment", *Journal of Business and Economic Statistics*, 19, 166-176.

Engle R. And Granger C. (1987), "Co-integration and error correction: Representation, estimation and testing", *Econometrica*, 55(2), 251-276.

Erol U. And Yu E. (1987), "On the causal relationship between energy and income for industrialized countries", *Journal of Energy and Development*, 13, 113-122.

Esso L. (2010), "Threshold cointegration and causality relationship between energy use and growth in seven African countries", *Energy Economics*, 32, 1383-1391.

Granger C. (1969), "Investigating causal relations by econometric models and cross-spectral methods", *Econometrica*, 37(3), 424-438.

Gurgul H. and Lach L. (2012), "The electricity consumption versus economic growth of the Polish economy", *Energy Economics*, 34, 500-510.

Hamilton J. (1989), "A new approach to the economic analysis of non-stationary time series and the business cycle", *Econometrica*, 57, 357-384.

Hansen B. (1996), "Inference when a nuisance parameter is not identified under the null hypothesis", *Econometrica*, 64(2), 413-430.

Hansen B. (1997), "Inference in TAR models", *Studies in Nonlinear Dynamics and Econometrics*, 2(1), 1-16.

Hansen B. (1999), "Testing for linearity", *Journal of Economic Surveys*, 13(5), 551-576.

Hansen B. (2000), “Sample splitting and threshold estimation”, *Econometrica*, 68(3), 575-604.

Hansen B. And Seo B. (2002), “Testing for threshold cointegration in vector error correction models”, *Journal of Econometrics*, 68, 575-603.

Herrerias M. (2013), “Regional cyclical behaviour between industrial output and electricity consumption in China: A panel smooth regression approach”, The University of Nottingham, Chain Policy Institute Working Paper No. 10, February.

Hu J. and Lin C. (2008), “Disaggregated energy consumption and GDP in Taiwan: A threshold co-integration analysis”, *Energy Economics*, 30, 2342-2358.

Hu J. and Lin C. (2013), “Examining asymmetric behaviour between energy consumption and economic growth in Taiwan”, *Energy Sources, Part B: Economics, Planning and Policy,* , 8(1), 76-85.

Jumbe C. (2004), “Cointegration and causality between electricity consumption and GDP: empirical evidence from Malawi”, *Energy Economics*, 26, 61-68.

Johansen S. (1988), “Statistical analysis of cointegration vectors”, Journal of Economic Dynamics and Control”, 12(2-3), 231-254.

Johansen S. (1991), “Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models”, *Econometrica*, 59(6), 1551-1580.

Johansen S. and Juselius K. (1990), “Maximum likelihood estimation and inference on cointegration with applications to the demand for money”, *Oxford Bulletin of Economics and Statistics*, 52(2), 169-210.

Kahsai M., Nondo C., Schaeffer P. and Gebremedhin T. (2012), “Income level and energy consumption-GDP nexus: Evidence from Sub-Saharan Africa”, *Energy Economics*, 34, 739-746.

Kapetanois G. and Shin Y. (2006), “Unit root tests in three-regime SETAR models”, *The Econometrics Journal*, 9(2), 252-278.

Kapetanois G, Shin Y. and Snell A. (2006), “Testing for cointegration in nonlinear smooth transition error correction models”, *Econometric Theory*, 22, 279-303.

Kocaaslan O. (2013), “The causal link between energy and output growth: Evidence from Markov switching granger causality”, *Energy Policy*, 63, 1196-1206.

Kouakou A. (2011), “Economic growth and electricity consumption in Cote d’Ivoire: Evidence from time series analysis”, *Energy Policy*, 39, 3638-3644.

Kraft J. and Kraft A. (1978), “On the relationship between energy and GDP”, *Journal of Energy Development*, 3, 401-403.

Lee C. And Chang C. (2005), “Structural breaks, energy consumption and economic growth revisited: Evidence from Taiwan”, *Energy Economics*, 27, 857-872.

Luukkonen R., Saikkonen P. and Terasvirta T. (1988), “Testing linearity against smooth transition autoregressive models”, *Biometrika*, 75, 491-499.

Morimoto K. and Hope C. (2004), “Impact of electricity supply on economic growth in Sri Lanka”, *Energy Economics*, 26, 77-85.

Mozumder P. and Marathe A. (2007), “Causality relationship between electricity consumption and GDP in Bangladesh”, *Energy Policy*, 35, 395-402.

Narayan P. and Prasad A. (2008), “Electricity consumption-real GDP causality nexus: Evidence from a bootstrapped causality test for 30 OECD countries”, *Energy Policy*, 36, 910-918.

Narayan P., Narayan S., and Popp S. (2010), “Does electricity consumption panel Granger cause GDP? A new global evidence”, *Applied Energy*, 87, 3294-3298.

Nazlioglu S., Kayhan S. and Adiguzel U. (2014), "Electricity consumption and economic growth in Turkey: Cointegration, linear and nonlinear granger causality", *Energy Sources, Part B: Economics, Planning and Policy*, 9, 315-324.

Odhiambo N. (2009), "Electricity consumption and economic growth in South Africa: A trivariate causality study", *Energy Economics*, 31, 635-640.

Odhiambo N. (2010), "Energy consumption, prices and economic growth in three SSA countries: A comparative study", *Energy Policy*, 38, 2463-2469.

Ouedraogo I. (2010), "Electricity consumption and economic growth in Burkina Faso: A cointegration analysis", *Energy Economics*, 32, 524-531.

Ouedraogo N. (2013), "Energy consumption and economic growth in Burkina Faso: Evidence from the economic community of West African states (ECOWAS)", *Energy Economics*, 36, 637-647.

Psaradakis Z., Sola M., and Spagnolo F. (2004), "On Markov error-correction-models with an application to stock prices and dividends", *Journal of Applied Econometrics*, 19, 69-88.

Payne J. (2010), "A survey of the electricity consumption-growth literature", *Applied Energy*, 87, 723-731.

Pedroni P. (1999), "Critical values for cointegration tests in heterogeneous panels with multiple regressors", *Oxford Bulletin of Economics and Statistics*, 61, 653-670.

Pedroni P. (2004), "Panel cointegration; asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis: New results", *Econometric theory*, 20, 597-627.

Pesaran M., Shin Y and Smith R. (2001), "Bounds testing approaches to the analysis of level relationships", *Journal of Applied Econometrics*, 16(3), 289-326.

Phiri A. (2012), “Threshold effects and inflation persistence in South Africa”, *Journal of Financial Economic Policy*, 4(3), 247-269.

Roula I. (2010), “Aggregate electricity demand in South Africa: Conditional forecasts to 2030”, *Applied Energy*, 87 (1), 197-204.

Shahiduzzaman M. and Alam K. (2012), “Cointegration and causal relationships between energy consumption and output: Assessing the evidence from Australia”, *Energy Economics*, 34, 2182-2188.

Seo M. (2006), “Bootstrap testing for no cointegration in a vector error correction model”, *Journal of Econometrics*, 134, 129-150.

Shiu A. and Lam P. (2004), “Electricity consumption and economic growth in China”, *Energy Policy*, 32, 47-54.

Sims C. (1980), “Macroeconomics and reality”, *Econometrica*, 48, 1-48.

Squalli J. (2007), “Electricity consumption and economic growth: Bounds and causality analyses of OPEC members”, *Energy Economics*, 29, 1192-1205.

Terasvirta T. (1994), “Specification, estimation and evaluation of smooth transition autoregressive models”, *Journal of American Statistical Association*”, 89, 208-218.

Thoma M. (2004), “Electrical energy usage over the business cycle”, *Energy Economics*, 26, 363-385.

Toman T. and Jemelkkova B. (2003), “Energy and economic development: An assessment of the state of knowledge”, *Energy Journal*, 24, 93-112.

Van Dijk D., Terasvirta T. and Franses P. (2002), “Smooth transition autoregressive models- A survey of recent developments”, *Economic Reviews*, 21, 1-47.

Westerlund J. (2006), "Testing for panel cointegration with multiple structural breaks", *Oxford Bulletin of Economics and Statistics*, 68, 101-132.

Wolde-Rafael Y. (2006), "Electricity consumption and economic growth: A time series experience for 17 African countries", *Energy Policy*, 34, 1106-1114.

Wolde-Rufel Y. (2011), "Bounds test approach to cointegration and causality between nuclear energy consumption and economic growth in India", *Energy Policy*, 38, 52-58.

Winkler H. (2005), "Renewable energy policy in South Africa: policy options for renewable electricity", *Energy Policy*, 33, 27-38.

Yoo S. (2005), "Electricity consumption and economic growth: Evidence from Korea", *Energy Policy*, 33, 1627-1632.

Yoo S. (2006), "The causal relationship between electricity consumption and economic growth in the ASEAN countries", *Energy Policy*, 34, 3573-3582.

Yoo S. and Kwak S. (2010), "Electricity consum.ption and economic growth in seven South American countries", *Energy Policy*, 38, 181-188.

Yu E. and Hwang B. (1984), "The relationship between energy and GNP, further results", *Energy Economics*, 6, 186-190.

Yu E. and Choi J. (1985), "The causal relationship between energy and GNP: an international comparison", *Journal of Energy and Development*, 10, 249-272.

Table 1: Review of previous studies examining the asymmetric relationship between electricity consumption and economic growth

Author	Country/Countries	Study period	Econometric model/ Methodology	Variables	Causality effects
Hu and Lin (2008)	Taiwan	1982-2006	TVEC (Threshold cointegration)		No causality analysis
Esso (2010)	Cameroon, Kenya, Nigeria, South Africa, Conga, Ghana, Cote d'Ivoire.	1970-2007	Two-step ECM and linear causality tests	Electricity consumption (E) and real gross domestic product (Y)	No causal relations for Cameroon, Kenya, Nigeria and South Africa; uni-directional GDP→EC for Congo and Ghana; bi-directional causality for Cote d'Ivoire
Cheng-Lang et. al. (2010)	Taiwan	1982-2008	Nonlinear granger causality tests	Real GDP, Total electricity consumption (TEC), industrial sector consumption (ISC), residential sector consumption (RSC).	TEC→GDP GDP→TEC
Binh (2011)	Vietnam	1976-2010	Threshold cointegration test and granger causal analysis	Electricity consumption (EC) and GDP per capita (GDP)	GDP→EC
Omay et. al. (2012)	G7 countries	1977-2007	PSTRVEC (Threshold co-integration and nonlinear causality analysis)	Electricity consumption (EC) and real gross domestic product per capita (GDP)	GDP→EC
Bildirici (2013)	Argentina, China, India, Brazil, Mexico, Turkey, South Africa	1970-2010	MS-VAR (Threshold cointegration and nonlinear causality analysis)	Electricity consumption (EC) and per capita GDP (Y)	Bi-directional
Herrerias (2013)	China	2003-2009	PSTR	Electricity consumption (EC) and industrial output (GDP)	No causality analysis
Kocaaslan (2013)	United States	1968-2010	MS granger causality analysis	Electricity consumption (EC) and gross domestic product (GDP)	Bi-directional
Hu and Lin (2013)	Taiwan	1982-2006	MTAR (Threshold cointegration)	Total electricity consumption (EC); transportation electricity consumption (TRA); industrial electricity consumption (IND); residential electricity consumption (RES); and gross domestic product (GDP)	No causal analysis

Nazlioglu et. al. (2014)	Turkey	1967-2007	Nonlinear granger causality tests	Electricity consumption and gross domestic product (GDP)	No causal effects