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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 2016: 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 detrended 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 Classifications: C32, C51, Q43

1. INTRODUCTION

The empirical investigation into the effects of electricity consumption on economic growth is a fairly novel field of exploration and has recently attracted increasing attention within the academic paradigm. Based on the current 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 the sign of the relationship, of which there exists overwhelming support in favour of a positive co-integration between the 2 time series variables. The second issue concerns the identification of granger causal effects existing between electricity consumption and economic growth. Whilst there seems to be very little contention concerning the sign of the relationship, however, there appears to be a greater debate on the causal effects between electricity consumption and economic growth. So far, four possibilities have emerged concerning the direction of causality among the variables. These possibilities are (i) uni-directional causality from electricity consumption to economic growth (i.e., conservation hypothesis), (ii) causality running from economic growth to energy consumption (i.e., growth hypothesis), (iii) bi-directional causal effects (i.e., feedback hypothesis), and (iv) no causality (i.e., neutrality hypothesis).

From an empirical perspective, different studies have focused on different economies using different spans of time periods and have obtained conflicting evidence concerning the electricity-growth relationship. Such conflicting evidence may be due 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. (Chen et al., 2007). Recently, it has been speculated that a range of nonlinearities may exist in the correlation between electricity consumption and economic growth. Reasons for this nonlinearity have been given in the literature. For instance, Hu and Lin (2013) attribute nonlinearity to the complex design of economic systems. On the other hand, Chiou-Wei et al. (2008) attribute nonlinearity to structural changes in the economic and policy environment as well as to fluctuations in energy prices. All-in-all, there is a growing consensus suggesting that ignoring nonlinearities may empirically produce misleading inferences when estimating the cointegration relationship between the time series.

In our study we examine possible asymmetric cointegration and causal effects between electricity consumption and economic growth using a momentum threshold autoregressive (MTAR) framework. Taking South Africa as a case study, we consider such an empirical undertaking as being worthwhile, since, to the best of our knowledge, no empirical studies have investigated possible asymmetric causal effects between electricity consumption and economic growth for the country. We also broaden 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 and thus presents a superior analytical strategy in comparison to the empirical approach of solely investigating cointegration effects between the time series variables.

Having provided the backdrop to our case study, we structure the rest of the paper as follows. In the following section, we provide a review of the associated literature. In section three, 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 four presents the empirical results of our study, whilst the paper is concluded in section five in the form of policy implications and possible future research avenues.

2. RELATED LITERATURE

Chronologically, the associated literature can be broadly classified into five main strands of empirical studies. The first group of empirical studies strictly made use of Granger's (1969) causality tests. Examples of these studies include Kraft and Kraft (1978); Akarca and Long (1980); Yu and Hwang (1984); Yu and Choi (1985); as well as Erol and Yu (1987). The second group of studies are those which turned to the use of cointegration analysis as first introduced by Engle and Granger (1987). 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 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 evident in Thoma (2004) who finds no cointegration relations between the series for the US economy, a result which invalidates earlier 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.

Under the third group of empirical studies, researchers turned to the use the multivariate cointegration analysis of Johansen and Juselius (1990). The studies of Shiu and Lam (2004); Lee and Chang (2005); Yoo (2006); 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. Extending along these studies, emerged the fourth group of studies which uses panel cointegration techniques such as those of Pedroni (1999, 2004); Pesaran et al. (2001) and Westerlund (2006). Inclusive of this group of studies are 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. Since the aforementioned panel data studies are criticized for generalizing their results over entire populations with differing economic disparities, a number of studies have opted 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 include Wolde-Rufael (2006) for African countries; Yoo (2006) for ASEAN countries; Squalli (2007) for OPEC countries; Narayan and Prasad (2008) for OECD countries; as well as Yoo and Kwak (2010) for South American countries.

The last cluster of empirical studies, are those which have incorporated nonlinearity in their empirical investigation of the electricity consumption-growth analysis. There are two sub-classifications under this group of nonlinear studies. The first sub-group are those conducted for individual countries as found in Hu and Lin (2008) for Taiwan, Binh (2011) for Vietnam, Kocaaslan (2013) for the United States and Nazlioglu et al. (2014) for Turkey. The second sub-group are those which employ nonlinear panel data estimation techniques and are inclusive of Esso (2010) for 6 African countries, Omay et al. (2014). For G7 countries and Bildiric (2013) for 7 seven developing countries. The nonlinear econometric models frequently used in these studies include the threshold vector error correction (TVEC) model of Hansen and Seo (2002), the smooth transition vector error correction model (STVEC) model of Kapetanois et al. (2006) and the Markov switching error correction model of Psaradakis et al. (2004).

3. DATA AND METHODOLOGY

3.1. Data

Our dataset consists of electricity consumption and gross domestic product (GDP) and is collected over a sample period of 20 years covering January 1984 – December 2016 from the Statistics South Africa (STATSSA) database. Since 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 follow in pursuit of Yuan (2007) and Akinlo (2009), by using the Hodrick-Prescott (HP) filter as a means of decomposing the trend and cyclical component of the observed time series. The HP filter provides an estimate of the unobserved variable (trend) as the solution to the following minimization problem:

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

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 = σ_T^2 / σ_c^2 is the smoothing components. We employ a value of $\lambda = 1600$ for our quarterly dataset. In extracting the trend component from the HP filter, we then derive the cyclical component as follows:

$$C_{y_t} = y_t - T_{yt} \tag{2}$$

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.

3.2. Unit Root Tests

Since we are investigating nonlinearities between electricity consumption and growth, it is ideal to begin by investigating asymmetries in the integration properties in the individual time series. To do so we use the nonlinear unit root tests of Kapetanois and Shin (2006) which is based upon the following three-regime TAR model specification:

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

For $t = 1,2,\ldots, T$, where the error tem, μ_t, is assumed to follow an iid sequence $N(0,\sigma^2)$ and γ_1 and γ_2 are the threshold parameters with $\gamma_1 < \gamma_2$ and $(\gamma_1, \gamma_2)\ \epsilon\Gamma=[\gamma_{min}, \gamma_{max}]$ with γ_{min} and γ_{max} picked such that $Pr(y_{t-1} < \gamma_{min}) = \pi_1 > 0$ and $Pr(y_{t-1} < \gamma_{min}) = \pi_2 < 0$. Unit root testing is facilitated by imposing the condition $\alpha_0 = 1$ 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:

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

Where $\beta_1 = \alpha_1 - 1$, $\beta_2 = \alpha_2 - 1$ and the indicator functions $y_{t-1} I_{\cdot(y_{t-1} \le \gamma_1)}$ 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 $\beta = [\beta_1, \beta_2]$, $X = \begin{bmatrix} y_0 I_{\cdot(y_0 \le \gamma_1)} & y_0 I_{\cdot(y_0 > \gamma_1)} \\ y_1 I_{\cdot(y_1 \le \gamma_1)} & y_1 I_{\cdot(y_1 > \gamma_1)} \\ \vdots & \vdots \\ y_{T-1} I_{\cdot(y_{T-1} \le \gamma_1)} & y_{T-1} I_{\cdot(y_{T-1} > \gamma_1)} \end{bmatrix}$, $\hat{\sigma}_\mu^2 = \frac{1}{T-2} \sum_{i=1}^{T} \hat{\mu}_t^2$ and $\hat{\mu}_t^2$ as the regression residuals obtained from (2); the Wald test statistic can be computed as:

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

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.

3.3. 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 γ_0 and γ_1 are the estimated parameters and ε_t is a disturbance term. 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:

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

According to Enders and Silkos (2001), asymmetric cointegration adjustment can be introduced by allowing the cointegration residuals to behave as a threshold process. In particular, four variations of threshold cointegration models can be specified, 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:

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

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

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

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

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). The unknown threshold term, τ, under the c-TAR and c-MTAR models are estimated using the minimization method pioneered by Hansen (2000).

For each of the threshold cointegration regressions from (9.1) to (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., $H_0^{(3)}: \rho_1, \rho_2 < 0$). 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:

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

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

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

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

Where:

$$x_t = \begin{pmatrix} lgec_t \\ lgY_t \end{pmatrix}, X_{t-1}(\beta) = \begin{pmatrix} 1 \\ \Delta\xi_{t-1}(\beta) \\ \Delta x_{t-1} \\ \Delta x_{t-2} \\ \vdots \\ \Delta x_{t-j} \end{pmatrix},$$

$$\Lambda_i^- = \begin{pmatrix} a_{i0}^- & 0 & 0 & 0 & \cdots & 0 \\ 0 & ^- & 0 & 0 & \cdots & 0 \\ 0 & 0 & a_{i1}^- & 0 & \cdots & 0 \\ 0 & 0 & 0 & a_{i2}^- & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & \cdots & a_{ij}^- \end{pmatrix} \text{ and}$$

$$\Lambda_i^+ = \begin{pmatrix} a_{i0}^+ & 0 & 0 & 0 & \cdots & 0 \\ 0 & ^+ & 0 & 0 & \cdots & 0 \\ 0 & 0 & a_{i1}^+ & 0 & \cdots & 0 \\ 0 & 0 & 0 & a_{i2}^+ & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & \cdots & a_{ij}^+ \end{pmatrix}$$

Table 1: Kapetanois and Shin (2006) unit test results: Unfiltered data

Time series	Test statistics									Threshold values	
	W_{sup}			W_{ave}			W_{exp}			γ_1	γ_2
	None	Constant	Trend	None	Constant	Trend	None	Constant	Trend		
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. The order of the unit root tests is determined through the AIC

Table 2: Co-integration and error correction tests: Unfiltered data

y_t	x_t	TAR-TEC				MTAR-TEC			
lgYp	*lgEC*	Reject	19.70 (0.00)***	2.18 (0.14)	1.32 (0.25)	Reject	19.59 (0.00)***	2.01 (0.15)	0.02 (0.90)
lgEC	*lgY*	Reject	20.71 (0.00)***	0.17 (0.68)	0.93 (0.34)	Reject	22.09 (0.00)***	2.18 (0.14)	3.26 (0.07)*
		c-TAR-TEC				c-MTAR-TEC			
lgY	*lgEC*	Reject	21.38 (0.00)***	4.71 (0.03)*	1.61 (0.21)	Reject	21.92 (0.00)***	5.51 (0.02)*	0.26 (0.61)
lgEC	*lgY*	Reject	21.61 (0.00)***	1.49 (0.23)	3.75 (0.06)*	Reject	24.67 (0.00)***	5.95 (0.02)*	3.69 (0.06)*

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

Table 3: 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)***
T		−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

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% levels, respectively

Where λ^- and λ^+ long-run adjustment parameters, a_i^- and a_i^+ are the short-run adjustment coefficients. There are three main hypothesis tested from the TECM models. The first test is F-test for the null hypothesis of no threshold error correction mechanism (i.e., $H_0^{(4)}: \lambda^+\xi_{t-1}^+ = \lambda^-\xi_{t-1}^-$). The second test 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., $H_0^{(4)}: \lambda^+\xi_{t-1}^+ = \lambda^-\xi_{t-1}^-$). If the computed F-statistic is greater than the critical values tabulated in Enders 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.

4. RESULTS

4.1. 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 results of the unit root test, as reported in Table 1, confirm that the all observed time series are stationary in their logarithm levels.

Table 4: Granger causal tests: Unfiltered data

Causality	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 *lgY*

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

Table 5: Kapetanois and Shin (2006) unit test results: Filtered data

Time series	Test statistics									Threshold values	
	W_{sup}			W_{ave}			W_{exp}			γ_1	γ_2
	None	Intercept	Trend	None	Intercept	Trend	None	Intercept	Trend		
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 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

Table 6: Co-integration and error correction tests: Filtered data

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

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

Having confirmed that the unfiltered time series are integrated of order I(1), we proceed to apply the three generic tests of cointegration and threshold effects to TAR-TEC, c-TAR-TEC, MTAR-TEC and c-MTAR-TEC model specifications of the data and report the results in Table 2. We observe that whilst none of the cointegration regressions fails to reject the null hypotheses of no cointegration effects, it is only the c-MTAR-TEC model with electricity consumption placed as the 'driving' variable which manages to reject both of the remaining null hypotheses of no threshold cointegration and no asymmetric error correction effects.

We therefore estimate the c-MTAR-TEC model and perform granger causality tests. The estimation results are reported in Table 3 whereas the granger causality tests are reported in Table 4. From Table 3, we find a significant income elasticity of electricity consumption of 0.21 for our estimated model and this result is consistent with existing theory. We also find that our threshold error term coefficients ρ_1 and ρ_2 are significantly negative and this result validates the existence of threshold error correction mechanism. In estimating our threshold error correction mechanisms, we find 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. From Table 4, we find no evidence of short-run causality and yet in the long-run electricity consumption is found to granger-cause economic growth.

4.2. Results From Filtered Data

We begin our analysis by checking for the stationary of the filtered data using Kapetanois and Shin (2006) unit root tests and report the results in Table 5. As can be observed, we find that both the trend and cyclical extractions of the series are first difference time series.

Subsequent to the unit root tests, we model relevant threshold cointegration and error correction estimations for both the trend and cyclical components of the time series and then apply the three threshold cointegration tests to the data. The results of these tests are reported in Table 6. For the cyclical components, we find that the c-TAR-TEC specifications with both electricity growth and electricity consumption placed as the driving variables pass all threshold cointegration tests. For the trend components, 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.

Having found regressions which have passed all threshold cointegration tests, we estimate these models for both the trend and the cyclical components and report the estimation results in Table 7. The associated causality tests are reported in Table 8. For each of the estimated models, as seen in Table 6, we find a positive income elasticity of electricity consumption, which again is coherent with academic theory. Moreover, we find that the threshold error coefficients from the long-run regression are significantly negative thus validating the existence of threshold error correction mechanisms for each of the regressions. All of the estimated regressions produce at least one negative error correction term thus implying that there must be at least granger causality in one direction for each regression. From Table 7, we find that for trend components there is bi-variate causality between electricity consumption and economic growth in both the short-run and long-run. For the cyclical components the same result holds true with the exception of the c-TAR-TEC model with electricity consumption being the driving variable, in which no causality effects are found in the short-run.

5. CONCLUSSION AND POLICY INSIGHTS

The main empirical findings of this study are that for the South African economy, there is uni-directional causality from electricity usage to economic growth, with the two variables moving in the same direction over the long-run. Notably, Odhiambo (2009), Menyah and Wolde-Rufael (2010) and Khasai et al. (2012) all conclude similar results for South Africa albeit using linear cointegration analysis. Thus from a policy point of view, we advise that conservative or demand-suppressing policies, such as the recent nation-wide load shedding scheme, will constrain the normal pace of economic growth over the long run. In other words, the continuous use of energy conservation policies will adversely affect South Africa's economic development seeing that a high proportion of households and businesses within the country rely exclusive

Table 7: TAR-TEC and MTAR-TEC model estimates: Filtered data

Model type	Trend components				Cyclical components			
	c-TAR-TEC		c-MTAR-TEC		c-TAR-TEC		c-TAR-TEC	
	lgY	*lgEC*	*lgY*	*lgEC*	*lgY*	*lgEC*	*lgY*	*lgEC*
γ_0		2.28 (0.00)***	6.73 (0.00)***		0.00 (0.99)			0.00 (0.99)
γ_1		0.27 (0.00)***	0.73 (0.00)***		0.32 (0.00)***			1.08 (0.00)***
T		0.043	−0.022		0.012			0.021
ρ_{0i}^{-}		−0.62 (0.00)***	−0.01 (0.94)		−0.54 (0.00)***			−0.65 (0.00)***
ρ_{1i}^{+}		−0.35 (0.00)***	−0.17 (0.01)**		−0.86 (0.00)***			−0.96 (0.00)***
β_i		0.19 (0.05)*	−0.361 (0.00)***		0.29 (0.01)**			0.53 (0.00)***
ΔlgY	−0.99 (0.00)***	−0.88 (0.01)**	−1.14 (0.00)***	−1.42 (0.00)***	−0.06 (0.63)	−0.77 (0.07)*	−0.34 (0.02)*	−1.32 (0.00)***
ΔlgY^{+}	−0.03 (0.78)	0.01 (0.99)	0.08 (0.52)	0.26 (0.37)	0.43 (0.00)***	0.84 (0.04)*	−0.89 (0.00)***	−0.89 (0.00)***
$\Delta lgEC^{-}$	0.61 (0.00)***	0.62 (0.01)**	0.25 (0.02)*	0.36 (0.09)*	0.11 (0.12)	−0.04 (0.88)	0.56 (0.00)***	1.21 (0.00)***
$\Delta lgEC^{+}$	0.33 (0.01)**	0.06 (0.80)	0.57 (0.00)**	−0.03 (0.91)	0.18 (0.04)*	−0.44 (0.14)	0.29 (0.03)*	1.26 (0.00)***
λ^{-}	−0.17 (0.01)*	0.64 (0.00)***	−0.08 (0.07)*	0.13 (0.19)	−1.46 (0.00)***	−0.61 (0.33)	−1.11 (0.43)	−1.90 (0.00)***
λ^{+}	−0.05 (0.40)	−0.26 (0.05)*	0.05 (0.07)*	0.06 (0.33)	−1.97 (0.00)***	−1.49 (0.03)*	0.04 (0.81)	−2.52 (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

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% levels, respectively

on electricity as an energy source. Therefore, well-designed energy policies need to be put into place in a manner as to not hinder industrial development and household welfare. For instance, the Department of Energy may consider a move away from traditional fossil fuels usage to more environmentally-friendly energy sources such as hydroelectricity, solar and wind power. The emission of carbon dioxide created by the burning of fossil fuel already possess as a threat to the economy. Thus, a legitimate case can be put forward for increased investment in environmentally-friendly energy infrastructures as well as increased investment in research and development on technological innovation for energy saving.

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 short-run and long-run fluctuations.

Collectively, 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%, which is believed to correspond with an annual electricity demand of 2.7%. However, these figures may be quite optimistic, taking into consideration that economic growth is currently within the 2% 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.

Table 8: Granger causal tests: Filtered data

Causality	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

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

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