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The Statistical Relationship between Economic Growth and Total Energy Use: Evidence from Panel Co-integration and Granger-causality Investigation of SSA Countries

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ABSTRACT

This study analyses the statistical relationship between economic growth and total energy use in 15 Sub Saharan Africa (SAA) member countries in the period between 1989 and 2017. The panel unit root test, panel co-integration test, vector error correction and vector auto regressive Granger Causality/Block Exogeneity Wald Tests are employed. The results are that economic growth in SAA is linked to total energy and total energy is linked to economic growth. The growth in available energy forecasts economic growth which, in turn, forecasts the use of energy in SAA. The bidirectional relationship is further explored for SSA sample countries. The results suggest that economic growth in SSA can be supported by promoting growth in productivity of the energy industries.

Keywords: Panel Vector, Error Correction Model, Economic Growth, Energy Use, Granger Causality
JEL Classifications: Q43, Q53, Q56

1. INTRODUCTION

In recent years, African countries have achieved strong economic growth despite many challenges (Resolution, 2021). Rapid growth is logically linked with energy contribution, as evidenced by findings from empirical. The use of energy can foster economic opportunities, reduce travel cost, stimulate technology and facilitate the industrial sector, resulting in modernization of the country's economy (Bildirici and Ersin, 2015) and (Bildirici and Özaksoy, 2016). Even so, if we compare the consumption of energy on the continent with other regions the rate is still low. The sub-Saharan Africa region with more than 950 million people is the most electricity-poor region in the world. More than 600 million households have no access to electricity as key for development of economy and other millions are connected to an unreliable grid that prohibit them to meet their daily energy service needs.

Despite a great number of studies, there is no consensus about the nature or direction of the causality between energy consumption and economic growth. This may be due to the structural characteristics of the sampled countries, to their stage of development, econometric methods applied as well as the time frame analyzed. Outcome from various researchers submit different outcomes. This includes the work done Mehrara and Rafiei (2014) and Arbex and Perobelli (2010), have shown that the use of energy stimulates high growth rate, and similarly growth leads to an increase in consumption of energy. Other studies were carried out by the pioneers of energy consumption and economic growth such for a period of three decades (1947-1974) and submit that there is a directional causality between GDP and energy use. The work done by (Paul and Bhattacharya, 2004) posted that there is a bidirectional causality between GDP and energy use. Furthermore, Liu (2020) and (Jebli et al., 2016), find a neutrality effect between economic growth and renewable energy consumption by using a granger causality method for the work done in 11 African countries between 1980-2008 periods. While the researchers like Zhang and Cheng (2009), Menyah and Wolde-Rufael (2006) and Mehrara and Rafiei (2014) show that there is unidirectional causality runs from economic growth to energy use. The study in Brazil for the period between 1980 to 2008 by Pao et al. (2014) uses the co-integration test to show long run equilibrium between energy consumption and economic growth in Brazil. The research done Nondo et al. (2012) about the co integration and causality between electricity consumption and GDP in Malawi from the period between 1974 to 2011 demonstrate that there is a bidirectional causal relationship between energy use and GDP in the long run period. Similar findings also were obtained in Tunisia Saidi and Hammami (2014) in Taiwan. But, the research done in China by Cheng and Liu (2019) and Mozambique by Gafur and Mahomed (2018) revels that energy of China tends to be stationary and co-integrated with GDP. Also Oh and Lee (2004) in Korea between 1960 and 2005, using VEC and improved VEC both show the long run unidirectional causality from energy consumption to economic growth. Likewise, the study done by El-aasar and Hanafy (2019) for South America using a panel error correction model, a panel co-integration analysis and a vector error correction model reveals a long-run equilibrium link between real GDP, energy consumption, labor, and real gross fixed capital formation. Kalimeris et al. (2014) and Marinaş et al. (2018) also reach similar conclusions.

Other studies have highlighted the existence of four different hypotheses in different literature through various tests Ozturk et al. (2010). This shows that there is a feedback link between two parameters and this include the work obtained in South Africa by Kouakou (2011) for Malawi, Côte d'Ivoire and Burkina Faso, respectively. Likewise, the same causal relationship was analysed between electricity, economic growth and urbanization in Angola by applying the Granger causality; by Solarin and Bello (2011) in Algeria using petroleum price, electricity consumption and economic growth. In addition, the study done in seven SSA countries for the period between 1970 and 2007 using the bounds testing approach to co-integration, shows that co-integration between parameter is occurred in the countries like Cameroon, Congo, Côte d'Ivoire, and South Africa. Their outcome given by the causality tests suggest bidirectional causality between energy consumption and real GDP in Côte d'Ivoire and unidirectional causality running from real GDP to energy usage in the case of Congo (Abderrahmani and Be,2013).

Furthermore, the research done from 1971 to 2005 by Ozturk et al. (2010) demonstrates that feedback, Granger causality as well as conservation hypothesis are supported for both low income and high-income countries. On the African continent, the findings submitted by Eggoh et al. (2018) show that there is a bi-directional causality between energy consumption and economic growth for 21 African countries over the period 1971-2005. This finding was also confirmed by the work done by El-aasar and Hanafy (2019) using panel co-integration method and also using panel VECM from 1980 to 2008 come with the same conclusion about feedback hypothesis. Recently, the study done by on oil exporting and oil importing Sub-Saharan African countries by applying the multivariate panel Granger causality method for the periods of 1985 through 2011 reveals an energy-growth nexus for oil exporting nations and feedback occurs for oil importing nations (Ouedraogo, 2017).

The results based on empirically tests by Twerefou et al. (2018) show that there is an increasing importance on the role of causality relationship between EC and GR and postulated that growth hypothesis occurs in Nigeria using the Johansen-Jeselius and the Engle Granger models from the year 1980-2006. The neutrality hypothesis is suggested in South Africa over the period 1980 Dogan and Walker (2009). The research done in Tanzania by Odhiambo (2009) shows the existence of unidirectional causality running from energy consumption to economic growth. The analysis made by analysing country by country also revealed the mixed results. As for example, the findings of Fatai (2014) in SSA, using autoregressive distributed lag (ARDL), show that GDP Granger causes energy consumption in Sudan and Zimbabwe. The neutrality hypothesis is supported in respect of Cameroon, Cote d'Ivoire, Nigeria, Kenya and Togo. On the other side, the literature focuses on the demand function of energy consumption and finally obtains a positive relationship between GDP and energy demand. Pempetzoglou (2014) applied an electricity demand function and the Augmented Dickey Fuller (ADF) bound testing to examine the relationship between electricity consumption and economic growth. The results demonstrate that industrial growth, income and urbanization are contributing factors to electricity consumption in Ghana. Since, the results from previous studies in SSA are contradictory, clarification by more recent econometric techniques, is more than needed.

This study employs a panel data method introduced by Pedroni (2004, 1995). This method may more quickly and accurately identify changes in the relationship between energy consumption and economic growth.

Many of the previous studies were carried out before world crisis of 2012; this study provides perspective on the relation of economic growth and energy consumption through this period. Furthermore, the African region needs electricity efficiency in order to develop (Chehabeddine and Tvaronavičienė, 2020; Pempetzoglou, 2015 and Chehabeddine and Tvaronavi, 2020). Finally, the choice of the countries of our sample is based on availability of data. Both through use of a more nuanced statistical method, and through the richness of the data set, this analysis contributes to the ongoing study of economic growth and energy consumption in Africa.

2. MATERIALS AND ECONOMETRIC METHODOLOGY

This study uses data from the World Development Indicators Database as of the year 2017. Variables used are economic growth and total energy consumption.

2.1. Data

The data of the total energy and GDP per capita used in this study covering the period between 1990 and 2017 for the countries

Benin, Kenya, Mauritius, Tanzania, Namibia, Togo, Eswatini, Botswana, Mozambique, Nigeria, Ethiopia, Senegal, Democratic Republic of Congo Democratic, Cameroun and Ghana.

2.2. Panel Unit Root Test and Panel Co-integration

The panel unit root test based on Levin et al.(2002); Breitung and Pesaran(2008) are adopted to establish the order of integration of the variables. According to Alege et al. (2018), these test statistics are an annex or supporters of the conventional augmented Dickey Fuller (ADF) test statistics used to explore variables in different dimension. This estimation has become popular due to their asymptotic distribution and standard normality in contrast to non-normal asymptotic distribution (Kahsai et al., 2012).

The advantage of using the LLC test is that its test depends on pooled data that allows for heterogeneity in the intercept term. The null hypothesis in these different tests postulates that all series in the panel setting have a unit root while the alternative hypothesis states that all the series in the panel are stationary. In order to assess the long run relation between the variables analysed by the panel, we used two tests of co-integration (Pedroni, 2004; Johansen and Juselius, 1990) and Kao, 1999). Both exploit the Engle Granger procedure applied to the residual of the regression. According to this technique the variables are co-integrated if some variables are stationary at the first difference I (1) and if the residual stationary at level I (0). Thus, if the residual becomes stationary at the first difference (I) there is no co-integration relationship between the two variables. A panel co-integration method is a good technique to test the equilibrium long-run causal relationship among panel variables. The tests used for this purpose are the ones proposed by Pedroni (1999) and Kao (1999). The former is the most commonly used test since it takes into consideration the heterogeneous short-run dynamics between time series. The first is a within-dimension approach, which assumes that a panel group shares the same AR process in the residuals and it includes four statistics: panel v-statistics, panel rho-statistics, panel PP-statistics and panel ADF-statistics. The second is a between-dimension approach, which allows for heterogeneity between groups and comprises three statistics: Group rho-statistics, group PP-statistics and group ADF-statistics. About the co-integration testing of the mentioned equation, two alternative specifications involving auxiliary regressions are possible; the two following equations representing the semi-parametric and the parametric case respectively are applied.

After determining the unit root test, the next step is to test for the presence of a co-integration using the Engle-Granger approach by Pedron and Kao. The application of these authors' procedure addresses heterogeneity in the panel data by using specific parameters which are permitted to vary across individual members.

2.3. Unit Root Test

The augmented Dickey-Fuller (ADF) test is used to test for stationary

$$Y_t = \alpha + \delta Y_{t-1} + \varepsilon_1 \tag{1}$$

Y_t = is the time series, t is the time index, α and δ are coefficienta and is the error term

By using Dickey- Fuller test, regression forms are the following:

a. With a Constant term and Trend, the equation is

$$\Delta Y_t = \alpha + \beta_T + \delta Y_{t-1} + \varepsilon_t \tag{2}$$

Where α is a constant and β_T is a trend

The null and alternative hypotheses are the following:

H_0: $\delta = 0$ (y_t is non-stationary) and H_1: $\delta < 0$ (y_t is stationary)

The co-integrating equation to be estimated for this study is specified as follows:

The two main methods for testing for co-integration are the Johansen procedure and Engle-Granger three-step method

2.4. Multivariate Co-integration Analysis - Johansen Test

The VAR (1) including the M I(1) variables can be expressed as:

$$Y_t = \beta + \Phi Y_{t-1} + \varepsilon_t \tag{3}$$

The approach of Johansen is based on the maximum likelihood estimation of the matrix (Φ–1) under the assumption of normal distributed error variables. From this, The hypothesis is H_0: r = 0, H_0: r = 1, H_0: r = M-1 are tested using likelihood ratio (LR) tests.

2.5. The Co-integration Model Used is Based on SVAR Model and is Specified as The Follows

$$\beta_0 Y_t = \beta + \sum_{i=1}^{k} \beta Y_{it-1} + \varepsilon_t \tag{4}$$

By including Autoregressive distributed lags ARDL used p and q vectors model the equation can be represented as follows:

$$Y_t = \beta_0 + \beta_{1t} + \sum_{i=1}^{k} \varphi_i Y_{t-1} + \beta' x_t + \sum_{i=0}^{q-1} \beta^{*'} \Delta x_{t-i} + \varepsilon_t \tag{5}$$

$$\Delta x_t = P_1 \Delta x_{t-1} + P_{2t} \Delta x_{t-2} + \ldots + P_S \Delta x_{t-s} + \varepsilon_t \tag{6}$$

X_t represents K-dimensional I (1) variables which are not co-integrated, P_i is coefficients for matrix to make autoregressive process and ε_t represent error term.

2.6. Error Correction Model

The determination of the dynamic relationship between co-integrated variables in terms of their stationary error terms for bivariate case in this study if GDP per capita and total energy consumption are integrated I(1), the two variables and becoming one co-integrated combination.

$$\Delta Y_{1t} = \varphi_1 \varepsilon_{t-1} + \sum_{i=1}^{p-1} (\alpha_{11} \Delta y_{1it-1} + \alpha_{12i} \Delta y_{2t-i} + \varepsilon_t \Rightarrow \varepsilon_t \approx I(0) \tag{7}$$

$$\Delta Y_{2t} = \varphi_2 \varepsilon_{t-1} + \sum_{i=1}^{p-1} (\alpha_{21} \Delta y_{1it-1} + \alpha_{22i} \Delta y_{2t-i} + \varepsilon_t \Rightarrow \varepsilon_t \approx I(0) \tag{8}$$

$$\Delta GDP_t = \alpha \Delta EC_t + \mu ECM_{t-1} + \varepsilon_t$$

The specific equation for short run is

$$\Delta GDP_t = \alpha \Delta EC_t + \mu ECM_{t-1} + \varepsilon_t \tag{9}$$

The specific long run equation is

$$\Delta GDP_t = \alpha EC_t + \sum_{i=1}^{p1} \varphi_1 \Delta GDP_t + \sum_{i=1}^{pi} \delta \Delta EC_t + \mu_t \tag{10}$$

Where ε_t is the random error term, α is the parameter to be estimated.

The equation is augmented with lead and lagged differences of the dependent and explanatory variable to control for serial correlation and endogenous feedback effects.

2.7. Bounds Test

$$\Delta Y_t = \phi + \sum_{i=1}^{\alpha} \alpha_{1,i} \Delta X_{v,t-i} + \sum_{i=1}^{\alpha} c_{1,i} \Delta Y_{t-i}$$
$$+ \delta_{1,v} X_{vt-1} + \delta_{1,v} Y_{v,t-1} + \varepsilon_t \tag{11}$$

a represent test appropriate lag length chosen through Schwarz Information Criteria, $a_{1,I}$ and $C_{1,I}$ represent short run coefficients, δ determines relative long run coefficients and ε_t is white error term.

The null hypothesis is H_0:$\delta_{1,v}$=0

H_1:$\delta_{1,v}$≠0;v=1,2,3,4,5,6

Where y_t is a g-vector of $I(1)$ variables, μ is a g-vector of constants, and ε_t is a g-vector of white noise residuals at time t with zero mean and constant variance.

The dynamic error correction (EC) model used in this study is based on Canning and Pedroni's (2008) approach within a panel data framework, summarized as follows:

$$\Delta X_t = \alpha + \beta X_{1-t} + \sum_{i=1}^{k} \lambda i \Delta Xt - i + \gamma T + \varepsilon_t \tag{12}$$

Where Δ is the difference operator, K = optimal number lags, ε_t = disturbance term, X = time series that is GDP per capita, α = constant.

For testing a long run relationship between X, the subscript i denotes a specific unit varies from 1 to N.

Pedroni derived seven[1] different test statistics to test for long run relationships. These test statistics can be categorised into two groups: The first group is the within-dimension approach comprising of panel statistics, panel rho statistics, panel PP statistics and panel ADF statistics. The other group is called the between-dimension approach and comprises group rho statistics, group PP statistics and group ADF statistics. According to Alege et al. (2018) the within dimension group estimators effectively pool the autoregressive coefficient across different members for the unit root test on the estimated residual, whereas the between-dimension group estimators take the average of the individual estimated coefficients for each member.

To explore the causal relationship between the variables, a panel vector error correction model is estimated to perform the short-run and long-run causality through this model. A short-run causal relationship is determined by the significance of the F-statistics. A long-run causal relationship is revealed by the statistical significance of the respective error correction term using a t test. The optimal lag length of the panel VAR model is lag 2 according to Schwarz criterion. Since this study uses data that are not stationary but stationary at first difference, lag 3 is taken as an optimal lag length for the panel VECM. The Error Correction Term (ECT) used in both models refers to the residual resulting after applying the long run equilibrium condition between the variables. According to the pooled mean group methodology, in the long run the same coefficients result for each cross-section from the group analysed.

2.8. Panel Granger Causality Test

In the context of total energy use and economic growth, the study applies the panel data approach developed by Granger (2010) especially based on a bivariate finite order vector autoregressive model. To make inference related to causality from panel data we include not only the slope of heterogeneity but also a cross- sectional dependence proposed. This study presents a panel data causality test which allows for slope heterogeneity. The weakness of this is that it does not consider cross-sectional dependence, thus, if it exists, substantial biases and size distortions occur. However, this weakness is mediated by the Vector error correction Model. This includes both slope heterogeneity and cross-sectional dependence. This new methodology allows identification of the countries for which there is Granger causality. To test the direction of causality, the method is carried out with the use of the Wald tests with country-specific critical values. The use of panel data models or approaches Panel data models are more likely to exhibit cross-sectional dependence in the errors, which may arise as a result of the presence of common shocks and unobserved components. Cross section dependence can take place because of a variety of consideration or factors. Indeed, during the last few decades there has been higher economic and financial integration of countries and financial entities, which induces strong interdependencies between cross sectional units. The research by Bildirici and Ersin (2015b) demonstrate that the default assumption of independence between cross sections seems to be inadequate both in the cointegration analysis and causality analysis. If economic linkages between countries are relatively strong, cross-sectional dependence (for instance, causality between the insurance market development and economic growth) is likely to appear. Thus, incorrect cross-sectional independence assumptions may lead to erroneous causal inferences. Therefore, considering commonly observed cross-sectional dependencies in panel analysis for macroeconomic data, first of all, we decide to verify the hypothesis of the existence of cross-sectional dependence. To test

1 The co-integration test statistics derived based on the estimated residuals are Panel v statistics, Panel rho statistics, Panel t statistics (semi-parametric), Panel t statistics (parametric), Group rho statistics, Group t statistics (semi-parametric) and Group t statistics (parametric). These are developed through equations. The common test used for these tests is known PP test.

for the presence of such cross-sectional dependence in our data, we apply cross section dependence tests.

The following is the methodology developed by Granger (2010) and Johansen and Juselius (1998) for analyzing the causal relationship between time series. Let us assume that X_t and Y_t are 2 stationary series of total energy and economic growth. The general econometric model can be developed as follow:

$$Y_t=\beta_0+\beta_1 Y_{2t}+\ldots+\beta_M Y_{Mt}+\varepsilon_t \quad (13)$$

2.9. Test the Residuals for Stationary

$$Y_{1t}=\beta_0+\beta_1 Y_{2t}+\varepsilon_t \Rightarrow \varepsilon_t = Y_{1t}-\beta_0-\beta_1 y_{2t}$$
$$\hat{\varepsilon}_t = y_{1t}-\hat{\beta}_0-\hat{\beta}_1 y_{2t} \quad (14)$$

H_0: Series are not co-integrated

The co-integration equation is

$$Y_t=\alpha+\sum_{k=1}^{K}\gamma k Y_{t-k}+\sum_{k=1}^{K}\beta k X_{t-k}+\varepsilon_t \text{ with } t=1\ldots T \quad (15)$$

This can be applied to test whether x Granger causes y. The meaning of Granger causality is that past values of y have been included in the model, then x forecasts y. using this model (1), it is easy investigate this Granger causality based on an F test with the following null hypothesis: $H_0{:}\beta_1=\ldots=\beta_k=0$.

If H_0 is rejected by considering the significance test, one can conclude that causality from to y exists. The x and y variables can be interchanged to test for causality in the other direction, and it is possible to observe bidirectional causality from one parameter to on other one knows as called feedback. The work by Dumitrescu and Hurlin (2012) provides an extension designed to detect causality in panel data. The underlying regression is

$$Y_{i,t}=\alpha_i+\sum_{k=1}^{K}\gamma_{ik}Y_{i,t-k}+\sum_{k}^{K}\beta_{ik}X_{i,t-k}+\varepsilon i,t \quad \text{with } i=1\ldots N \text{ and } t=1\ldots T \quad (16)$$

where x_i, t and y_i, are the observations of two stationary variables for individual I in period t. Coefficients are allowed to differ across individuals (note th I subscript attached to coefficients) but are assumed to be time invariant. The lag order K is assumed to be identical for all individuals, and the panel must be balanced.

As in Granger (2010), the procedure to determine the existence of causality is to test for significant effects of past values of x on the present value of y. The null hypothesis is specified as follow:

$$H_0{:}\ \beta_{i1}=\ldots=\beta_i K=0\ \forall i=1,\ldots,N \quad (17)$$

which corresponds to the absence of causality for all individuals in the panel. The DH test assumes there can be causality for some individuals but not necessarily for all. Thus, the alternative hypothesis is H_1: $\beta_{i1}=\ldots=\beta_i K=0\ \forall i=1,\ldots,N_1$

$$\beta_{i1}\neq 0 or\ldots or \beta_{1K}\neq 0 \qquad \forall i=N_1+,\ldots\ldots,N \quad (18)$$

Where N_1 ϵ[0, N–1] is unknown. If N_1=0, there is causality for all individuals in the panel. N_1 must be strictly smaller than N; otherwise, there is no causality for all individuals, and H_1 reduces to H_0.

From equation 2 and 3, the specific is developed as follow:

$$Total.energy(E_{it})=\alpha_{1i}+\sum_{j=1}^{p1i}\beta_{1,i,j}Total.energy(E_{it-j})+\sum_{j=1}^{p2,i}\gamma_{1,i,j}ECON_{it-j}+\varepsilon_{1,it}$$
$$t=1,\ldots,T_t=1,\ldots N \quad (19)$$

$$ECON_{it}=\alpha_{1i}+\sum_{j=1}^{p1i}\beta_{2,i,j}Total.energy(E_{it-j})+\sum_{j=1}^{p2,i}\gamma_{2,i,j}ECON_{it-j}+\varepsilon_{2,it}$$
$$t=1,\ldots,T_t=1,\ldots N \quad (20)$$

Where the index i (i=1..., N) denotes the country, the index t (t =1...,T) the period, j the lag, and $p1i$, $p2i$ and $p3i$ indicate the longest lags in the system. The error terms, 1, i, t ε and 2, i, t ε, are white-noise (i.e. they have zero means, constant variances and are individually serially uncorrelated) and may be correlated with each other for a given country, but not across countries.

Furthermore, the condition is that "If two or more time-series are co-integrated, then there must be Granger causality between them - either one-way or in both directions. However, the converse is not true." So, if data are co-integrated but one cannot find any evidence of causality, there is a conflict in the results (This might occur if the sample size is too small to satisfy the asymptotic that the co-integration and causality tests rely on.) If the series have been co-integrated and find one-way causality, everything is fine. (One may still be wrong about there being no causality in the other direction.) This is reason why this study applied VEC Granger Causality/Block Exogeneity Wald Tests because the use of Pairwise Granger Causality Tests does not provide the answers based on VEC and VAC) If the data are not co-integrated, then there is no cross-check on causality results.

Energy does Granger cause GDP growth: The null hypothesis is rejected if F-statistic is greater than the critical value under specified confidence level. The number of lags is selected according to AIC or SBIC. If both null hypotheses are not rejected, the Granger causality does not exist between two analysed variables. If the first hypothesis is rejected and the second is not, then unidirectional causality is present. If both rejected – bidirectional causality occurs between two variables. The null hypothesis is that energy does not Granger cause GDP growth where by β_1, β_2,…, m=0 while the alternative is β_1, β_2,…, $\beta m\neq 0$.

The results show that in most of the panels considered (Egypt, DRC, Kenya, Morocco, Senegal, Tanzania and Tunisia), energy use positively Granger causes economic growth. This positive impact suggests that an increase in energy use increases the

GDP. This is found in most of the literature (Arbex and Perobelli 2010).

GDP does Granger cause energy utilization/consumption: The null hypothesis is that GDP does not Granger cause energy utilization/consumption: $\delta_1, \delta_2,\ldots, \delta m=0$, the alternative hypothesis is that $\delta_1, \delta_2,\ldots, \delta m\neq 0$ This hypothesis is rejected when the probability calculated is less than five percent of confidence interval.

3. FINDINGS AND DISCUSSION

3.1. Unit Root

The primary objective of using the unit root test is to see whether or not the variables GDP per capita and total energy consumption are stationary series. A time series for a given variable is stationary if and only if it does not include a unit at all. The null hypotheses with an option of no trend; trend first and second difference are reported in Appendix Table 1 in total energy and economic growth for the panel countries has a unit root, and alternative hypothesis is that neither has a unit root. The result of no trend, trend; first and second difference p-values demonstrate that total energy consumption and GDP per capita in sample panel countries has no a unit root because the study reject the null hypothesis at 1% level of significance both in trends and levels. The outcome from result show that variables are stationary at the same order I (1). Two or more time-series are said to be co-integrated if the variables have the same order of co-integration, and in this case, the variables at levels do not cause a spurious regression. As a result, co-integration methods are performed for the variables or countries that have the same order of integration for EC and GDP. This study has employed the unit Root Test based on LLC, IPS, ADF-Fisher, ADF-Fisher and Breitung are summarized in Table 1a and b and reported as Appendix 1.

3.2. Co-integration Test

Co-integration implies that at least one or more linear combinations resulted in time series parameters or variables are stationary even though they are individually non-stationary. It is therefore to determine the optimal lag length by using selection- order criteria like Log L; LR; FPE; AIC; SC and HQ. In this study the ADF test (Appendix 2) procedure is applied to determine the lag order of each variable, the maximum lag of 1 to 8 is used in this study. VAR Model Identification I estimate VAR model of l GDP and Total energy. With number of lags order of 8 bases on information criteria the values of AIC, HQC, and BIC are given by the result in Table 2. VAR system, maximum lag order 8, the asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwartz Bayesian criterion and HQC = Hannan-Quinn criterion.

After determining the lag length, Johansen co-integration tests have been applied and this test takes the following vector auto-regression (VAR). When a co-integration is revealed between 2 time series, the two series will have a long- run relation as proposed by Johansen and Juselius. This test is based on the maximum likelihood and 2 statistics namely the maximum eigen value and the trace –statistics. The null hypothesis is that the rank (r) is to zero (no co-integration) against alternative hypothesis of r>0. The test statistics indicate that the null hypotheses of no co-integrations versus one co-integrating equations can be rejected at 5% level of significance since trace statistics of linear deterministic trend (in first differences). First differences (and second and third differences) help determine whether there is a pattern in a set of data, as well as the nature of the pattern of 0.0638 is greater than 5% critical value and it is rejected at 5% of significance level. We find that null hypothesis of no co-integration is rejected as trace statistics exceed critical value at 5% level of significance. This

Table 1: Johansen fisher panel co-integration test for SSA

Group 1: No Linear deterministic trend (Lags interval (in first differences): 1 to 1))				
a. Unrestricted cointegration rank test (trace and maximum eigenvalue)				
Hypothesized No. of CE (s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	431.8	0.0000	275.4	0.0000
At most 1	337.4	0.0000	337.4	0.0000
Group 2: Linear deterministic trend (in first differences): 1 2)				
Hypothesized No. of CE (s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	169.7	0.0000	148.9	0.0000
At most 1	72.93	0.0638	72.93	0.0638
b. Unrestricted cointegration rank test (trace)				
Hypothesized No. of CE (s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.221125	274.2274	15.49471	0.0001
At most 1 *	0.119074	92.29694	3.841466	0.0000
c. Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized No. of CE (s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.221125	181.9305	14.26460	0.0001
At most 1 *	0.119074	92.29694	3.841466	0.0000

Source: Researchers' computation from EViews 8.0. Max-eigenvalue test indicates 2 cointegrating eqn (s) at the 0.05 level. *Denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) P-values leads us to conclude that there is a co-integration relationship between biomass energy consumption and economic growth for the period 1989–2017.

3.3. Estimating the Long Run and Short Run Dynamics Estimation Relationship and Policy Implications

The coefficients of the co-integrating vector are analysed using the dynamic OLS estimator and the fully modified OLS estimator. If a long -term relationship between parameters is revealed due to the panel co-integration test, the coefficients for a group sample must be estimated. Having obtain that there is a long run relation between GDP and total energy use, as suggested by Ouedraogo (2017), the FMOLS is determined in order to produce more robust results which is requires less assumptions compared to the DOLS. We use DOLS and FMOLS to estimate the nature of this relationship between variables and the result is presented in Table 3. The findings obtained from the OLS and FMOLS estimation techniques also demonstrate that there is a long-run, positive relationship between energy consumption and economic growth. Thus, a 1% increase in energy consumption in the long term will increase economic growth by 0.88 without trend and 0.67% when there is deterministic trend based on the DOLS estimator and by 0.31% based on the FMOLS estimator. Both the DOLS and FMOLS estimates reveal that the level of total energy use is an influential factor on economic growth in the SSA country groups. The results show that an increase of 1 GJ in total energy, the level of GDP per capita in SSA increases at 27.54USA dollar. This results confirm the findings obtained by Jebli and Ozturk (2016). According to the error correction parameter, the results are negative and significant for all of the sample countries. This indicates the presence of a long-term relationship between the variables for the country group analysed.

The error correction parameter represents the adjustment speed of the short-run deviations caused by the non-stationarity of the series to equilibrium in the next period (Appendix 3). This method shows that approximately 24% of the disequilibrium in a period can be corrected in the following period, and thus, long-term equilibrium can be attained.

3.4. VEC Granger Causality/Block Exogeneity Wald Tests

VEC and VAC Granger Causality/Block Exogeneity Wald test, in Table 4, shows Granger causality between economic growth and total energy use. The Chi-sq value (7.972138 and its probability of 0.0186) associated with GDP and energy use suggests that energy Granger causes GDP growth (eq.1) and also GDP Granger causes

Table 2: Pedroni panel cointegration test

Group 1: Pedroni cointegration test results (without trend)					
Within-dimension test statistics			**Between-dimension test statistics**		
User-specified lag length: 1	**Statistic**	**Prob.**	**User-specified lag length: 1**	**Statistic**	**Prob.**
Panel v-Statistic	–1.37418	0.9153	Group rho-Statistic	–12.3834	0.0000
Panel rho-Statistic	–13.0443	0.0000	Group PP-Statistic	–21.2173	0.0000
Panel PP-Statistic	–13.4513	0.0000	Group ADF-Statistic	–11.7698	0.0000
Panel ADF-Statistic	–8.38194	0.0000			
Group 2: Pedroni cointegration test results (with trend and intercept)					
Within-dimension test statistics			**Between-dimension test statistics**		
User-specified lag length: 1	**Statistic**	**Prob.**	**User-specified lag length: 1**	**Statistic**	**Prob.**
Panel v-Statistic	–5.5746	1.0000	Group rho-Statistic	–7.71024	0.0000
Panel rho-Statistic	–8.67121	0.0000	Group PP-Statistic	–22.0499	0.0000
Panel PP-Statistic	–15.3739	0.0000	Group ADF-Statistic	–9.9378	0.0000
Panel ADF-Statistic	–9.24697	0.0000			
Group 3: Pedroni cointegration test results (without trend or intercept)					
Within-dimension test statistics			**Between-dimension test statistics**		
User-specified lag length: 1	**Statistic**	**Prob.**	**User-specified lag length: 1**	**Statistic**	**Prob.**
Panel v-Statistic	6.343672	0.0000	Group rho-Statistic	–14.1677	0.0000
Panel rho-Statistic	–16.4216	0.0000	Group PP-Statistic	–15.6798	0.0000
Panel PP-Statistic	–11.8304	0.0000	Group ADF-Statistic	–8.15581	0.0000
Panel ADF-Statistic	–6.83488	0.0000			

Number of countries (N)=15 and sample period (T)=28. ***, ** And * indicated the significance level of null hypothesis rejection at 1, 5 and 10% respective

Table 3: Dynamic least squares (DOLS), long-run variance estimate

Dependent variable	Co-integrating equation deterministic without trends				
	Independent Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
GDP	Energy	0.88618	0.25958	3.41392	0.019
	C	1.68602	1.24909	1.3498	0.235
	R-squared	0.91097			
	Cointegrating equation deterministic with trends				
GDP	Energy	0.67198	0.33864	1.98432	0.0876
	C	2.12237	1.60502	1.32233	0.2276
	R-squared	0.8375			

Source: Researchers' computation from EViews 8.0

Table 4: Fully modified least squares (FMOLS)

Dependent variable: GDP				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ENERGY	27.54193	2.918541	9.436884	0.000
C	–70.9733	7.838509	–9.05444	0.000
R-squared	0.936342			
a: VAR granger causality/block exogeneity Wald tests				
Dependent variable: GDP				
Excluded	**Chi-sq**	**df**		**Prob.**
Total energy	7.972138	2		0.0186
All	7.972138	2		0.0186
Dependent variable: Total energy				
Excluded	Chi-sq	df		Prob.
GDP	68.96037	2		0.0000
All	68.96037	2		0.0000
b: VEC granger causality/block exogeneity Wald tests				
Dependent variable: D (GDP)				
Excluded	**Chi-sq**	**df**		**Prob.**
D (Total energy)	32.22779	2		0.0000
All	32.22779	2		0.0000
Dependent variable: D (total energy)				
Excluded	**Chi-sq**	**df**		**Prob.**
D (GDP)	20.47544	2		0.0000
All	20.47544	2		0.0000

Source: Researchers' computation from EViews 8.0

GDP growth (Table 4b) with the Chi-sq of 68.96 and its probability of <0.001. Thus, the causality runs from economic growth to energy use and energy use to economic growth (i.e. GDP□ENERGY). The results show that, with 756 observations after adjustment, the null hypothesis that GDP does not Granger cause energy consumption had Chi-squared of 68.96 which is significant at 1%. Thus, we reject the hypothesis that energy consumption does not Granger cause and accept alternative hypothesis.

Energy also Granger causes GDP growth (ENERGY□GDP). Development of energy is a key factor for the domestic economic growth of SSA. The finding of this paper is consistent and lends supports to previous studies obtained by Abderrahmani and Be (2013) who find bidirectional causality for Algeria. This positive impact suggests that an increase in energy use increases the GDP. This is found in most of the literature (Arbex and Perobelli, 2010). Moreover, by the increase of energy use the export capacity of the country increases (Abosedra et al., 2009). On the side of VEC Granger Causality/Block Exogeneity Wald Tests, a Granger causal relationship was also revealed with the Chi-sq of 32 and the probability of <0.0005 on the side of total energy towards economic growth. The Chi-sq of association running from GDP to total energy use is 20.47 with its correspondent probability of 0.000. Analyzing the results in Table 4 we find bidirectional Granger causality between GDP and total energy.

5. CONCLUSIONS

The causal relation between economic growth and energy use using advanced econometric tests like stationarity, co-integration vector error correction and Granger causality tests have shown that variables are integrated, co integrated and manifest a causal relationship between variables.

This study has the purpose of analyzing the causality relationship between energy consumption and economic growth in 15 Sub-Saharan African countries including Benin, Kenya, Mauritius, Tanzania, Namibia, Togo, Eswatini, Botswana, Mozambique, Nigeria, Ethiopia, Senegal, Democratic Republic of Congo, Cameroun and Ghana using annual data on total energy use and economic growth from 1990-2017. The study employed econometrics in time-series methods: The augmented Dickey-Fuller (ADF) unit root test, the Johansen co-integration test, dynamic least squares (DOLS), long-run variance estimate, fully modified least squares (FMOLS), vector autoregressive analysis (VAR), and VER Granger Causality/Block Exogeneity Wald Tests. The study tested the series for stationarity and found all series are stationary at level, at first difference and second difference. The Johansen co-integration results found co-integrating relation among the series. The significance of ECT and F-statistics indicates a causal and long-term relation among the variables in terms of bi-directional causality. The VEC Granger Causality test found causality between economic growth and energy use. The limitation of this paper is that it is a study of a panel in SSA countries.

Empirical results show that economy and energy use depend on each other as there is bi-directional causality between variables. The result of co-integration analysis based on different methods and the Granger causality test is similar with that obtained by using a bootstrap panel analysis of causality between energy use and economic growth for a sample of 16 African countries over the period 1988-2010.

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APPENDIX

Appendix 1: Panel Unit Root Test for variables

1a: Panel unit root test for GDP								
Series	**Form**	**Method**	**t-stat**	**Prob.****	**Cross- sections**	**Obs**	**Order**	**Conclusion**
GDP		LLC	–11.9942	0.0000	28	756	I (1)	Stationary
	No trend	ADF-Fisher	271.403	0.0000	28	756	I (1)	Stationary
		PP-Fisher	438.579	0.0000	28	784	I (1)	Stationary
	With trend	LLC	–8.40575	0.0000	28	756	I (1)	Stationary
		Breitung	–5.83913	0.0000	28	728	I (1)	Stationary
		IPS	–10.4178	0.0000	28	756	I (1)	Stationary
		ADF-Fisher	215.731	0.0000	28	756	I (1)	Stationary
		PP-Fisher	821.588	0.0000	28	784	I (1)	Stationary
	First diff	LLC	–13.1381	0.0000	28	728	I (1)	Stationary
		Breitung	–12.1217	0.0000	28	700	I (1)	Stationary
		IPS	–22.0064	0.0000	28	728	I (1)	Stationary
		ADF-Fisher	448.655	0.0000	28	728	I (1)	Stationary
		PP-Fisher	5158.01	0.0000	28	756	I (1)	Stationary
	Second	LLC	–16.3584	0.0000	28	700	I (1)	Stationary
		Breitung	–16.8388	0.0000	28	672	I (1)	Stationary
		IPS	–32.1244	0.0000	28	700	I (1)	Stationary
		ADF-Fisher	718.122	0.0000	28	700	I (1)	Stationary
		PP-Fisher	7374.94	0.0000	28	728	I (1)	Stationary
1b: Panel unit root test for total energy								
Series	**Form**	**Method**	**t-stat**	**Prob.****	**Cross- sections**	**Obs**	**Order**	**Conclusion**
Total energy	At level/No trend	LLC	–19.9806	0.0000	28	756	I (1)	Stationary
		ADF-Fisher	456.967	0.0000	28	756	I (1)	Stationary
		PP-Fisher	746.369	0.0000	28	784	I (1)	Stationary
	With trend	LLC	–19.9082	0.0000	28	780	I (1)	Stationary
		Breitung	–12.5019	0.0000	28	752	I (1)	Stationary
		IPS	–22.3557	0.0000	28	780	I (1)	Stationary
		ADF-Fisher	451.695	0.0000	28	780	I (1)	Stationary
		PP-Fisher	1225.02	0.0000	28	784	I (1)	Stationary
	First diff	LLC	–27.1614	0.0000	28	739	I (1)	Stationary
	and trend	Breitung	–15.0639	0.0000	28	711	I (1)	Stationary
		IPS	–34.0383	0.0000	28	739	I (1)	Stationary
		ADF-Fisher	824.799	0.0000	28	739	I (1)	Stationary
		PP-Fisher	6297.27	0.0000	28	756	I (1)	Stationary
	Second diff	LLC	–30.0968	0.0000	28	704	I (1)	Stationary
		Breit	–14.1538	0.0000	28	676	I (1)	Stationary
		IPS	–43.6678	0.0000	28	704	I (1)	Stationary
		ADF-Fisher	1486.01	0.0000	28	704	I (1)	Stationary
		PP-Fisher	7374.94	0.0000	28	728	I (1)	Stationary

Source: Researchers' computation from EViews 8.0. **Significant at 1% level and *significant at 5% level

Appendix 2: VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	–4999.219	NA	83716.66	17.01095	17.02583	17.01675
1	–4902.924	191.6056	61161.18	16.69702	16.74168	16.71442
2	–4894.506	16.69397	60248.89	16.68199	16.75643	16.71099
3	–4865.751	56.82537	55383.67	16.59779	16.70200	16.63839
4	–4848.329	34.30982	52912.30	16.55214	16.68612	16.60434
5	–4720.599	250.6810	34736.44	16.13129	16.29505	16.19509
6	–4702.546	35.30804	33115.29	16.08349	16.27702*	16.15890
7	–4696.202	12.36522	32852.52	16.07552	16.29882	16.16252
8	–4684.650	22.43614*	32019.70*	16.04983*	16.30290	16.14843*

Source: Researchers' computation from EViews 8.0. *Indicates lag order selected by the criterion. LR: Sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

Appendix 3: Estimates of the error correction model and the associated errors

Variables	Coefficients	Stand. Error	T. statist	R-squared	Adj. R-squared	F-statistic
GDP	–0.24935	–0.03792	–6.57565	0.280165	0.275180	56.20148
Total energy	1.991630	0.15799	12.6064	0.580691	0.577788	199.9764

Source: Researchers' computation from EViews 8.0