Income Elasticities of Electric Power Consumption: Evidence from African Countries

December 2006

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Abstract
The paper examines the income elasticity of electric power consumption power (YEEPC) in Africa. This study constitutes the first attempt to explore the relationship between electricity consumption per capita and real GDP per capita for 16 African countries in a panel dimension over the period 1971 – 2002. Bi-directional causality exists and all tests support a long run relationship between the two variables. As such, the long run elasticities are computed by employing FMOLS and DOLS and are found to be below unity. Furthermore, the YEEPC is found to be pro-cyclical.

Keywords: Electric power consumption, panel cointegration, Africa
JEL: C23, Q41

1. Introduction

Energy consumption in Africa remains a dominant concern despite its huge potential in fossil and renewable energy sources. A large proportion of the African community still relies very much on traditional energy sources such as biomass[1] while only about one-third has accessed to electricity (Kauffman, 2005). Within the spirit of the New Partnership for Africa's Development[2] (NEPAD), electricity embodies the root of the productive advancements of the new digital economy and represents one of the building blocks of any modern nation.

The income elasticity of energy consumption has been vastly investigated in the literature. Fiebig *et al* (1987) use cross-section data of aggregate energy for thirty nations and find income elasticity of between 1.24 and 1.64. Using time-series data for the OECD countries, Kouris (1983) find for primary energy demand a short-run income elasticity of 1.08 for the period 1961-1981, while Prosser (1985) yields an income elasticity of 1.02 for the period 1960-1982. Bentzen and Engsted (1993) estimate the income elasticities for aggregate energy consumption in Denmark to be 0.67 and 1.21 in the short and long run respectively. Hunt and Manning (1989) find for the UK, an income elasticity of 0.80 and 0.38 in the short and long run respectively. Kouris (1976) uses pooled data for eight nations and find the income elasticity for primary energy consumption to be 0.84. Using panel data for seven nations on aggregate energy

[1] It constitutes about 58% of total energy consumption (Kauffman, 2005).

[2] The NEPAD was officially formed in July 2001 with the main objectives of fighting poverty, consolidating democracy and good governance, fostering trade, investment, economic growth and sustainability. For instance, one of the NEPAD's priorities is the creation of a fiber-optic network which will connect all African countries to each other in a view to reduce transaction costs.

consumption, Nordhaus (1977) estimates the short-run income elasticities to be between 1.26 and 1.42, and the long run income elasticities between 0.26 and 1.42.

Along the same line, a few studies have focused on the income elasticity of electricity consumption. Branch (1993) uses a generalized least squares estimator (GLS) for the panel data based on the Consumer Expenditure Interview Survey (CE) of the Bureau of Labor Statistic in the US and find an income elasticity of demand for residential electricity of 0.23. Holtedahl and Joutz (2004) examine the residential demand for Taiwan and find a short run and long run income elasticity of 0.23 and 1.04 respectively. Liu (2004) estimates the income elasticities of several energy goods in OECD countries over 1978 to 1999 by applying the one-step generalized methods-of-moments (GMM) estimation method to the panel data set. His results show that the income elasticity of electricity is between 0.06 and 0.30 in the short run and between 0.30 and 1.04 in the long run.

The use of state-of-the-art panel data techniques for the period 1971-2002 on 16 African countries[3] allows us to add empirical evidence to the already vast literature. The remaining of the paper is organized as follows: Section 2 presents the econometric model and specification tests, section 3 provides the empirical analysis, and section 4 summarizes our empirical findings and concludes.

[3] The data were gathered from the World Development Indicators (2005). The selection of countries is done purely on the availability of data.

2. The Testing Framework

To determine the income elasticity of electric power consumption (YEEPC) the following reduced-form equation is formulated:

$$ELEC_{it} = \beta_0 + \beta_1 LGDP_{it} + \varepsilon_{it} \qquad \text{----- (1)}$$

From equation (1), ELEC is natural logarithm of per capita electric power consumption, measured in kWh. LGDP is the natural logarithm of real GDP per capita in US dollars. β_1 captures the YEEPC. If $\beta_1 < 0$, $0 < \beta_1 < 1$ and $\beta_1 > 1$, electricity consumption is deemed to be an inferior, necessity and luxury good respectively. Since electricity is a normal good (service), higher disposable income is expected to increase the consumption through greater activity and purchases of electricity-using appliances in both the short and long run (Holtedahl and Joutz, 2004). ε_{it} is the error term.

Before estimating the YEEPC, a causality test is conducted mainly to check the direction of the any causal relationship. As such, a reverse relationship will yield inconsistent ordinary least squares (OLS) estimators (Gramlich, 1994). The presence of bi-directional causality may be synonymous endogenous regressors which can produce both inconsistent and biased parameters. To date, causality tests have been mainly applied to time series data. Guttormsen (2004) provides a good survey of the literature for the energy-GDP nexus. For instance, Ghosh (2002) also finds unidirectional causality from economic growth to electricity consumption in India while Shiu and Lam (2004) discover that the reverse holds true for the Chinese economy.

Practically all these studies have been done using time series data. The problem while modeling time-series regression is that it is difficult to control for omitted variable bias and measurement errors. To tackle these problems the system GMM panel data technique will be employed to estimate equation (2). Such method helps to reduce the estimation bias inherent in the panel data set when lagged dependent variables are utilized as regressors. Arellano and Bond (1991) derive a one-step GMM estimator for the coefficients of equation (1) using as instruments lagged levels of the dependent variable and the predetermined variables, and differences of the strictly exogenous variables. Such methodology assumes no second-order autocorrelation in the first-differenced idiosyncratic errors. Arellano and Bond (1991) offer a test of this assumption. Moreoever, the Sargan test can be computed to look at the validity of the instruments if one can maintain the assumption of homoskedasticity. The null hypothesis that the overindentifying restrictions are not binding is tested.

The procedure revolves around the concept of Granger causality as in time series analysis. As such, causality is inferred when lagged values of a variable (e.g. LGDP) have explanatory power in a regression model of another variable (e.g. ELEC) on lagged values of both variables (ELEC and LGDP). The model is specified as:

$$\mathrm{ELEC}_{it} = \alpha_0 + \sum_{e=1}^{m} \alpha_e \mathrm{ELEC}_{it\text{-}k} + \sum_{k=1}^{n} \beta_k \mathrm{LGDP}_{it\text{-}k} + \eta_i + u_{it} \qquad \text{----- (2)}$$

,where $i = 1, ..., N$; $t = m+2, …., T$; α_0, α_e, and β_k are parameters to be estimated. The lag lengths m and n are sufficient to ensure that u_{it} is a stochastic error. Although it is not necessary that m equals n, the typical practice of assuming they are identical is adopted.

The test of whether LGDP causes ELEC is simply a Wald test of the joint hypothesis where $\beta_1 = \beta_2 = \ldots = \beta_n$ are all equal to zero. If this null hypothesis is accepted, then it means that LGDP does not cause ELEC. To account for the individual effects, the intercept is often allowed to vary with each unit in a panel analysis, which is represented as η_i.

There are however a few caveats to be accounted while estimating equation (2). First, the Granger causality test is conditioned on the set of variables introduced (or omitted), and the number of lags of the dependent and exogenous variables (Holtz-Eakin *et al.*, 1988). Thus, the test cannot be considered as 'final', rather as contingent on the choice of variables and lags exercised. Moreover, Deaton (1997) cautions that dynamic panel estimation relies on asymptotics both in terms of units and time and that in small samples, the estimation may be complex. Second, our estimation is affected by the fact that the sample becomes unbalanced. If the number of lags is increased, not only must more parameters be estimated in the regression, but observations will be dropped from the estimation. Finally, by removing the fixed effect, we also remove from the estimation any variable of potential interest that is fixed through time (e.g., price of kWh per minute). The first difference transformation will remove such variables from the estimation.

A variety of unit root tests has been employed in the literature. We henceforth employ three panel unit tests. First, the Levin-Lin-Chu (2002, LLC) assumes that each individual unit in the panel shares the same AR(1) coefficient, but allows for individual effects, time effects and possibly a time trend. Lags of the dependent variable may be introduced to allow for serial correlation in the errors. The test may be viewed as a pooled Dickey-Fuller test, or an Augmented Dickey-Fuller (ADF) test when lags are included, with the null hypothesis that of non-stationarity (I(1) behavior). After transformation by factors provided by LLC, the t-star statistic is distributed standard normal under the null hypothesis of non-stationarity. The LLC test assumes an identical regression parameter ρ for all units. The following hypothesis is tested:

$$H_0 = \rho_1 = \rho_2 = ... = \rho_i = ... = \rho_N = \rho = 0 \qquad \text{----- (3a)}$$

The alternative is

$$H_1 = \rho_1 = \rho_2 = ... = \rho_i = ... = \rho_N = \rho < 0 \qquad \text{----- (3b)}$$

To allow for heterogeneity, the ADF test:

$$\Delta y_{it} = \rho_i y_{it-1} + \sum_{j=1}^{j_i} \theta_{ij} \Delta y_{it-j} + a_i + c_i t + \varepsilon_{it} \qquad \text{----- (3c)}$$

is split into two steps:

$$\Delta y_{it} = \sum_{j=1}^{j_i} \theta_{ij} \Delta y_{it-j} + a_i + c_i t + e_{it} \qquad \text{----- (3d)}$$

$$y_{it-1} = \sum_{j=1}^{j_i} \theta_{ij} \Delta y_{it-j} + a_i + c_i t + V_{it} \qquad \text{----- (3c)}$$

Using the residuals the unit individual parameters are estimated:

$$\widehat{e}_{it} = \widehat{\rho} \widehat{V}_{it-1} + \varepsilon_{it} \qquad \text{----- (3d)}$$

Short term variance:

$$\widehat{e}_{e_i}^2 = \frac{1}{T - J_i - 1} \sum_{t=J_i+2}^{T} \left(\widehat{e}_{it} - \widehat{\rho}_i \widehat{V}_{it-1} \right)^2 = \frac{1}{T - J_i - 1} \sum_{t=J_i+2}^{T} \widehat{\varepsilon}_{it}^2 \qquad \text{----- (3e)}$$

and long term variance for the unit *i*:

$$\widehat{\sigma}_{y_i}^2 = \frac{1}{T-1} \sum_{t=2}^{T} \Delta y_{it}^2 + 2 \sum_{k=1}^{K} w_k \left(\frac{1}{T-1} \sum_{t=k+2}^{T} \Delta y_{it} \Delta y_{it-k} \right) \qquad \text{----- (3f)}$$

are used to calculate the following ratio of variances:

$$\widehat{S}_{NT} = \frac{1}{N} \sum_{i=1}^{N} \frac{\widehat{\sigma}_{y_i}}{\widehat{\sigma}_{e_i}} \qquad \text{----- (3g)}$$

The parameter ρ is assumed to be identical for all units and estimated using the now homoscedastic residuals:

$$\tilde{e}_{it} = \rho \widehat{V}_{it-1} + \tilde{\varepsilon}_{it} \qquad \text{----- (3h)}$$

with

$$\tilde{e}_{it} = \frac{\widehat{e}_{it}}{\widehat{\sigma}_{e_i}} \qquad \text{----- (3i)}$$

and

$$\widehat{V}_{it-1} = \frac{\widehat{V}_{it-1}}{\widehat{\sigma}_{e_i}} \qquad \text{----- (3j)}$$

The variance estimator is given by:

$$\widehat{\sigma}_{\varepsilon}^{2}=\frac{1}{N\tilde{T}}\sum_{i=1}^{N}\sum_{t=J_i+2}^{T}\left(\tilde{e}_{it}-\widehat{\rho}_i\widehat{V}_{it-1}\right)^2=\frac{1}{N\tilde{T}}\sum_{i=1}^{N}\sum_{t=J_i+2}^{T}\widehat{\tilde{\varepsilon}}_{it}^{2} \qquad \text{----- (3k)}$$

with $\tilde{T}=T-\overline{J}-1$ and $\overline{J}=\frac{1}{N}\sum_{i=1}^{N}J_i$

The standard error of ρ is given by:

$$\widehat{\sigma}_{\rho}=\widehat{\sigma}_{\varepsilon}\left[\sum_{i=1}^{N}\sum_{t=J_i+2}^{N}\tilde{V}_{it-1}^{2}\right]^{-\frac{1}{2}} \qquad \text{----- (3l)}$$

which leads to the following *t*-statistic:

$$t_{p=0}=\frac{\widehat{\rho}}{\widehat{\sigma}_{\rho}} \qquad \text{----- (3m)}$$

As this *t*-statistic doesn't follow the usual *t*-distribution, a correction is suggested:

$$\therefore\ t_{\rho}^{*}=\frac{t_{\rho=0}-N\tilde{T}\widehat{S}_{NT}\widehat{\sigma}_{\varepsilon}^{-2}\widehat{\sigma}_{\rho}\mu_{\tilde{T}}^{*}}{\sigma_{\tilde{T}}^{*}} \qquad \text{----- (3n)}$$

The parameters $\mu_{\tilde{T}}^{*}$ and $\sigma_{\tilde{T}}^{*}$ have to be derived by Monte Carlo simulations. Beside these correction terms the following standard errors and variances are calculated using the actual data under inspection: $\widehat{S}_{NT}$, $\widehat{\sigma}_{\varepsilon}^{2}$ and $\widehat{\sigma}_{\rho}$. The corrected test statistic follows approximately the standard error normal distribution:

$$H_0=\rho=0,\ t_{\rho}^{*}\Rightarrow N\left(0,1\right) \qquad \text{----- (3o)}$$

LLC test is based on the idea of the homogeneity. Im, Pesaran, and Shin (2003, IPS) criticize the LLC test and present an alternative method to test the unit root in the panel data. The advantage of their test which is a statistic average ADF, consists of inducing heterogeneity between the groups.

The IPS test statistics are based on the averaged of *N* country-specific ADF *t*-statistics. Following Dickey and Fuller (1979) the ADF test can be presented as:

$$\Delta x_{it} = \mu_i + \gamma_i t + \beta_i x_{i,t-1} + \sum_{j=1}^{\rho_i} \phi_{i,j} \Delta x_{i,t-j} + \varepsilon_{it} \qquad \varepsilon_{it} \sim iid\left(0, \sigma^2\right) \qquad \text{----- (4a)}$$

where variable t time trend, t = 1, …. …., *T* and j = 1, … …, *K*. *K* is the number of lags, determined such that the error term is autocorrelation free. The maintained hypothesis of common dynamics is relaxed and the relevant hypotheses are:

$H_0 : \beta_i = 0, \ \forall\, i,$

$H_1 : \exists\, i \text{ s.t. } \beta_i < 0.$

The null hypothesis that all series contain unit root is tested against the alternative that some series are stationary. Due to the heterogeneity each equation is estimated separately and the test statistics are obtained as (studentized-*t*) averages of the test statistics for each equation. The IPS *t*-bar statistic is defined as the average of the individual Dickey-Fuller τ statistics as:

$$\overline{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} \tau_i \qquad , \tau_i = \frac{\widehat{\beta}_i}{\widehat{\sigma}_{\phi_i}} \qquad i = 1, 2, \dots \dots, N \qquad \text{----- (4b)}$$

where τ_i is the ADF test statistic for the i^{th} country.

Assuming that the cross-sections are independent, Im, Pesaran and Shin (1997) propose to use the following standardized *t*-bar statistic:

$$\psi_{\bar{t}} = \frac{\sqrt{N}\left\{\bar{t}_{NT} - \frac{1}{N}\sum_{i=1}^{N} E\left[t_{iT}(\rho_i, 0)\right]\right\}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} Var\left[t_{it}\left(\rho_i, 0\right)\right]}} \qquad \text{----- (4c)}$$

IPS suggest a fixed T, fixed *N* panel unit root test based on the ADF test statistics:

$$\bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N}\tau_i \qquad ,\tau_i = \frac{\hat{\beta}_i}{\hat{\sigma}_{\phi_i}} \qquad i = 1, 2, \ldots \ldots, N \qquad \text{----- (4d)}$$

where N is the number of panels, $\bar{t}_{NT}$ is the average of the ADF test for each series across the panel and values for $E[t_{iT}(p_i,0)]$ and $Var[t_{it}(p_i,0)]$ are obtained from the results of the monte carlo simulation. The latter conjecture that the standardized *t*-bar statistic $\Psi_{\bar{t}}$ converge weakly to a standard normal distribution as N and T $\rightarrow \infty$. Hence the panel unit root inference can be conducted by comparing the obtained Ψ_t statistic to critical values from the lower tail of the $N(0,1)$ distribution. There are yet a number of questionable aspects of this test.

First, despite the increase in power gained from the use of a panel, the test is still based on the null that the series in question are unit root processes. Second, the null hypothesis is that all of the series in the panel contain a unit root against the alternative that none do.

This assumption can be criticized by arguing that it is thus possible that outliers (in the sense of a relatively high or low ADF for a particular series) have the potential to bias the results and that the all-or-nothing approach is unattractive.

Hadri (2000) panel unit root tests are based on the average of the *N* country-specific KPSS *LM*-statistics. The ADF unit root test as proposed by Dickey and Fuller (1979) is assumed to have a H_0 of unit root as opposed while the KPSS test as engineered by Kwiatkowski *et al* (1992) assumes a H_0 of stationarity.

According to Kwiatkowski *et al* (1992), a time series can be decomposed into three components, a deterministic trend, a random walk and a stationary error. There are presented as:

$$x_{i,t} = \theta_i t + r_{i,t} + \varepsilon_{i,t} \qquad \text{----- (5a)}$$

where *t* captures the deterministic trend and $r_{i,t}$ is the random walk:

$$r_{i,t} = r_{i,t-1} + u_{i,t} \qquad , u_{i,t} \sim i.i.d\left(0, \sigma_u^2\right) \qquad \text{----- (5b)}$$

The test statistic is one-sided LM statistic under the null of level stationary that for the *N* panel the variance of the errors is such that:

$$\mathrm{H}_0 = \sigma_{\mu 1}^2 = \ldots = \sigma_{\mu N}^2 = 0 \qquad \text{---- (5c)}$$

against the alternative hypothesis that some $\sigma_{\mu i}^2 > 0$. This alternative allows for heterogeneous $\sigma_{\mu i}^2$ across the cross-sections and includes the homogeneous alternative ($\sigma_{\mu i}^2 > \sigma_{\mu}^2$ for all *i*) as a special case. The LM test statistics is defined as:

$$\eta_i = \frac{1}{T^2}\sum_{t=1}^{T} S_{\varepsilon,i}^2 / \widehat{\sigma}_{\varepsilon,i}^2(l) \qquad \text{----- (5d)}$$

where T is the sample size, $\widehat{\sigma}_i^2(l)$ is estimated of the error variance, l, is the lag truncation parameter and $S_{i,t}$ is the partial sums of the residuals, $S_{i,t} = \sum_{j=1}^{i} \widehat{\varepsilon}_{i,j}$. The lag truncation is set to integer $[4(T/100)^{1/4}]$ to correct the estimate of the error variance. The KPSS test makes a non-parametric correction of the estimate of the error variance such that:

$$\widehat{\sigma}_i^2(l) = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_{i,t}^2 + \frac{2}{T}\sum_{s=1}^{1}\left(\frac{1-2}{1+l}\right)\sum_{t=s+1}^{T}\widehat{\varepsilon}_{i,t}\widehat{\varepsilon}_{i,t-s} \qquad \text{----- (5e)}$$

The extension of the KPSS test for panel data has been performed by Hadri (2000). The panel LM test statistic is defined as the mean of the individual test statistic under the null of level stationary:

$$L\widehat{M}_{\mu} = \frac{1}{N}\sum_{i=1}^{N}\eta_i \qquad \text{----- (5f)}$$

The null hypothesis of level or trend stationary is tested against the alternative of unit root in panel. Under the assumption that $\mathrm{E}\left[u_{i,t}\right]=\mathrm{E}\left[\varepsilon_{i,t}\right]=0$, $u_{i,t}$ and $\varepsilon_{i,t}$ are iid across i and over t, the test statistic has the following limiting distribution:

$$Z_{\mu}=\frac{\sqrt{N}\left(L\widehat{M}_{\mu}-\xi_{\mu}\right)}{\zeta_{\mu}}\Rightarrow N\left(0,1\right) \qquad \text{----- (5g)}$$

where $\Rightarrow$ represents weak convergence in distribution, ξ_{μ}, ζ_{μ} are mean and variance of the standard Brownian bridge $\int_0^1 V^2\left(r\right)dr$. The computed numerical values of ξ_{μ}, ζ_{μ} are 1/6 and 1/45 for the level case and 1/15 and 11/6300 for the trend case respectively.

Karlsson and Löthgen (2000) suggest a caveat in using the IPS unit test which tends to have high power in panels with large T and low power in panels with small T. As such, researchers may draw wrong conclusions in claiming a whole panel is stationary even though most individual series are non-stationary in case T is large. The reverse is true for small T. On the contrary, the Hadri test performs well for panel data with short time dimension (Barhoumi, 2005). A direct way of overcoming such shortcoming is to reconcile the results of panel unit root tests.

In case the series are non-stationary and have the same integration order, two panel cointegration tests will be considered. First, Nyblom and Harvey (2000, NH) postulates a test of common trends where H_0 is the stationarity of the series around a deterministic trend, i.e. there exists $k < n$ common trends (i.e. rank (Σ_{η}) = k), against the alternative of a random walk component occurrence i.e. there exists more than k common trends (i.e. rank (Σ_η) > k). The NH statistics test the H_0 of 0 common trends against the hypothesis of common trends among the variables. No model needs to be estimated as the test is based on the rank of covariance matrix of the disturbances driving the multivariate random walk. If the rank is equal to a certain number of common trends, cointegration is supported. Failure to reject H_0 is synonymous no cointegration. If **A**, the r x n matrix of cointegrating vectors, is known, then their test statistic can be written as:

$$\xi_r(\mathbf{A}) = \mathrm{tr}(\mathbf{ASA'})^{-1}\mathbf{ACA'} \qquad \text{----- (6a)}$$

where **S** is the nonparametric estimator of the spectral density at frequency zero using a Bartlett Window following KPSS:

$$S = \hat{\Gamma}_0 + \sum_{j=1}^{m}\left[1 - \frac{j}{m+1}\right]\left[\hat{\Gamma}_j + \hat{\Gamma}_{j'}\right] \qquad \text{----- (6b)}$$

where m is the number of lags in the transitory component and

$$\hat{\Gamma}_j = \frac{1}{T}\sum_{t=j+1}^{T}(y_t - \bar{y})(y_{t-j} - \bar{y})' \qquad \text{----- (6c)}$$

Add **C** is an estimator of the second moments of partial sums of the time series:

$$C = \frac{1}{T^2}\sum_{i=1}^{T}\left[\sum_{i=1}^{i}(y_t - \bar{y})\right]' \qquad \text{----- (6d)}$$

This test is more specifically a test of the pre-specified cointegrating vectors, i.e. a test of **A**. In many cases, the correct matrix **A** is not known, but we may still be interested the testing for common trends. When **A** is not known, NH propose the following modification to the above equation (6a):

$$\zeta_{k,n} = \min_{A} tr\left[\left(ASA'\right)^{-1} ACA'\right] \qquad \text{----- (6e)}$$

This allows **A** to be estimated for common trends. The univariate version of this test was shown by Nyblom and Mäkeläinen (1983) to be the locally best invariant test of the null hypothesis that $\sigma_{\eta}^{2} = 0$, i.e. that the series is stationary. Note that this test can also be interpreted as a one-sided Lagrange multiplier (LM) test. The test statistic in this case is:

$$\zeta_1 = C/S \qquad \text{----- (6f)}$$

, since C and S will both be scalars when n = 1

NH also suggest a multivariate joint test for unit roots, a test for unit roots, a test for $\sum_{\eta} = 0$. The test statistic in this final case is:

$$\zeta_n = tr\left[S^{-1}C\right] \qquad \text{----- (6g)}$$

The alternative is $\sum_{\eta} = q\sum_{\varepsilon}$. The test maximizes the power against homogeneous alternatives, but it is consistent against all non-null $\sum_{\eta}$'s. An advantage of the parametric test is that is allows the inclusion of variables which may be correlated with the variables of interest, thus they provide additional information, but they may not be cointegrated with the variables of interest. But this is not possible in the NH world as the vector A is required in order to work with a spectral density at frequency zero. From the state-space representation of the correlated unobserved components model, Morley and Sinclair (2005) derive the following variance-covariance matrix is obtained:

$$E\left(\begin{bmatrix}\eta_t \\ \varepsilon_t\end{bmatrix}\begin{bmatrix}\eta_t & \varepsilon_t\end{bmatrix}\right)=\begin{bmatrix}\sum_{\eta} & \sum_{\eta\varepsilon} \\ \sum_{\varepsilon\eta} & \sum_{\varepsilon}\end{bmatrix} \qquad \text{----- (6h)}$$

where η_{it} represents the innovation to the permanent component of series *i* in the model. Hence, the submatrix of interest from the variance-covariance matrix is Σ_η. If this matrix is of full rank then the series are all integrated but there does not exist any cointegration vector. If it is of less than full rank, then either one or more of the series is stationary or there exists at least one common trend.

The general correlated unobserved components model nests in this case the restricted unobserved components model with at least one of the innovations to the permanent component of one series is equal to a scale constant λ times the innovation to the permanent component of another series. The distribution of the likelihood ratio test statistic is once again nonstandard, but a Monte Carlo simulation can again be used to establish appropriate confidence bands. The data for the Monte Carlo simulation can be generated under the assumption that the restricted unobserved components model is the true model. Consider the two-series example under the null of cointegration:

$$\sum_{\eta}=\begin{bmatrix}\sigma_\eta^2 & \lambda\sigma_\eta^2 \\ \lambda\sigma_\eta^2 & \lambda^2\sigma_\eta^2\end{bmatrix} \qquad \text{----- (6i)}$$

Moreover, the correlated unobserved components model also finds information relevant for the test of cointegration from the variance-covariance submatrix of permanent-transitory covariances. If under the null η_1=η_2 and $\eta_2 = \lambda\eta_1 = \lambda\eta$, then:

$$\sum_{\eta\varepsilon} = \begin{bmatrix} \sigma_{\eta 1\varepsilon 1} & \sigma_{\eta 1\varepsilon 2} \\ \sigma_{\eta 2\varepsilon 1} & \sigma_{\eta 2\varepsilon 2} \end{bmatrix} = \begin{bmatrix} \sigma_{\eta\varepsilon 1} & \sigma_{\eta\varepsilon 2} \\ \lambda\sigma_{\eta\varepsilon 1} & \lambda\sigma_{\eta\varepsilon 2} \end{bmatrix} \qquad \text{----- (6j)}$$

The Pedroni (1997, 1999) panel cointegration test statistics are calculated by using the residuals of Engle and Granger (1987) cointegrating regression based on equation (2). β_{0i} is included to control for country-specific fixed effects. Pedroni (1997, 1999) develops seven panel cointegration statistics. Four of these statistics, called panel cointegration statistics, are *within-dimension* based statistics. The other three statistics, called group mean panel cointegration statistics, are *between-dimension* based statistics. Each statistic is distributed asymptotically as a standard normal when $T \rightarrow \infty$ and $N \rightarrow \infty$. H_0 corresponds to no cointegration amongst the series.

Pedroni (1999) compute the residuals from the following hypothesized cointegration:

$$y_{i,t} = a'_t + \ddot{a}_t t + \hat{a}_{1t} x_{1i,t} + \hat{a}_{2t} x_{2i,t} + \ldots + \hat{a}_{Mt} x_{Mi,t} + e_{i,t}$$

for $t = 1, \ldots\ldots, T$; $i = 1, \ldots\ldots, N$; $m = 1, \ldots\ldots, M$ ----- (7a)

where T refers to the number of observations over time, N refers to the number of individual members in the panel, and M refers to the number of regression variables. Since there are N different members of the panel, N different equations can be thought, each of which has M regressors. The $\hat{a}_{1i}$, $\hat{a}_{2i}$, ... , $\hat{a}_{Mi}$ are permitted to vary across individual members of the panel. The parameter á is the member specific intercept, or fixed effects parameter which of course is also allowed to vary across individual members. In addition, deterministic time trends are included. These are specific to individual members of the panel and are captured by the term ä$_i$$t$, although it will also often be the case that these ä$_i$$t$ terms are omitted.

Based on the residuals $e_{i,t}$, Pedroni(1997, 1999) develops seven panel cointegration statistics. Four of these statistics, called panel cointegration statistics, are within-dimension based statistics which are constructed by summing both the numerator and the denominator terms over the *N* dimension separately. The other three statistics, called group mean panel cointegration statistics, are between-dimension based statistics and are constructed by first dividing the numerator by the denominator prior to summing over the N dimension. For the within-dimension statistics the test for the null of no cointegration is implemented as a residual based test of the null hypothesis $\mathrm{H}_0 : \tilde{a}_i = 1$ *for all i*, versus the alternative hypothesis $\mathrm{H}_1 : \tilde{a}_i = \tilde{a} < 1$ *for all I*, so that it presumes a common value for $\tilde{a}_i = \tilde{a}$. By contrast, for the between-dimension statistics the null of no cointegration is implemented as a residual based test of the null hypothesis $\mathrm{H}_0 : \tilde{a}_i = 1$ *for all i*, versus the alternative hypothesis $\mathrm{H}_1 : \tilde{a}_i < 1$ *for all i*, so that it does not presume a common value for $\tilde{a}_i = \tilde{a}$ under the alternative hypothesis. Thus, the between-dimension based statistics allow one to model an additional source of potential heterogeneity across individual members of the panel. The asymptotic distributions of these panel cointegration statistics are derived in Pedroni (1997). The panel cointegration statistics are shown in Box 1.

Box 1: Pedroni Panel Cointegration Statistics

1. Panel v-Statistics: $T^2 N^{3/2} Z_{\hat{V}_{N,T}} \equiv T^2 N^{3/2} \left(\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1}$

2. Panel ρ-Statistics: $T\sqrt{N} Z_{\rho_{N,T^{-1}}} \equiv T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^2\right)^{-1} \sum_{i=1}^{N}\sum_{i=1}^{T} \hat{L}_{11i}^{-2}\left(\hat{e}_{i,t-1}\text{Ä}\hat{L}_{11i}^{-2}\hat{e}_{i,t} - \hat{\ddot{e}}_i\right)$

3. Panel pp-Statistics: $Z_{pp_{N,T}} \equiv \left(\tilde{\text{o}}_{N,T}^2 \sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^2\right)^{-1/2} \sum_{i=1}^{N}\sum_{i=1}^{T} \hat{L}_{11i}^{-2}\left(\hat{e}_{i,t-1}\text{Ä}\hat{L}_{11i}^{-2}\hat{e}_{i,t} - \hat{\ddot{e}}_i\right)$

4. Panel adf-Statistics: $Z_{adf_{N,T}} \equiv \left(\tilde{\text{s}}_{N,T}^{*2} \sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^2\right)^{-1/2} \sum_{i=1}^{N}\sum_{i=1}^{T} \hat{L}_{11i}^{-2}\hat{L}_{11i}^{-2}\hat{e}_{i,t}^{*} - \text{Ä}\hat{e}_{i,t}^{*}$

5. Group ρ-Statistics: $TN^{-1/2}\hat{Z}_{\hat{n}_{N,T^{-1}}} \equiv TN^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{e}_{i,t-1}^2\right)^{-1}\sum_{t=1}^{T}\left(\hat{e}_{i,t-1}\text{Ä}\hat{e}_{i,t} - \hat{\ddot{e}}_i\right)$

6. Group pp-Statistics: $N^{-1/2}\hat{Z}_{pp_{N,T}} \equiv N^{-1/2}\sum_{i=1}^{N}\left(\hat{\text{o}}_i^2\sum_{t=1}^{T}\hat{e}_{i,t-1}^2\right)^{-1/2}\sum_{t=1}^{T}\left(\hat{e}_{i,t-1}\text{Ä}\hat{e}_{i,t} - \hat{\ddot{e}}_i\right)$

7. Group adf-Statistics: $N^{-1/2}\hat{Z}_{adf_{N,T}} \equiv N^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{s}_i^{*}\hat{e}_{i,t-1}^{*2}\right)^{-1/2}\sum_{t=1}^{T}\hat{e}_{i,t-1}^{*}\text{Ä}\hat{e}_{i,t}^{*}$

i.e., $\hat{\ddot{e}}_i = \frac{1}{T}\sum_{s=1}^{K_i}\left(1-\frac{s}{k_i-1}\right)\sum_{t=s+1}^{T}\hat{\mu}_{i,t}\hat{\mu}_{i,t-s}$, $\hat{s}_i^2 \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{\mu}_{i,t}^2$, $\tilde{\text{o}}_i^2 = \hat{s}_i^2 + 2\hat{\ddot{e}}_i$, $\tilde{\text{o}}_{N,T}^2 \equiv \frac{1}{N}\sum_{i=1}^{N}\hat{L}_{11i}^{-2}\tilde{\text{o}}_i^2$,

$$\hat{s}_i^{*2} \equiv \frac{1}{T}\sum_{i=1}^{T}\hat{\mu}_{i,t}^{*2},\quad \tilde{\text{s}}_{N,T}^{*2} \equiv \frac{1}{N}\sum_{i=1}^{N}\hat{s}_i^{*2},\quad \hat{L}_{11i}^2 = \frac{1}{T}\sum_{t=1}^{T}\hat{\text{ç}}_{i,t}^2 + \frac{2}{T}\sum_{s=1}^{K_i}\left(1-\frac{s}{K_i+1}\right)\sum_{t=s+1}^{T}\hat{\text{ç}}_{i,t}\hat{\text{ç}}_{i,t-s},$$

and where the residuals $\hat{\mu}_{i,t}$, $\hat{\mu}_{i,t}^{*}$ and $\hat{\text{ç}}_{i,t}$ are obtained from the following regressions:

$$\hat{e}_{i,t} = \tilde{a}_i\hat{e}_{i,t-1} + \hat{u}_{i,t},\quad \hat{e}_{i,t} = \tilde{a}_i\hat{e}_{i,t-1} + \sum_{k=1}^{K_i}\tilde{a}_{i,k}\text{Ä}\hat{e}_{i,t-k} + \hat{u}_{i,t}^{*},\quad \text{Ä}y_{i,t} = \sum_{m=1}^{M}\hat{b}_{m1}\text{Ä}x_{mi,t} + \hat{\text{ç}}_{i,t}$$

Source: Adopted from Pedroni (1999)

The standardized distributions for the panel and group statistics are given by:

$$\frac{x_{N,T} - \mu\sqrt{N}}{\sqrt{i}} \Rightarrow N(0,1) \qquad \text{----- (7b)}$$

where $x_{N,T}$ is the appropriately standardized (with respect to the dimensions *N* and *T*) form for each of the *N*, *T* statistics as described in Box 1, and the values for μ and *v* are functions of the moments of the underlying Brownian motion functionals.

OLS estimators are consistent in case of cointegrating relationship. However, as pointed out by Dreger and Reimers (2005), the asymptotic distribution of the OLS estimator depends on nuisance parameters. Within the panel data, biases can accrued with the size of the cross section. Unbiased long run estimates can be obtained by employing efficient methods like the *fully modified* OLS (FMOLS) and *dynamic* OLS (DOLS). Potential problems arising from endogenous and serially correlated regressors can be avoided by making use of those techniques.

For the FMOLS, non-parametric techniques are applied to transform the residuals from the cointegration regression and get rid off nuisance parameters (Pedroni, 2001). For instance, in view of the model below:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it}$$

$$x_{it} = x_{it} + \varepsilon_{it}, \quad \varpi_{it} = \left(u_{it}, \varepsilon_{it}\right)' \qquad \text{----- (8a)}$$

the asymptotic distribution of the OLS depends on the long run covariance matrix of the residual process ω. The matrix is given by

$$\Omega_i = \lim_{T\to\infty}\frac{1}{T}E\left(\sum_{t=1}^{T}\varpi_{it}\right)\left(\sum_{t=1}^{T}\varpi_{it}\right)' = \Sigma_i + \Gamma_i + \Gamma_i{}' = \begin{pmatrix}\varpi_{u,i} & \varpi_{u\varepsilon,i}\\ \varpi_{u\varepsilon,i} & \varpi_{\varepsilon,i}\end{pmatrix} \qquad \text{----- (8b)}$$

for the *i*-th panel member, where

$$\sum\nolimits_i = \lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}E\left(\varpi_{it}\varpi_{it}'\right) = \begin{pmatrix}\sigma_{u,i}^2 & \sigma_{u\varepsilon,i}\\ \sigma_{u\varepsilon,i} & \sigma_{\varepsilon,i}^2\end{pmatrix} \qquad \text{----- (8c)}$$

$$\sum\nolimits_i = \lim_{T\to\infty}\frac{1}{T}\sum_{k=1}^{T-1}\sum_{t=k+1}^{T}E\left(\varpi_{it}\varpi_{it-k}'\right) = \begin{pmatrix}\gamma_{u,i} & \gamma_{u\varepsilon,i}\\ \gamma_{u\varepsilon,i} & \gamma_{\varepsilon,i}\end{pmatrix} \qquad \text{----- (8d)}$$

denote the matrices of contemporaneous correlation coefficients and the autocovariances, respectively, where the latter are weighted according to the Newey and West (1994) proposal. For convenience, the matrix

$$\theta_i = \begin{pmatrix}\theta_{u,j} & \theta_{u\varepsilon,i}\\ \theta_{\varepsilon u,j} & \theta_{\varepsilon,j}\end{pmatrix} = \Sigma_i + \Gamma_i = \sum_{j=0}^{\infty}E\left(w_{ij}w_{io}\right)' \qquad \text{----- (8e)}$$

is defined. The endogeneity correction is achieved by the transformation

$$y_{it}^* = y_{it} - \widehat{\varpi}_{u\varepsilon,i}\widehat{\varpi}_{u\varepsilon,i}^{-1}\Delta x_{it} \qquad \text{----- (8f)}$$

and the fully modified estimator is

$$\widehat{\beta}_i^* = \left(X_i'X_i\right)^{-1}\left(X_i'y_i^* - T\widehat{\theta}_{\varepsilon u}^i\right) \qquad \text{----- (8g)}$$

where $\widehat{\theta}_{\varepsilon u}^* = \widehat{\theta}_{eu} - \widehat{\theta}_e\varpi_{\varepsilon,i}^{-1}\varpi_{\varepsilon u,i}$

In the DOLS framework, the long run regression is augmented by lead and lagged difference of the explanatory variables in order to control for endogenous feedback effects (Saikkonen, 1991). Besides, lead and lagged differences of the dependent variable can be included to handle the serial correlation issue (Stock and Watson, 1993). The following equation

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{j=-p_1}^{p_2} \delta_j \Delta y_{it-j} + \sum_{j=-q_1}^{q_2} \lambda_j \Delta x_{it-j} + u_{it} \quad \text{----- (9)}$$

is run for the *i*-th panel member, where the appropriate choice of leads and lags is based on data dependent criteria (Nelson and Donggyu, 2003). Standards errors are computed using the long run variance of the cointegration residuals. Kao and Chaing (2000) show that the asymptotic laws of OLS, FMOLS and DOLS in cointegrated panel are normal. Their Monte Carlo results show that the DOLS outperforms the FMOLS estimators in term of mean biases.

3. Results

The causality test will be discussed first. The maximum lag length is set to be 10. Following Holtz-Eakin *et al* (1988), the lag length should be less than 1/3 of the total time period, or else the covariance matrix will not be correctly estimate due to over identification problem. Results of the estimations are presented in Table 1. If the null hypothesis under the Wald test is rejected there is a causation effect from the lagged regressors. But the GMM consistency depends on the Sargan test of overidentifying restrictions and absence of second order correlation in the error term. All these three conditions should be fulfilled before drawing any conclusion about the causal effects.

The Wald test for the null hypothesis that LGDP does not cause ELEC is rejected throughout. Moreover, when the lag length is equal to two the pre-requite conditions for the GMM consistency are fulfilled. As such there may to be an immediate impact of LGDP on ELEC. However, it seems the impact of ELEC on LGDP might not be instantaneously exerted. Causality conditions are achieved when the lag length is equal to nine. This result suggests a possible long-run induced effect of electricity consumption on income. This might be because African countries are lagging behind in terms of technology to assist national production. As such better infrastructural conditions and higher investment in R & D is required to boost economic growth. The relatively short lag length of LGDP on ELEC indicates higher income has more immediate impact on electricity consumption, which will in turn lead to higher demand in electricity in the long run. However, because of multicollinearity problems among the lagged variables, the causality test cannot distinguish whether LGDP has a positive or negative effect on long run electric power consumption. Further analyses are required to answer this question. As such we move on to unit and cointegration tests.

Results as shown in Table 2(a) and Table 2(b) regarding the order of integration of time series for the ADF seem to match those of the KPSS. However mixed results are obtained for the panel unit root tests as tabulated below. ELEC is I(0) as per LLC but I(1) following IPS and Hadri. This most probably demonstrates the lack of power of the LLC statistics as compared to more powerful test specifications. However, for order of integration for LGDP seems to converge for all three tests. LLC and IPS clearly shows that LGDP is I(1). For the Hadri test we can accept the null hypothesis for the first-differenced data at 5% level of significance when controlling for serial correlation. Thus, based on these tests, our series are apparently I(1).

As such we move on to apply the cointegration tests. In table 4(a), the NH test statistics are reported under both the independent and identically distributed (iid) random walk errors (NH-*t*) and the serially correlated residuals (NH a*dj-t*) assumptions. The test is calculated under two different specifications i.e. with fixed effects only while the second with fixed effects plus time trends. Under the both specifications, H_0 is rejected thus revealing the existence of cointegrating vectors. The results for Pedroni's (1997, 1999) tests are presented in Table 4(b). Pedroni (1997) examined the small sample size and properties of all these tests. In terms of power when *T* is small, the group-adf statistic usually performs best, followed by the panel-adf statistic, whereas panel variance and the group-ρ statistics do poorly. Our results tend to confirm Pedroni's (1997) presumptions. H_0 is systematically rejected when referring to the group-adf and panel-adf statistics. As maintained by both tests, cointegration between ELEC and LGDP is established. This means that there is causality relationship between the two (Engle and Granger, 1987).

With this knowledge in mind, we move on to studying the income elasticities of electric power consumption across various model specifications. As illustrated in Table 6, in general, the Hausman's (1978) specification test tends to favour the random-effects models against the fixed-effects models. The coefficients in the random effects model are assumed to constant across individuals and the variance unit-specific error term is zero. However, the Breusch and Pagan's (1980) Lagrangian multiplier test strongly rejects the null hypothesis of Var(ν) = 0. In addition, in both fixed-effects and random-effects, groupwise heteroskedasticity is detected by Greene's (1993) methodology. Next, by computing Wooldridge's (2002) serial correlation test, the null of no first-order autocorrelations in the residuals is not rejected. In case disturbances are not independent and identically distributed Prais and Winsten (1954, PW) recommend a panel-corrected standard error, which can correct for both correlated and heteroskedastic residuals. However, given the lack of evidence of serial correlation we can estimate the PW model assuming there is no first-order autocorrelation. We also conduct an error correction mechanism (ECM) as popularized by Engle and Granger (1987) by using pooled data.

As shown in Table 5, the YEEPC seems to vary across models. In the PW models, the YEEPC is less than one meaning a rather income inelastic demand for electric power prevails in Africa. The above results seem to match those of the error correction mechanism[4] (ECM). The significance of the error term reinforces our knowledge about the cointegrated relationship among the variables. Following Westerlund (2005), if the null hypothesis of no error correction is rejected, then the null hypothesis of no cointegration is also rejected. The small value signifies a moderate convergence speed towards long run equilibrium prior to an exogenous shock. The short run elasticity of the ECM is 0.39 as tabulated below.

The two-way causality as shown in Table 1 may create endogeneity and heterogeneity problems which yield inconsistent estimates when using OLS to estimate the YEEPC. As discussed above, to overcome such problems, efficient methods such as the FMOLS and

[4] See Appendix 1 for derivation.

DOLS are required. These methods will allow us to compute long run asymptotic unbiased estimates of the YEEPC. Table 6 reports Pedroni's FMOLS and DOLS estimates of the long run relationship between ELEC and LGDP. These estimates exclude common time dummies given the lack of evidence that residuals are correlated across countries. The FMOLS and DOLS group estimates are quite close to each other and confirm a long run relationship between ELEC and GDP given the high significance of β. These also confirm our a-priori expectation about the sign of the coefficient which is positive and below unity. Electric power consumption is inelastic and considered as a necessity in the long run. As shown in Table 6, a considerable degree of heterogeneity appears to prevail in Africa even in the long run. For instance, when considering the least biased estimator i.e. the DOLS estimates, the YEEPC ranges from -1.90 (Egypt) to 3.70 (Benin). In addition, with a few exceptions (Gabon, Nigeria, Senegal, South Africa, Zimbabwe), the YEEPC is significantly less than zero, indicating evidence against the ordinary electric power consumption-income relationship.

Finally, the YEEPC is modelled in relation to business cycles at an international level. The measure of business cycle indicator is obtained as a cyclical component of the Hodrick-Precott decomposition[5] of natural logarithm of GDP of the individual countries. A YEEPC series is constructed by running cross-sectional regressions over the period 1971-2002. Expect for the year 1972, all income elasticities were found to statistically significant at conventional levels with their p-values which average around 0.02.

[5] The smoothing parameter $\lambda = 100$ as per the frequency power rule of Ravn and Uhlig (2002) i.e. the number of periods per year divided by, raised to a power (which equals 2 following Hodrick and Prescott, 1997) and multiplied by 1600.

To evaluate the effects of our cluster-level dependent income elasticity variable, the use of the population-averaged generalized estimating equations (GEE) approach as pioneered by Liang and Zeger (1986), is arguably most appropriate. The GEE makes efficient and appropriate use of the available data and neither sacrifices power by collapsing observations over clusters nor overstates the amount of observations over the amount of information contained in the data by ignoring dependencies among the observations. It yields inferences for both individual- and cluster-level covariates that are adjusted for intra-cluster as well as intra-individual correlation, in a manner that is consistent with the way the study was designed. Put more plainly, the GEE allows the number of repeat observations to vary among individual countries without affecting the interpretation of the coefficients.

The estimates of the GEE are presented in Table 7. We make use of an unstructured intra-individual correlation matrix *R*, which imposes no restrictions on the pairwise correlations. This is recommended by Liang and Zeger (1986) when the number of repeated observations per individual is not large, which is the case in our study. A positive relationship between YEEPC and the cyclical component is found. This implies a pro-cyclical pattern of electric power consumption where low levels of YEEPC are associated with recession periods (i.e. electricity consumption is a necessity in periods of recession) while high levels of income elasticities are associated with expansion periods (i.e. electricity consumption becomes a luxury good in boom periods).

4. Conclusion

In this paper we have examined the non-stationarity and cointegration issues related to electric power consumption and income for 16 African countries. Bi-directional causality exists between ELEC and LGDP. Moreover both variables are found to be I(1) and cointegrated. Panel FMOLS and DOLS long run estimates are positive and below unity. Moreover, income elasticity of electric power consumption is found to be pro-cyclical. Electricity consumption is a necessity in recession periods and luxury in boom periods. Electricity demand studies have practical applications. The estimation of consistent and stable income elasticity estimates can be of vital information for the African government planners and private investors in regards to any privatization program for electric utility sector. Greater access to electricity is bound to reduce the reliance on biomass which will in turn lead to a decline in environmental degradation and sustain economic growth.

5. Reference

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Table 1: Panel Causality Tests on ELEC and LGDP

	ELEC										LGDP									
ELEC(-1)	0.761	0.498	0.542	0.548	0.525	0.542	0.539	0.542	0.586	0.568	0.965	1.215	1.254	1.264	1.254	1.223	1.276	1.217	1.240	1.218
	(0.027)*	(0.040)*	(0.048)*	(0.049)*	(0.049)*	(0.052)*	(0.052)*	(0.051)*	(0.055)*	(0.056)*	(0.017)*	(0.044)*	(0.048)*	(0.047)*	(0.049)*	(0.047)*	(0.051)*	(0.050)*	(0.054)*	(0.054)*
ELEC(-2)		0.266	0.187	0.160	0.186	0.174	0.176	0.173	0.142	0.166		-0.277	-0.318	-0.366	-0.357	-0.400	-0.429	-0.283	-0.304	-0.258
		(0.037)*	(0.046)*	(0.055)*	(0.055)*	(0.057)*	(0.059)*	(0.058)*	(0.061)**	(0.064)*		(0.044)*	(0.070)*	(0.072)*	(0.074)*	(0.072)*	(0.077)*	(0.078)*	(0.082)*	(0.084)*
ELEC(-3)			0.065	0.035	-0.069	-0.079	-0.080	-0.092	-0.097	-0.113			0.005	0.023	(0.045)	0.133	0.158	0.088	0.050	0.064
			(0.040)	(0.048)	(0.055)	(0.058)	(0.059)	(0.058)	(0.061)	(0.062)‡			(0.046)	(0.069)	(0.073)	(0.070)‡	(0.077)**	(0.075)	(0.081)	(0.082)
ELEC(-4)				0.031	-0.019	0.017	0.017	0.025	0.028	0.011				0.005	-0.046	-0.114	-0.172	-0.155	-0.130	-0.218
				(0.041)	(0.049)	(0.058)	(0.060)	(0.059)	(0.063)	(0.064)				(0.045)	(0.069)	(0.068)‡	(0.073)**	(0.072)**	(0.077)‡	(0.080)*
ELEC(-5)					0.125	0.104	0.100	0.092	0.083	0.088					0.038	0.116	0.143	0.102	0.078	0.146
					(0.042)*	(0.052)**	(0.060)‡	(0.060)	(0.063)	(0.064)					(0.044)	(0.063)‡	(0.070)**	(0.069)	(0.074)	(0.075)‡
ELEC(-6)						-0.009	-0.009	-0.048	-0.040	-0.048						-0.060	-0.010	-0.017	0.008	-0.045
						(0.044)	(0.053)	(0.059)	(0.063)	(0.063)						(0.041)	(0.066)	(0.066)	(0.071)	(0.073)
ELEC(-7)							0.001	0.029	0.023	0.018							-0.056	0.037	-0.003	0.025
							(0.045)	(0.052)	(0.060)	(0.063)							(0.042)	(0.062)	(0.067)	(0.069)
ELEC(-8)								0.007	0.008	0.008								-0.074	-0.003	-0.023
								(0.044)	(0.054)	(0.062)								(0.040)‡	(0.063)	(0.066)
ELEC(-9)									-0.003	-0.05									-0.050	0.013
									(0.046)	(0.054)									(0.041)	(0.062)
ELEC(-10)										0.058										-0.060
										(0.046)										(0.041)
LGDP(-1)	0.293	0.285	0.260	0.298	0.344	0.349	0.344	0.378	0.337	0.363	-0.017	0.0004	-0.004	0.012	0.012	0.036	0.027	0.019	0.035	0.047
	(0.060)*	(0.050)*	(0.054)*	(0.057)*	(0.062)*	(0.069)*	(0.076)*	(0.082)*	(0.094)*	(0.106)*	(0.007)**	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)*	(0.012)**	(0.013)	(0.014)**	(0.015)*
LGDP(-2)		0.005	0.105	-0.145	0.013	-0.311	-0.260	-0.270	-0.043	-0.138		.0165	-0.026	0.031	-0.0001	-0.046	-0.036	-0.007	-0.050	-0.136
		(0.124)	(0.172)	(0.219)	(0.263)*	(0.324)	(0.382)	(0.433)	(0.527)	(0.613)		(0.014)	(0.025)	(0.033)	(0.040)	(0.043)	(0.051)	(0.054)	(0.062)	(0.068)**
LGDP(-3)			-0.118	0.303	0.111	1.053	1.114	1.107	0.262	1.029			0.027	-0.102	-0.019	0.051	0.063	0.060	0.045	0.372
			(0.132)	(0.284)	(0.472)	(0.723)	(1.028)	(1.372)	(1.900)	(2.468)			(0.015)‡	(0.038)*	(0.068)	(0.100)	(0.143)	(0.181)	(0.235)	(0.286)
LGDP(-4)				-0.234	-0.003	-1.376	-1.592	-2.164	-0.312	-2.874				0.048	-0.031	-0.082	-0.122	-0.179	0.009	-0.752
				(0.134)‡	(0.401)	(0.878)	(1.593)	(2.579)	(4.186)	(6.219)				(0.014)*	(0.051)	(0.110)	(0.216)	(0.339)	(0.528)	(0.745)
LGDP(-5)					-0.058	0.892	1.169	2.121	-0.627	4.044					0.027	0.052	0.094	0.168	-0.176	0.987
					(0.132)	(0.540)‡	(1.419)	(2.971)	(5.879)	(10.272)					(0.015)‡	(0.061)	(0.180)	(0.373)	(0.723)	(1.220)
LGDP(-6)						-0.247	-0.417	-1.197	1.353	-4.213						-0.009	-0.023	-0.059	0.265	-0.931
						(0.136) ‡	(0.679)	(2.070)	(5.329)	(11.413)						(0.014)	(0.078)	(0.243)	(0.624)	(1.313)
LGDP(-7)							0.040	0.376	-1.092	3.376							0.001	0.002	-0.170	0.653
							(0.137)	(0.805)	(3.033)	(8.500)							(0.014)	(0.087)	(0.334)	(0.933)
LGDP(-8)								-0.064	0.418	-1.906								0.003	0.050	-0.317
								(0.136)	(0.990)	(4.084)								(0.013)	(0.101)	(0.424)
LGDP(-9)									-0.070	0.639									-0.005	0.091
									(0.143)	(1.149)									(0.013)	(0.112)
LGDP(-10)										-0.096										-0.011
										(0.145)										(0.013)
No. Observations	480	464	448	432	416	400	384	368	352	336	480	464	448	432	416	400	384	368	352	336
Sargan Test	1.000	0.756	0.967	0.989	0.992	0.999	0.997	0.990	1.000	0.999	0.219	1.000	1.000	1.000	1.000	0.998	1.000	0.997	1.000	1.000
AR(1)	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
AR(2)	0.039**	0.483	0.018**	0.010*	0.988	0.388	0.794	0.488	0.035**	0.310	0.027**	0.502	0.141	0.001*	0.031**	0.019**	0.006*	0.345	0.126	0.211
Wald Tests:																				
χ^2 -test, LGDP lags	23.76 [0.000]*	36.40 [0.000]*	32.23 [0.000]*	35.18 [0.000]*	44.12 [0.000]*	33.60 [0.000]*	29.76 [0.000]*	33.39 [0.000]*	30.69 [0.000]*	31.70 [0.000]*										
χ^2 -test, ELEC lags											5.47 [0.019]**	1.50 [0.473]	4.06 [0.222]	14.95 [0.005]*	24.43 [0.000]*	19.48 [0.000]*	12.22 [0.094]‡	9.99 [0.2658]	14.88 [0.094]‡	19.70 [0.032]**

Source: Computed. The p-value for the Sargan test, AR(1) and AR(2) serial correlation tests are shown. *, ** and ‡ denote 1%, 5% and 10% significance level respectively. The standard errors are given in parentheses while the p-values are in square brackets.

Table 2(a): Individual ADF statistics

Country	ELEC								LGDP							
	Level Form				First Difference				Level Form				First Difference			
	With Constant and Without Trend		With Constant and With Trend		With Constant and Without Trend		With Constant and With Trend		With Constant and Without Trend		With Constant and With Trend		With Constant and Without Trend		With Constant and With Trend	
	ADF	ρ	ADF	ρ	ADF	ρ	ADF	ρ	ADF	ρ	ADF	ρ	ADF	ρ	ADF	ρ
Algeria	-1.885	0	-0.876	0	-3.508**	0	-3.697**	2	-2.070	1	-.1573	3	-6.637*	0	-4.384	2
Benin	-2.020	2	-4.084*	0	-5.264*	1	$-5.382^{\ddagger}$	1	-2.001	0	-2.226	1	-3.903*	0	-3.506	1
Cameroon	-1.432	0	-2.139	1	-3.434**	0	$-3.409^{\ddagger}$	0	-1.721	3	-1.583	2	0.192	3	-0.790	3
Congo, Dem.	-0.525	0	-1.442	0	-4.658*	0	-5.057*	0	0.180	1	-3.020	3	-4.658*	0	-5.057	0
Congo, Rep.	-0.517	1	-1.687	3	-2.321	3	-11.606*	0	-1.778	1	-2.283	1	-2.127	0	-2.161	0
Egypt	-0.692	0	-1.546	0	-4.298*	0	-4.723*	1	-1.113	0	-.5397	0	-2.457	0	-5.985	3
Gabon	-2.624	3	-0.336	2	-0.999	2	-4.021*	3	-2.552	1	-3.274	1	-3.089**	0	-3.107	0
Ghana	-2.753	1	-3.119	1	-3.998*	1	-3.898**	1	-1.886	0	-.8371	0	-3.330**	0	-3.571	0
Kenya	-1.698	0	-2.553	0	-4.876*	0	-4.940*	0	-1.686	3	-2.397	3	-3.780*	2	-3.699	2
Nigeria	-2.067	2	-1.952	0	-5.269*	1	-5.775*	1	$-2.855^{\ddagger}$	3	-2.333	3	-1.4780	3	-1.370	3
Senegal	-2.291	0	-1.626	0	-4.841*	0	-4.635*	1	$-2.886^{\ddagger}$	0	-4.088**	1	-5.776*	1	-5.547	1
South Africa	-4.550*	0	-1.360	0	-2.444	0	-3.622**	0	-1.565	0	-1.953	0	-3.638**	0	-3.921	0
Sudan	-1.929	0	-3.041	2	-3.614**	0	-3.605**	0	-3.862*	2	-3.882**	2	-4.422*	2	-4.361	2
Tunisia	-1.815	0	-1.616	0	-2.011	3	-3.647**	2	-3.030*	0	$-3.257^{\ddagger}$	0	-7.390*	0	-7.812	0
Zambia	0.721	0	-2.242	0	-4.191*	0	-5.065*	0	-.0133	0	-3.641**	0	-6.371*	0	-6.1260	0
Zimbabwe	-1.647	1	-2.138	1	-2.576	1	$-3.285^{\ddagger}$	1	-3.218*	2	-2.742	1	-3.555**	2	-4.071	2

Source: Computed. Note: To select the order of lag ρ, we start with a maximum lag length of 3 and pare it down as per the Akaike Information Criterion. There is no general rule on how to choose the maximum lag to start with. Researchers usually employ a rule of thumb which is the cube root of the number of observation (Al Mamun and Nath, 2005). Hence, $\sqrt[3]{32} \approx 3.174$. Critical values for the individual ADF tests are computed by means of the Cheung and Lai (1995) response surface equation. The critical values for the ADF test at level form are given as follows: For lag 0, 1, 2 and 3 the critical values for ADF unit root tests which include only a constant are -3.676, -3.660, -3.650 and -3.645; -2.972, -2.953, -2.935 and -2.919; and -2.627, -2.607, -2.588 and -2.569 at 1%, 5% and 10% significance level respectively. For lag 0, 1, 2 and 3 the critical values of the ADF unit root tests which include a constant and a trend are -4.323, -4.298, -4.282 and -4.277; -3.586, -3.561, -3.537 and -3.517; and -3.235, -3.209, -3.183, -3.158 at 1%, 5% and 10% significance level respectively. In addition, the critical values for first-differenced variables are as follows: The critical values for the ADF test at level form are given as follows: For lag 0, 1, 2 and 3 the critical values for ADF unit root tests which include only a constant are -3.687, -3.672, -3.662 and -3.660; -2.977, -2.958, -2.939 and -2.925; and -2.629, -2.609, -2.590 and -2.571. For lag 0, 1, 2 and 3 the critical values of the ADF unit root tests which include a constant and a trend are -4.340, -4.317, -4.300 and -4.297; -3.594, -3.569, -3.545 and -3.524; -3.239, -3.213, -3.189 and -3.164 at 1%, 5% and 10% significance level respectively.

Table 2(b): Individual KPSS η-statistics

Country	ELEC								LGDP							
	Level Form				First Difference				Level Form				First Difference			
	η_m	ρ	η_t	ρ	η_m	ρ	η_t	ρ	η_m	ρ	η_t	ρ	η_m	ρ	η_t	ρ
Algeria	1.220*	2	0.310*	2	0.647*	2	0.080	2	0.322	2	0.257*	2	0.539**	2	0.226*	2
Benin	1.660*	2	$0.133^{\ddagger}$	2	0.142	2	0.111	2	0.675**	2	0.136**	2	0.158	2	0.082	2
Cameroon	0.331	2	0.249*	2	0.213	2	0.050	2	0.268	2	0.264*	2	0.330	2	$0.151^{\ddagger}$	2
Congo, Dem.	1.140*	2	0.176**	2	0.080	2	0.069	2	1.200*	2	0.257*	2	0.267	2	0.086	2
Congo, Rep.	0.481**	2	0.250*	2	0.213	2	0.105	2	0.342	2	0.262*	2	0.262	2	0.068	2
Egypt	1.240*	2	0.296*	2	0.263	2	0.090	2	1.220*	2	0.266*	2	0.222	2	0.074	2
Gabon	0.750*	2	0.281*	2	0.283	2	0.086	2	$0.356^{\ddagger}$	2	0.080	2	0.145	2	0.086	2
Ghana	0.173	2	0.104	2	0.040	2	0.039	2	$0.353^{\ddagger}$	2	0.305*	2	0.548**	2	0.049	2
Kenya	1.180*	2	0.240*	2	$0.387^{\ddagger}$	2	0.041	2	0.743*	2	0.224*	2	0.354	2	0.049	2
Nigeria	0.852*	2	0.296*	2	$0.510^{\ddagger}$	2	0.047	2	0.604**	2	0.198**	2	0.092	5	0.076	5
Senegal	1.140*	2	$0.158^{\ddagger}$	2	0.158	2	$0.154^{\ddagger}$	2	0.255	2	0.178**	2	0.150	2	0.049	2
South Africa	1.090*	2	0.294*	2	0.680**	2	$0.124^{\ddagger}$	2	0.860*	2	$0.134^{\ddagger}$	2	0.080	2	0.075	2
Sudan	1.080*	2	0.061	2	0.075	1	0.074	1	0.760*	1	0.179**	1	0.119	2	0.054	2
Tunisia	1.260*	2	0.275*	2	$0.392^{\ddagger}$	2	0.090	4	1.240*	4	$0.156^{\ddagger}$	4	0.259	2	0.195**	2
Zambia	1.210*	2	0.233*	2	0.262	1	0.112	2	1.240*	2	$0.144^{\ddagger}$	2	0.155	2	$0.119^{\ddagger}$	2
Zimbabwe	0.308	2	$0.129^{\ddagger}$	2	0.300	3	$0.142^{\ddagger}$	2	0.115	2	0.073	2	0.103	2	0.074	2

Source: Computed. Note: η_m and η_t are the level and trend stationarity cases respectively. The 1%, 5% and 10% critical values are 0.739, 0.463 and 0.347 for level stationarity and 0.216, 0.176 and 0.119 for tend stationarity correspondingly. Theses critical values are given by Kwiatkowski *et al* (1992). The order of lag ρ is determined by the automatic bandwidth selection procedure as proposed by Newey and West (1994). The test's denominator is computed by employing the Quadratic Spectral kernel function.

Table 3(a): LLC Panel Unit Root Test statistics

Variable	Deterministics	Level Form		First Difference	
		t-value	*t**	*t*-value	*t**
ELEC	Constant	-4.174	-2.020 [0.022]**	-21.303	-13.789 [0.000]*
	Constant + Trend	-10.614	-4.355 [0.000]*	-25.086	-14.147 [0.000]*
LGDP	Constant	-4.216	-1.163 [0.122]	-18.194	-12.321 [0.000]*
	Constant + Trend	-8.908	-1.862 [0.031]**	-18.822	-9.077 [0.000]*

Source: Computed. Note: The LLC test can be viewed as a pooled Dickey-Fuller test, or an Augmented Dickey-Fuller (ADF) test when lags are included, with the null hypothesis that of non-stationarity (I(1) behavior). The lag lengths for the panel test are based on those employed in the univariate ADF test. These statistics are distributed as standard normal as both N and T grow large. Assuming no cross-country correlation and T is the same for all country, the normalized t^* test statistic is computed by using the *t*-value statistics. After transformation by factors provided by LLC, the t^* tests is distributed standard normal under the null hypothesis of non-stationarity. Hence, it is compared the 1%, 5% and 10% significance levels with critical values of -2.326, -1.645 and -1.282 correspondingly. The p-values are in square brackets.

Table 3(b): IPS Panel Unit Root Test statistics

Variable	Data	Deterministics	Level Form		First Difference	
			t-bar	Ψ_t	*t*-bar	Ψ_t
ELEC	Raw	Constant	-2.173*	-2.972 [0.001]*	-4.628*	-13.991 [0.000]*
		Constant + Trend	-2.546**	-1.866 [0.031]**	-5.323*	-15.344 [0.000]*
	Demeaned	Constant	-1.586	-0.328 [0.371]	-5.355*	-17.257 [0.000]*
		Constant + Trend	-2.704*	-2.636 [0.001]*	-5.999*	-18.629 [0.000]*
LGDP	Raw	Constant	-1.915**	-1.825 [0.034]**	-4.449*	-13.203 [0.000]*
		Constant + Trend	-2.231	-0.370 [0.356]	-4.186*	-9.835 [0.000]*
	Demeaned	Constant	-1.728	-0.987 [0.164]	-4.445*	-13.182 [0.000]*
		Constant + Trend	-2.253	-0.476 [0.317]	-4.563*	-11.657 [0.000]*

Source: Computed. Note: The IPS test statistics are computed as the average ADF statistics across the sample. The lag lengths for the panel test are based on those employed in the univariate ADF test. These statistics are distributed as standard normal as both N and T grow large. *t*-bar is the panel test based on the ADF statistics. Critical values for the *t*-bar statistics without trend at 1%, 5% and 10% significance levels are -1.980, -1.850 and -1.780 while with inclusion of a time trend, the critical values are-2.590, -2.480 and -2.410 respectively. Assuming no cross-country correlation and T is the same for all country, the normalized Ψ_t test statistic is computed by using the *t*-bar statistics. The Ψ_t- tests for H_0 of joint non-stationarity and is compared to the 1%, 5% and 10% significance levels with critical values of -2.326, -1.645 and -1.282 correspondingly.

Table 3(c): Hadri Panel Unit Root Test Statistics

Variables	Level Form						First Difference					
	Homoskedastic Disturbances		Heteroskedastic Disturbances		Controlling for Serial Dependence in Errors		Homoskedastic Disturbances		Heteroskedastic Disturbances		Controlling for Serial Dependence in Errors	
	Z_μ	Z_t	Z_μ	Z_t	Z_μ	Z_t	Z_μ	Z_t	Z_μ	Z_t	Z_μ	Z_t
ELEC	57.007 [0.000]*	35.528 [0.000]*	50.847 [0.000]*	34.889 [0.000]*	20.371 [0.000]*	14.194 [0.000]*	-1.856 [0.968]	-3.129 [0.991]	3.268 [0.001]*	-0.390 [0.6519]	0.029 [0.488]	-0.008 [0.503]
LGDP	56.655 [0.000]*	39.226 [0.000]*	35.682 [0.000]*	31.982 [0.000]*	19.159 [0.000]*	13.339 [0.000]*	3.487 [0.000]*	4.225 [0.000]*	3.894 [0.000]*	3.807 [0.000]*	1.544 [0.061]‡	2.478 [0.007]*

Source: Computed. Note: Z_μ and Z_t denote the statistics without and with a deterministic trend respectively.

Table 4(a): Nyblom-Harvey Panel Cointegration Test Statistics

	Statistics	LELEC	LGDP
Fixed Effects	NH-*t*	8.6390*	9.3623*
	NH adj-*t*	20.3294*	18.6796*
	Critical Values 10%	2.2819<CV<4.1794	2.2819<CV<4.1794
	Critical Values 5%	2.5332<CV<4.4957	2.5332<CV<4.4957
	Critical Values 1%	3.1387<CV<5.1142	3.1387<CV<5.1142
Fixed Effects and Time Trends	NH-*t*	8.6200*	9.3518*
	NH adj-*t*	22.3523*	23.4827*
	Critical Values 10%	0.837<CV<1.5798	0.837<CV<1.5798
	Critical Values 5%	0.9001<CV<1.6650	0.9001<CV<1.6650
	Critical Values 1%	1.0348<CV<1.8425	1.0348<CV<1.8425

Source: Computed. Note: The H_0 of the test is no cointegration (H_0: rank(var-cov)=K=0) against the alternative hypothesis of cointegration (H_1: rank(var-cov)=K≠0). H_0: 0 common trends among the 16 series in the panel. NH-*t*: the test is performed under the hypothesis of iid errors. NH *adj-t*: errors are allowed to be serially correlated and the test is performed using an estimate of the long-run variance derived from the spectral density matrix at frequency zero. The critical values (CV) pertain to *N* equals to 10 and 20 respectively.

Table 4(b): Pedroni Panel Cointegration Test statistics

	Statistics	Without Trend	With Trend
Without Trend	Panel ν-statistic	-0.512	1.207
	Panel ρ-statistic	-0.712	-2.029*
	Panel pp-statistic	-1.737**	-3.835*
	Panel adf-statistic	-1.755**	-3.145*
	Group ρ-statistic	-0.951	-0.217
	Group pp-statistic	-2.681*	-2.873*
	Group adf-statistic	-2.909*	-2.526*

Source: Computed. Note: The *panel* statistics are the within-dimension statistics while *group* statistics are between-dimension ones. Panel-ν, panel-ρ, and panel-pp represent the non-parametric variance ratio, Phillips-Perron ρ, and student's *t*-statistics respectively while panel-adf is a parametric statistic based on ADF statistic. Group-ρ, group-pp and group-adf represent Phillips-Perron ρ-statistic, Phillips-Perron t-statistic and the ADF-statistic correspondingly. The number of lag truncation is equalled to 2. These are one-sided standard normal test with critical values of 1%, 5% and 10% given by -2.326, -1.645 and -1.282. A special case is the panel ν-statistic which diverges to positive infinity under the alternative hypothesis. As such, rejection of the H_0 of no cointegration requires values larger than 2.326, 1.645 and 1.282 at 1%, 5% and 10% significance level. The critical values for the mean and variance of each statistic are obtained from Pedroni (1999).

Table 5: Regression Results

Variables	Pooled OLS	Between-Effects	Fixed-Effects	Random-Effects	Prais-Winsten	ECM
$LGDP_{it}$	0.89	0.88	1.18	1.16	0.89	-
	(0.05)*	(0.28)*	(0.08)*	(0.07)*	(0.03)*	-
$\Delta LGDPPC_{it}$	-	-	-	-	-	0.39
	-	-	-	-	-	(0.19)**
ε_{it-1}	-	-	-	-	-	-0.03
	-	-	-	-	-	(0.01)**
Constant	-0.36	-0.28	-2.25	-2.12	-0.36	-
	(0.31)	(1.84)	(0.49)*	(0.53)*	(0.14)*	-
R^2	0.40	0.41	0.33	0.40	0.41	0.05
Observations	512	512	512	512	512	496
Countries	16	16	16	16	16	16
Period	1971-2002	1971-2002	1971-2002	1971-2002	1971-2002	1972-2002

Source: Computed. Note: The standard errors are given in parentheses. Excluding the Prais-Winsten model, all of these are robust ones. R^2 is the within-R^2 for fixed effects (FE) and overall-R^2 for random-effects (RE).

Table 6: Diagnostic Tests

Tests	ELEC Model
Hausman specification test	$\chi^2(1)$ = 1.10 [0.2947]
Breush-Pagan Lagrangian multiplier test (RE)	$\chi^2(1)$ = 6260.70 [0.000]*
Green groupwise heteroskedasticity test (FE)	$\chi^2(511)$ =798.28 [0.000]*
Green groupwise heteroskedasticity test (RE)	$\chi^2(420)$ = 1101.84 [0.000]*
Wooldridge first-order autocorrelation test	F(1,27) = 2.933 [0.1074]

Source: Computed. Note: According to the Hausman specification test, H_0: difference in coefficients not systematic. The FE model is defined as $\boldsymbol{y}_{it} = \alpha_i + \gamma_t + \beta\boldsymbol{x}_{it} + v_i + \varepsilon_{it}$. The constant term α_i varies over individual countries but not with time. α_i can be treated as an additional random error. The RE model can be defined as $\boldsymbol{y}_{it} = \alpha + \beta\boldsymbol{x}_{it} + v_i + \varepsilon_{it}$. v_i is the unit-specific residual. The coefficients are assumed to be constant across individuals and the variance unit-specific error term is zero. The H_0 of Var(v) = 0 is tested by the Breusch and Pagan Lagrangian multiplier. As derived by Green groupwise heteroskedasticity test, H_0: homoskedasticity, while for under Wooldridge's test, H_0: no first-order autocorrelation.

Table 6: Individual and Panel FMOLS and DOLS Estimators

Country	FMOLS		DOLS	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Algeria	-0.93	-0.45	0.26	0.20
Benin	2.48	1.97**	3.70	3.73*
Cameroon	0.47	4.05*	0.49	5.60*
Congo, Dem	0.99	10.12*	1.03	14.33*
Congo, Rep.	0.97	1.81**	1.52	4.56*
Egypt	1.70	37.59*	1.73	45.46*
Gabon	0.05	0.05	-1.90	-4.64*
Ghana	1.87	3.65*	1.72	3.31*
Kenya	1.56	2.34*	3.07	7.28*
Nigeria	-1.51	-2.91*	-1.82	-4.67*
Senegal	-0.36	-0.40	-1.09	-1.50‡
South Africa	-0.91	-1.63‡	-1.46	-3.88*
Sudan	1.02	2.67*	1.34	3.39*
Tunisia	2.44	11.49*	2.62	19.04*
Zambia	1.12	8.41*	1.17	13.53*
Zimbabwe	0.19	0.70	-0.15	-0.36
Panel	0.70	19.87*	0.76	26.35*

Source: Computed. Note: For the panel DOLS, maximum lag and lead length are set to 1. Nelson and Donggyu (2003) recommend a lag and lead length of 1 in case *T* is around 30. For the FMOLS, the selection of bandwidth for kernels is automatically computed.

Table 7: Relationship of YEEPC with Business Cycle

Variable	Semi-Robust Estimations
Cyclical component of natural logarithm of GDP	0.0123966 (0.0072002)‡
Constant	0.8960711 (0.0000856)*
Wald $\chi^2(1)$	2.96 [0.0851]‡
Overall observations	512
Number of groups	16
Observations per group	32

Source: Computed.

Appendix 1: Derivation of the First-Order Panel ECM model

Consider the equation below:

$$ELEC_{it} = \beta_0 + \beta_1 LGDP_{it} + \varepsilon_{it} \qquad \text{----- (1)}$$

To derive the long run equilibrium dynamics we re-write equation (1) as follows, while assuming $ELEC_{it}$ and $LGDP_{it}$ are non-stationary, integrated of the same order and ε_{it} is white-noise:

$$ELEC_{it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LGDP_{it-1} + \beta_3 ELEC_{it-1} + \varepsilon_{it}$$

Subtracting $ELEC_{it-1}$ on both sides:

$$ELEC_{it} - ELEC_{it-1} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LGDP_{it-1} + \beta_3 ELEC_{it-1} - ELEC_{it-1} + \varepsilon_{it}$$

$$\Delta ELEC_{it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LGDP_{it-1} + (\beta_3 - 1)ELEC_{it-1} + \varepsilon_{it}$$

Repametrizing the above equation:

$$\Delta ELEC_{it} = \beta_0 + \beta_1 LGDP_{it} - \beta_1 LGDP_{it-1} + \beta_1 LGDP_{it-1} + \beta_2 LGDP_{it-1} + (\beta_3 - 1)ELEC_{it-1} + \varepsilon_{it}$$

$$\Delta ELEC_{it} = \beta_0 + \beta_1 \Delta LGDP_{it} + (\beta_1 + \beta_2)LGDP_{it-1} + (\beta_3 - 1)ELEC_{it-1} + \varepsilon_{it}$$

$$\Delta ELEC_{it} = \beta_1 \Delta LGDP_t + (\beta_1 + \beta_2)LGDP_{it-1} + \beta_0 + (\beta_3 - 1)ELEC_{it-1} + \varepsilon_{it}$$

$$\Delta ELEC_{it} = \beta_1 \Delta LGDP_{it} - (1 - \beta_3)\left[ELEC_{it-1} - \frac{\beta_0}{1 - \beta_3} - \frac{\beta_1 + \beta_2}{1 - \beta_3} LGDP_{it-1} \right] + \varepsilon_{it}$$

$$\Delta ELEC_{it} = \beta_1 \Delta LGDP_{it} - \lambda\left[ELEC_{it-1} - \lambda_0 - \lambda_1 LGDP_{it-1} \right] + \varepsilon_{it}$$

$$\therefore\ \Delta ELEC_{it} = \beta_1 \Delta LGDP_{it} - \lambda \varepsilon_{it,-1} + \varepsilon_{it},$$

The disequilibrium error $\varepsilon_{it,-1} = ELEC_{it-1} - \lambda_0 - \lambda_1 LGDP_{it-1}$ and is assumed to be I(0). λ measures the speed of adjustment towards the long run equilibrium.