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Effects of Industrialization, Technology and Labor efficiency on Electricity Consumption: Panel Data Experience of Rwanda, Tanzania and Kenya

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ABSTRACT

The objective of this paper is to investigate the effects of industrialization, technology and labor efficiency on electricity consumption in East African Region especially in Rwanda, Kenya and Tanzania over the period from 1990 to 2019. This study adopts a three-stage approach, we used four different panel unit root tests including Levin, Lin and Chu (LLC); Im, Pesaran, and Shin (IPS); ADF - Fisher Chi-square and PP - Fisher Chi-square. The results reveal that all variables are stationary and integrated with order one. Pedroni's cointegration tests reveals that the variables are not cointegrated while Johansen Fisher and error correction-based panel cointegration tests reveal that all variables are cointegrated with at most one cointegrating equation. The study uses full modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) to estimate the long run relationship among the variables. We find that the increase in industrialization increases electricity consumption whiles increase in technology and enhanced labor efficiency decreases electricity consumption. The study recommends that countries need to consider the current level and the future GCF in planning of electricity supply and production to meet demand, promote efficient use of innovative technology and improve labor efficiency in the industrial sector.

Keywords: Co-integration, Electricity Consumption, Industry Sector, Stationarity
JEL Classifications: C22, C52, E17

1. INTRODUCTION

In developing countries, industrial development is one of the key factors to enhance employment and economic growth in general. It is mostly recognized that energy including electricity plays a significant role in economic development, because it enhances the productivity of capital, labor and other factors of production (Jumbe, 2004). Most of the developing countries set diverse strategic plans and programs to boost their industrial sector. It is now commonly recognized that the lack of access to affordable and reliable energy services is a major impediment to rapid industrialization. Preceding to the first oil shock, the energy sector had a supply-oriented focus where the objective was to meet a given exogenous energy demand by expanding the supply. Since the early 1970s, when energy caught the attention of policymakers because of sudden price increases, the research on energy has grown significantly in size (MacKerron, 1980).

Therefore, extensive research has been conducted on interactions between energy consumptions and different economic variables using various methods and technics. Many researchers have focused their studies on causal relationship between electricity consumption and economic growth (Shao, 2017). Nevertheless, the general observation from the existing literature is that most studies on the causal relationship between energy consumption and economic growth have been concentrated on the economic growth in general but not on a specific sector such as industrial development. Electricity consumption and demand of any country depends mostly on its economic structure. Most of the developing economies have set industrialization as the main pillar of their economic growth, but most of them are still facing the challenge of insufficient electricity supply. However, the efficient use of innovative technology and labor efficiency in industrial sector could improve energy conservation while serving as a catalyst for industrial development.

It is worth noting that most of the research carried out in the area of energy consumption and economic growth focused on energy consumption and GDP nexus (Akinlo, 2008; Jumbe, 2004; Odhiambo, 2010; Ouedraogo, 2013; Yakubu and Jelilov, 2017). It seems that the literature has neglected the impact of efficient use of innovative technologies, labor efficiency and industrialization on electricity consumption. A limited number of studies focused on energy consumption and industrial growth (Abid and Mraihi, 2015; Abokyi et al., 2018; Akiri et al., 2015; Asaleye et al., 2021; Mawejje and Mawejje, 2016; Olufemi, 2015; Shahbaz et al., 2014). According to these authors, until now no one has incorporated in one model the following variables: Gross capital formation and Industrial Value added per worker in determining the level of electricity consumption in the case of developing economies, especially in East African region.

This paper is motivated by the shortage of empirical works on effects of industrialization, labor and technology efficiency on electricity consumption in East African Community countries and other African countries. The novelty of the study resides in factors considered in the analysis, the panel data model as well as in the countries and region selected for the research. The structure of this paper is as follows: Section 2 provides a review of the literature, Section 3 describes the used variables, while Section 4 outlines the econometric methodology used. Section 5 presents and discusses the empirical estimations of results for the research and the section 6 makes recommendations with some policy and regulatory implications, as well as offering concluding remarks.

2. LITERATURE REVIEW

There have been extensive studies on causal relationship between electricity consumption and economic growth. Different authors have summarized the results from various studies in four hypotheses (Akinlo, 2008; Mawejje and Mawejje, 2016; Odhiambo, 2009). First is the growth hypothesis where causality is one-way from electricity consumption to output growth, second is the conservation hypothesis in which causality rather runs from output growth to electricity consumption, the third is the feedback hypothesis, which proposes a two-way causality between electricity consumption and output growth. Fourth, the neutrality hypothesis which is related to no causality between electricity consumption and output growth (Jumbe, 2004; Mawejje and Mawejje, 2016; Odhiambo, 2010; Shahbaz et al., 2014). However, to date empirical findings have been mixed or conflicting. Many factors have contributed to these discrepancies, among which are: the economic structure of analyzed countries, dissimilar variables employed, differences in period of study, disparities in energy consumption of nations investigated and diverse methodology employed (Danmaraya and Hassan, 2016). A combination of two or more of these factors may lead to different findings for countries with the same economic structure.

Hossain (2012) used cointegration and Vector Error Correction Model to investigate the relationship between carbon dioxide emissions, energy consumption, economic growth, foreign trade and urbanization using time series data for the period of 1960-2009 in Japan. Short-run unidirectional causalities are found from energy consumption and trade openness to carbon dioxide emissions, from trade openness to energy consumption, from carbon dioxide emissions to economic growth, and from economic growth to trade openness. The test results also support the evidence of existence of long-run relationship among the variables.

Odhiambo (2010) examine the causal relationship between energy consumption and economic growth in three sub-Saharan African countries, namely South Africa, Kenya and Congo (DRC). Using the ARDL-bounds testing procedure, He reported that there is a long-run relationship between energy consumption, prices and economic growth in South Africa, Kenya and Congo (DRC). The results show that for South Africa and Kenya there is a unidirectional causal flow from energy consumption to economic growth. However, for Congo (DRC), economic growth drives energy consumption. Akinlo (2008) used also the autoregressive distributed lag (ARDL) bounds test to investigate the causal relationship between energy consumption and economic growth for eleven countries in sub-Saharan Africa for a period 1980–2003. The study finds that energy consumption is cointegrated with economic growth in Cameroon, Cote d'Ivoire, Gambia, Ghana, Senegal, Sudan and Zimbabwe. Moreover, this test suggests that energy consumption has a significant positive long run impact on economic growth in Ghana, Kenya, Senegal and Sudan. Granger causality test based on vector error correction model (VECM) shows bi-directional relationship between energy consumption and economic growth for Gambia, Ghana and Senegal. However, Granger causality test shows that economic growth Granger causes energy consumption in Sudan and Zimbabwe. The neutrality hypothesis is confirmed in respect of Cameroon and Cote d'Ivoire. The same result of no causality was found for Nigeria, Kenya and Togo. Wolde-Rufael (2006) contrary to Akinlo (2008), tests the long-run and causal relationship between electricity consumption per capita and real gross domestic product (GDP) per capita for 17 African countries for the period 1971–2001. He used cointegration test proposed by Pesaran et al. (2001) and a modified version of the Granger causality test due to Toda and Yamamoto (1995). The results show a positive uni-directional causality running from real GDP per capita to electricity consumption per capita for Cameroon, Senegal, Ghana and Nigeria. These studies have led to different results despite that the countries of the study have approximately the same economic structure. This can be attributed mostly to difference in covered period.

While most of the literature used aggregated GDP, few studies used disaggregated GDP for the examination of the relationship between electricity consumption and economic growth. Jumbe (2004), used the Granger-causality and error correction techniques for 1970–1999 period data for Malawi to examine cointegration and causality between electricity consumption (kWh) and, respectively, overall GDP, agricultural-GDP (AGDP) and nonagricultural-GDP (NGD). He reports that kWh is cointegrated with GDP and NGDP, but not with AGDP. The results show also a bi-directional causality between kWh and GDP, but a unidirectional causality running from NGDP to kWh. In additional, the results detect one-way causality running from GDP to kWh and from NGDP to kWh. Within this context, Mawejje and Mawejje (2016) disaggregated GDP into its major sectors of agriculture, industry and services and test for Granger causality between sectoral output growth and electricity consumption. While Jumbe (2004); Mawejje and Mawejje (2016) disaggregated GDP, Abid and Mraihi (2015) in their study, empirically investigated the relation of industrial production and energy consumption at both aggregated and disaggregated levels in relation to oil, natural gas, and electricity.

The literature identifies two main types of data mostly used in exploring energy-economic growth relationship, which are panel data and time series data. Models for processing time series data include autoregressive distributed lag (ARDL) model, vector autoregressive model (VAR), error correction model (ECM), ordinary least squares method (OLS), dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS). Models for processing panel data include panel cointegration, panel Granger causality test and panel vector error correction model (VECM) (Shao, 2017). Different methods and models may result in different conclusions, even when they are applied to countries with the same economic structure (Abid and Mraihi, 2015; Noomen and Montasser, 2013). However, panel and time series data present different advantages mostly related of the availability of data and the nature of the study. Panel data allows a significant increase in sample size and higher degrees of freedom, (Shao, 2017) clearly notes that panel data is more accurate, allows heterogeneity among countries, reduce the multicollinearity among the explanatory variables and have reliable statistical testing. He concludes that panel cointegration analysis is an effective method to investigate the relationship between long-term electricity consumption and economic development if the panel data is considered in different regions. This method has been used by several authors such as Eggoh et al. (2011); Fatai (2014); Ouedraogo (2013); Li et al. (2019). Nevertheless, in case of short data span, most of the research with time series data employ Autoregressive distributed lag (ARDL)-bounds testing approach developed by Pesaran et al. (2001). This is because, in finite sample data, the ARDL approach has proven to be more efficient than the other traditional cointegration approaches (Abokyi et al., 2018). He adds that this approach is suitable for models with a mixture of variables, which are I(0) and I(1). However, Shao (2017) concluded that VAR and VECM model are the methods that are most frequently utilized to explore the relationship between electricity consumption and economic growth.

Most of the studies carried out in the area of energy consumption and economic growth, focused generally on the entire economy with few studies on the industrial sector (Kassim and Isik, 2020). Appropriate selection of indicator variables to represent the level of electricity consumption and industrial development is of great importance. Different indicator selection often leads to different results. Shahbaz et al. (2014) used Industry Value Added (IVA) as a percentage of GDP as a proxy to industrialization to investigate the relationship between industrialization, electricity consumption and CO2 emissions in case of Bangladesh. Also, Abid and Mraihi (2015) used IVA as a proxy to industrial production in Tunisia for the period 1980–2007. While some authors used IVA variable as a proxy to industrial growth, others used Manufacturing Value added as a proxy to industrialization. Abokyi et al. (2018) employed Manufacturing value-added (MNF) computed as a ratio of GDP to examine the causative relationship amongst electricity consumption and industrial growth in Ghana for the period of 1971–2014. He used MNF as a proxy for industrial growth and interpreted it as industrialization. Similarly, Sankaran et al. (2019) used manufacturing value added to examine the effects of electricity consumption, per capita income, real exchange rate, import and export on manufacturing output by using yearly time series data for the period of 1980–2016 with regard to ten late industrialized nations. Recently, using Manufacturing value added as a proxy to industrial growth, Kassim and Isik (2020) explores the impact of energy consumption on industrial growth with yearly time series data from 1985 through 2017 in Nigeria.

Adom et al. (2012) and Zuresh and Peter (2007) in their models used the Industry Value Added (IVA) to capture the industrial efficiency and value addition effect. They also point out that innovative technologies and structural changes are the main factors of improvement IVA. However, for this study Industry Value Added per Worker (IVW) is used to capture technology and labour productivity while the measure of industrialization follows the studies of Olufemi (2015), Yakubu and Jelilov (2017) and Eggoh et al. (2011). In their models, Gross Capital Formation (GCF) is used capture the industrialization and Consumer Price Index (CPI) as proxy to electricity prices as the determinants of electricity consumption. In most of the literature, electricity prices are not available, most of the authors use CPI as a proxy to electricity prices (Akinlo, 2008; Odhiambo, 2010; Ouedraogo, 2013). It seems that most of the previous studies on energy-economic growth largely focus on total GDP and there is a need to investigate the effects of industrialization, technology and labor efficiency on electricity consumption in East African Region.

3. METHODOLOGY

3.1. Definition and Rationale for Econometric Variables

3.1.1. Dependent variable

As most of the previous studies on energy-economic growth, this study uses electric power consumption per capita (EC) as the dependent variable. According to International Energy Agency (IEA), Electric power consumption per capita (kWh) is the production of power plants and combined heat and power plants less transmission, distribution, and transformation losses and own use by heat and power plants, divided by midyear population. Tapsın (2017) used Electricity consumption as a dependent variable to analyze nature of the link between Industry Value Added and Electricity Consumption. Like many other studies (Asaleye et al., 2021; Kassim and Isik, 2020; Sankaran et al., 2019; Wolde-Rufael, 2006), the use of EC as a dependent variable is of great importance in assessing the main determinants of the changes in electricity consumption of East African countries like Rwanda, Kenya and Tanzania.

3.1.2. Independent variables

3.1.2.1. Gross capital formation (GCF)

World Development Indicators of 2020 define Gross capital formation (GCF), also called "investment," as the acquisition of assets including purchases of second-hand assets, as well as the production of such assets by industrial producers for their own use. The relevant assets relate to assets that are intended for use in the production of other goods and services for a period of more than a year. Economic structure and productivity are important determinants of energy demand, at the macro level, each of them influences energy intensity (Medlock, 2009). The decision to invest in capital stock, the type of capital stock, and the rate of utilization have a great impact on energy demand. As more energy efficient capital is deployed, the energy requirement for a given level of output declines, requiring less energy. This implies that it is possible for industrial sector growth to increase without an increase in energy demand.

Dan (2002) finds that there has been a gradual decline in energy consumption in China since 1978 despite increasing industrial growth and attributed this to energy efficiency. After the oil price shocks in 1973/74 and 1979/80, average productivity in energy use has increased due partly to the replacement of energy-inefficient capital with efficient ones (Berndt, 1990). This implies that the increase in gross capital can reduce the consumption of energy if the investment is made in energy efficient capital. Consequently, GCF is expect to reduce the electricity consumption of the sector if the investment is made in energy efficient capital replacing the energy inefficient ones. It is however possible to experience an increase in electricity consumption if the country is on starting phase of industrial development. In the latter case, the accumulated capital stock is not replacing the existing ones but rather new ones that will start to consume energy. The data for GCF has been extracted from World Development Indictors (2020).

3.1.2.2. Industry value added per worker (IVW)

Manufacturing is one of the pillars of development, this is based on transformation of raw materials in consumable goods and using complex technical transformation processes. Despite that some studies incorporated IVA as a measure of industrialization like for example Shahbaz et al. (2014), the current research uses IVW as a measure of technology and labor efficiency in industrial sector. This is because, it is clear that the main sources of higher value added and greater economic welfare is technological advancement and capital accumulation. The use of scale economies, the information and communication technology (ICT) revolution of recent decades has been the principal source of productivity growth for firms (Commission, 2016). For this study technology and labor efficiency are measured by Industry Value Added per Worker. The data for IVW has been extracted from World Development Indictors (2020).

3.1.2.3. Consumer price index (CPI)

Most of the literature used consumer price index (CPI) as a proxy for energy prices because energy prices time series for developing countries, particularly for African countries are difficult to obtain. Odhiambo (2010) incorporates prices in the bivariate setting between energy consumption and economic growth thereby creating a simple trivariate model. The price level has been chosen as an intermittent variable because of its effects on both energy consumption and economic growth. He explains that an increase in prices is expected to lead to a decrease in energy demand, thereby leading to a decrease in energy consumption. He adds that an increase in prices leads to a decrease in demand, thereby leading to a contraction in aggregate output. Since data on energy prices are not available in most of the developing countries for a long period, like many other authors, Akinlo (2008); Eggoh et al. (2011); Ouedraogo (2013) proxied energy prices by CPI. The use of CPI as a proxy for energy or electricity prices in some of the previous studies can however be problematic because the CPI is not used as the main or only variable to establish the base electricity price. At best, CPI can only be used to adjust the annual electricity price in a country, using the typical Price Cap formula as follows:

$$P_{t+1}=P_t\,(1+CPI_t)$$

Where: P_t and P_{t+1} are the electricity prices in the current and next periods.

Therefore, in the econometric model used for the current study, CPI has simply been used to reflect the general level of annual price changes in a country including changes in electricity price. The CPI data has been extracted from World Development Indictors (2020).

4. ECONOMETRIC ESTIMATIONS

4.1. Panel Data and Econometric Issues

The use of panel cointegration techniques to test for the presence of long-run relationships among integrated variables has been appreciated by an increasing number of researchers. The literature concerned with the development of such tests has thus far taken two broad directions (Westerlund, 2007). The first consists of taking cointegration as the null hypothesis. This is the basis of the panel cointegration tests proposed by McCoskey and Kao (1998) and Westerlund (2005) cite Westerlund (2007). The second approach is to take no cointegration as the null hypothesis whereby the residuals of a static least squares regression is subjected to a unit-root test (Engle and Granger, 1987; Pedroni, 2004).

Most of the literature agrees on the advantages of using panel cointegration techniques, for example Shao (2017) reports that Panel cointegration analysis is an effective method to investigate the relationship between long-term electricity consumption and economic development if the panel data is considered in different regions. Panel data enables a substantial increase in sample size, higher degree of freedom, more accurate and reliable statistical testing. Shao (2017) clearly notes that panel cointegration techniques reduces the multicollinearity among the explanatory variables and allows heterogeneity among countries.

In spite of this, however, many studies such as that of Ho (2002) fail to reject the null hypothesis, even in cases when cointegration is strongly suggested by theory. Westerlund (2007) explains that one plausible explanation for this failure to reject the null, centres on the fact that residual-based tests require the long-run cointegrating vector for the variables in their levels being equal to the short-run adjustment process for the variables in their differences. This is commonly known as common factor restriction and its failure can cause a significant loss of power for residual-based cointegration tests. However, Eggoh et al. (2011) report that the Westerlund tests avoid the problem of common factor restriction and are designed to test the null hypothesis of no cointegration by inferring whether the error-correction term in a conditional error-correction model is equal to zero.

Our investigation on the effects of industrialization, technology and labor efficiency on electricity consumption in Rwanda, Tanzania and Kenya is conducted in three steps. The first is panel unit root tests, the second is panel cointegration tests and the third is estimating the long run cointegration relationship in a panel context.

4.1.1. Panel unit root tests

The variables used in panel data analysis should be non-stationary at level and stationary at first difference to avoid causing possible spurious relationships among the variables. To assess the stationarity properties of the variables used, this study utilizes four different panel unit root tests including Levin, Lin and Chu (hereafter referred to as LLC); Im, Pesaran, and Shin, (hereafter referred to as IPS); ADF - Fisher Chi-square and PP - Fisher Chi-square. IPS panel unit root test was developed by Im et al. (2003), this test is less restrictive and more powerful compared to others like (LLC) developed by Levin et al. (2002) which do not allow for heterogeneity in the autoregressive coefficient. The test proposed by IPS solves Levin and Lin's serial correlation problem by assuming heterogeneity between units in a dynamic panel framework (Eggoh et al., 2011). We used two types of models to assess the unit roots in the panel. The first model has only a constant and no trend and the second has a constant and a deterministic trend. The basic equation for the panel unit root test for IPS is as follows:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p} \phi_{ij} \Delta y_{i,t-j} + \varepsilon_{i,t}; i = 1,2,\ldots, N; t = 1,2,\ldots,T, \tag{1}$$

Where y_{it} stands for each variable under consideration in our model, α_i is the individual fixed effect and ρ_i is selected to make the residuals uncorrelated overtime.

4.1.2. Panel cointegration tests

In this study, we use the panel cointegration techniques proposed by Westerlund (2007) that is the second step of our empirical work. This includes investigating the long-run relationship between electricity consumption, gross capital formation (GCF), industry value added per worker (IVW) and energy prices proxied by consumer price index (CPI) for three countries of East African region. The error-correction tests are provided by the following equation:

$$\Delta y_{it} = \delta_i^{'} d_t + \alpha_i (y_{it-1} + \beta_i^{'} x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{it-j} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta x_{it-j} + e_{it}. \tag{2}$$

Where d_t contains the deterministic components, y_{it} denotes the natural logarithms of the EC and x_{it} denotes the natural logarithms of a set of exogenous variables, including GCF, IVW and CPI. The equation (2) can be rewritten as follows:

$$\Delta y_{it} = \delta_i^{'} d_t + \alpha_i (y_{it-1} + \beta_i^{'} x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{it-j} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta x_{it-j} + e_{it}. \tag{3}$$

where d_t contains the deterministic components, y_{it} denotes the natural logarithms of the EC and x_{it} denotes the natural logarithms of a set of exogenous variables, including GCF, IVW and CPI. $\lambda i = -\alpha_i\beta_i$'; the parameter $-\alpha_i$ determines the speed at which the system $y_{it-j} - \beta_i' x_{it-j}$ corrects back to the equilibrium after a sudden shock. If α_i<0, then the model is error-correcting, implying that y_{it} and x_{it} are cointegrated. If α_i=0, then there is no error correction and thus no cointegration.

As highlighted in the literature, residual-based tests such as Padroni's cointegration test, have been criticized for the common factor restriction condition to hold and its failure can cause a significant loss of power for residual-based cointegration tests. Despite that, for comparison purposes this study will also apply cointegration tests advanced by Pedroni (2004) as well as Johansen Fisher Panel Cointegration Test. Pedroni has proposed seven different statistics to test panel data cointegration. Out of these seven statistics, four are based on pooling, what is referred to as the "Within" dimension and the last three are based on the "Between" dimension. Both kinds of tests focus on the null hypothesis of no cointegration.

4.1.3. Estimating the long run cointegration relationship

Once the variables considered in our model are cointegrated, the next step is the estimation of the unbiased coefficients of this relationship. Given that the variables are expressed in natural logarithms; the coefficients can be interpreted as elasticities. In a panel context, there are several estimators that can be used to estimate a cointegration vector like fully modified ordinary least squares (FMOLS), ordinary least squares (OLS), pooled mean group (PMG) and dynamic ordinary least squares (DOLS). However, several authors raised up weaknesses of some estimators to show the more appropriate estimator in panel framework. Ouedraogo (2013) clearly points out that in the cointegrated panels, using the ordinary least squares (OLS) method to estimate the long-run equation leads to a biased estimator of the parameters unless the regressors are strictly exogenous and conclude that the OLS estimators cannot generally be used for valid inference. Nevertheless, various researchers like Chen et al. (1999) examined the proprieties of the OLS estimator and suggest that alternatives estimators, such as the FMOLS or the DOLS estimators, may be more promising in cointegrated panel regressions. Therefore, this study uses FMOLS and DOLS to estimate the coefficients of the long run relationship between EC, GCF, IVW and CPI for Rwanda, Tanzania and Kenya. The FMOLS and DOLS estimators are generated from following equation:

$$y_{it} = \alpha_i + X_{it}^{'} \beta + \sum_{j=-q_1}^{j=q_2} c_{ij} \Delta X_{i,t+j} + v_{it} \tag{4}$$

Where Y_{it} represents the log of electricity consumption, X the log of explanatory variables GCF, IVW and CPI; c_{ij} represents the coefficients of lag differenced variables.

4.2. Data and Functional Model

Annual data covering the period from 1990 to 2019 for Rwanda, Tanzania and Kenya were obtained from the World Development Indicators (WDI 2020). The number of countries was determined by the availability of data for 1990–2019 and the region of the study. Hence, the functional relationship between Electricity Consumption and other variables is as follows:

$$Log(EC)_{it}=\beta_0+\beta_1 Log(GCF)_{it}+\beta_2 Log(IVW)_{it}+\beta_3 Log(CPI)_{it}+\alpha_{it}+\mu_{it} \quad (5)$$

Where:

EC_{it} = Average electricity consumption per capita of country "i" at time "t"
GCF_{it} = The gross capital formation of country "i" at time "t"
IVW_{it} = Industrial value added per worker of country "i" at time "t"
CPI_{it} = Consumer price index of country "i" at time "t"
α_{it} = Individual Effects
μ_{it} = Error Term
β_{it} = Coefficients to be estimated

5. ANALYSIS AND DISCUSSION OF RESULTS

5.1. Panel Unit Root Results

In this section, the unit root test has been carried out to establish whether the variables are stationary or non-stationary at "level" and in "first-differences". The results of the Levin, Lin & Chu (LLC), Im, Pesaran and Shin (IPS), ADF - Fisher Chi-square and PP - Fisher Chi-square panel unit root tests are shown in Table 1. The unit root statistics reported are for the level and first differenced series of the variables considered in the model. For the variables in level form, the null hypothesis of a unit root cannot be rejected for all tests for the variables EC, IVW with constant only and constant and trend. This means that the variables are non-stationary.

For GCF the LLC and ADF - Fisher Chi-square tests reject the null hypothesis with constant and trend while for CPI the LLC and PP - Fisher Chi-square tests rejects the null hypothesis with constant, but, considering IPS test the variables has a unit root at level. This means that these variables are non-stationary.

After taking the first difference of the variables, IPS, ADF - Fisher Chi-square and PP - Fisher Chi-square panel unit root tests reject the null hypothesis at 1% significance level for all variables while LLC reject the null hypothesis for all variables at less than 5% except for IVW where the test LLC fails to reject the null hypothesis.

These results support the findings of Eggoh et al. (2011) who point out that the test proposed by IPS solves Levin and Lin's serial correlation problem by assuming heterogeneity between units in a dynamic panel framework. Therefore, we can conclude that all variables are non-stationary and integrated with order one denoted as I(1).

5.2. Panel Cointegration Results

The second step of our empirical assessment consist of exploring the long-run relationship between electricity consumption, gross capital formation (GCF), industry value added per worker (IVW) and consumer price index (CPI) for Rwanda, Kenya and Tanzania, countries of East African region. The Table 2 reports the within and between dimension results of the panel cointegration tests known as Pedroni' panel cointegration tests. This use four within-group tests which are panel statistics based on estimators that pool the autoregressive coefficient across different countries for the unit root tests on the estimated residual and three between-group tests which group statistics based on estimators that average individually estimated coefficients for each country. The obtained results from statistics suggest that the null hypothesis of no cointegration cannot be rejected for all tests. As Pedroni cointegration tests have the disadvantage of requiring the cointegrating vector for the variables in level to be equal to the short-run adjustment process for the variables in the differences and to assume cross-country independence. Failure of this common factor restriction causes significant loss of power in the Pedroni procedures (Eggoh et al., 2011). In order to check the robustness of the previous results, the other panel cointegration tests are performed to confirm (or infirm) these first results.

The Table 3 provides trace test and max-eigen test and their respective probabilities. From both test the null hypothesis of none cointegrating equation is rejected as their probabilities equal to zero. This implies that all variables are cointegrated with at most one cointegrating equation and have a long run relationship. The existence of at most one cointegrating vector indicates that the system under examination is stationary in one direction from independent variables to dependent variable and the Wald test in Table 5 confirms that No short run causality from independent variables to dependent variable.

Table 4 provides the error correction-based cointegration tests proposed by Westerlund as generated by the equation (2). We estimate the Panel VECM using Eviews 12 that provides the following estimated equation (2) which is equation (2'):

D(EC)=C(1)*(EC(–1)–0.75588586926*GCF(–1)+5.03158687325*IVW(–1)–4.79660986969*CPI(–1)–4.71537320874)+C(2)*D(EC(–1))+C(3)*D(EC(–2))+C(4)*D(GCF(–1))+C(5)-*D(GCF(–2))+C(6)*D(IVW(–1))+C(7)*D(IVW(–2))+C(8)*D(CPI(–1))+C(9)*D(CPI(–2))+C(10) (2')

Table 1: Panel unit root results for EC, GCF, IVW and CPI

Null Hypothesis: Has Unit Root→Non-Stationary Alternate Hypothesis: Does not have Unit Root→Stationary								
Methods	**Levin, Lin & Chu**		**Im, Pesaran and Shin W-stat**		**ADF - Fisher Chi-square**		**PP - Fisher Chi-square**	
	Constant	**Constant & trend**	**Constant**	**Constant & trend**	**Constant**	**Constant & trend**	**Constant**	**Constant & trend**
Variables								
Level								
Log (EC)	1.78775	0.21210	2.94402	–0.43128	0.34959	10.3985	0.45192	14.7708
Prob	(0.9631)	(0.5840)	(0.9984)	(0.3331)	(0.9992)	(0.1088)	(0.9984)	(0.0221)
Log (GCF)	1.72616	–2.53727	3.33323	–2.44172	0.33889	16.3414	0.30160	11.1169
Prob	(0.9578)	(0.0056)	(0.9996)	(0.0073)	(0.9993)	(0.0120)	(0.9995)	(0.0848)
Log (IVW)	–0.39325	–0.11510	-0.11249	0.07562	8.13778	6.89647	8.07931	5.18339
Prob	(0.3471)	(0.4542)	(0.4552)	(0.5301)	(0.2282)	(0.3305)	(0.2324)	(0.5205)
Log (CPI)	–2.38236	–1.52496	–0.85461	–1.78058	7.46229	13.4897	23.4361	10.3001
Prob	(0.0086)	(0.0636)	(0.1964)	(0.0375)	(0.2802)	(0.0359)	(0.0007)	(0.1126)
First difference								
Δlog (EC)	–3.93454	–3.00994	–5.84784	–5.56383	41.3544	37.0313	63.4662	61.1210
Prob	(0.0000)	(0.0013)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Δlog (GCF)	–2.21129	–1.13027	–3.80673	–2.98432	26.6584	19.7157	49.4917	44.2612
Prob	(0.0135)	(0.1292)	(0.0001)	(0.0014)	(0.0002)	(0.0031)	(0.0000)	(0.0000)
Δlog (IVW)	–1.20510	–0.64552	–2.72595	–2.09114	20.5137	16.0705	38.3484	36.4428
Prob	(0.1141)	0.2593)	(0.0032)	(0.0183)	(0.0022)	(0.0134)	(0.0000)	(0.0000)
Δlog (CPI)	–1.78600	–1.47013	–1.88925	–1.42031	13.8554	11.6109	22.4625	20.4015
Prob	(0.0370)	(0.0708)	(0.0294)	(0.0178)	(0.0313)	(0.0112)	(0.0010)	(0.0023)

Table 2: Pedroni (1999, 2004) panel cointegration tests

Pedroni Residual Cointegration Test					
Methods	**Within dimension (panel statistics)**			**Between dimension (individuals statistics)**	
	Test	**Statistics**	**Prob.**	**Statistics**	**Prob.**
EC, GCF, IVW, CPI Pedroni (1999)	Panel v-statistic	–0.625646	0.7342	-	-
	Panel rho-statistic	1.015099	0.8450	0.760737	0.7766
	Panel PP-statistic	0.826298	0.7957	–2.002761	0.0226
	Panel ADF-statistic	1.921027	0.9726	–0.360579	0.3592
Pedroni (2004) Weighted statistic)	Panel v-statistic	–0.179024	0.5710	-	-
	Panel rho-statistic	0.606401	0.7279	-	-
	Panel PP-statistic	–0.146550	0.4417	-	-
	Panel ADF-statistic	0.686473	0.7538	-	-

Table 3: Johansen fisher panel cointegration test

Series: log (EC) log (GCF) log (IVW) log (CPI)				
Sample: 1990 2019				
Included observations: 90				
Trend assumption: Linear deterministic trend				
Lags interval (in first differences): 1 1				
Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)				
Hypothesized	**Fisher Stat.***		**Fisher Stat.***	
No. of CE (s)	**(from trace test)**	**Prob.**	**(from max-eigen test)**	**Prob.**
None	43.90	0.0000	30.46	0.0000
At most 1	19.13	0.0040	10.65	0.1000
At most 2	13.82	0.0318	8.326	0.2152
At most 3	17.94	0.0064	17.94	0.0064

*Probabilities are computed using asymptotic Chi-square distribution

Table 4: Error correction-based cointegration tests

System: VECM estimation				
Estimation	**Method: Least squares**			
Sample: 1993 2019				
Included observations: 81				
Total system (balanced) observations 324				
	Coefficient	**Std. Error**	**t-Statistic**	**Prob.**
C (1)	–0.009998	0.003815	–2.620569	0.0093

From the equation (2’), we can extract our cointegrated equation with the error correction term known as error correction mechanism represented by α_i $(y_{it-1})+\beta_i$’ $x_{it-1})$ from the equation (2) where C (1) = α_i. If α_i < 0, then the model is error-correcting, implying that y_{it} and x_{it} are cointegrated. If α_i=0, then there is no error correction and

Table 5: Short run model estimation

Wald Test:			
System: vecmestimation			
Test Statistic Value		df	Probability
Chi-square 3.159236		6	0.7886
Null Hypothesis: C (4)=C (5)=C (6)=C (7)=C (8)=C (9)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)	Value	Std. Err.	
C (4)	–0.055374	0.046676	
C (5)	–0.000142	0.078955	
C (6)	–0.038629	0.126649	
C (7)	0.083651	0.101808	
C (8)	0.054258	0.169810	
C (9)	0.008236	0.130238	

Restrictions are linear in coefficients

Table 6: Panel DOLS long-run estimates

Dependent Variable: LOG (EC)				
Method: Panel Dynamic Least Squares (DOLS)				
Sample (adjusted): 1992 2018				
Periods included: 27				
Cross-sections included: 3				
Total panel (balanced) observations: 81				
Panel method: Pooled estimation				
Cointegrating equation deterministic: C				
Fixed leads and lags specification (lead=1, lag=1)				
Coefficient covariance computed using default method				
Long-run variance (Bartlett kernel, Newey-West fixed bandwidth) used for coefficient covariances				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG (GCF)	0.203431	0.078365	2.595946	0.0125
LOG (IVW)	–0.359052	0.095002	–3.779401	0.0004
LOG (CPI)	0.205728	0.119101	1.727345	0.0905
R-squared	0.988312	Mean dependent var		1.830634
Adjusted R-squared	0.980519	S.D. dependent var		0.288755
S.E. of regression	0.040302	Sum squared resid		0.077965
Long-run variance	0.001168			

thus no cointegration. The following is our error collection mechanism:

C (1) *(EC (–1)–0.75588586926*GCF (–1)+5.03158687325*IVW (–1)–4.79660986969*CPI (–1)–4.71537320874)

The Table 4 shows that C (1) = –0.009998 which is negative and statistically significant at 1%, we can then conclude that all the variables are cointegrated and have a long run relationship and the next step is to estimate this long run relationship.

5.3. Panel Estimation with FMOLS and DOLS Results

As mentioned in the literature, this study uses two techniques to obtain the parameter estimates of the panel error-correction model for the long-run relationship between electricity consumption (EC), gross capital formation (GCF), industry value added per worker (IVW) and energy prices (CPI). Eq. (4) has been estimated by using the FMOLS and the DOLS methods and the Tables 6 and 7 reports the results. The Table 6 shows the DOLS results, given that the variables are expressed in natural logarithm, the coefficients can be expressed interpreted as elasticities. GFC coefficient is positive and statistically significant at 1% significance level, the IVW is negative and statistically significant at 1% significance level while CPI is positive and not statistically significant for DOLS as well as FMOLS. The global results of this model show that there is a long run relationship between EC, GCF, IVW and CPI.

The independent variables explain the variations in electricity consumption at 98.8% and 94% respectively for DOLS and FMOLS as showed by the R^2. The results taken globally, suggest that 1% increase in Gross Capital Formation increases electricity consumption by 0.2% in both DOLS and FMOLS models, while 1% increase in industry value added per worker decreases

Table 7: Panel FMOLS long-run estimates

Dependent variable: LOG (EC)				
Method: Panel Fully Modified Least Squares (FMOLS)				
Sample (adjusted): 1991 2019				
Periods included: 29				
Cross-sections included: 3				
Total panel (balanced) observations: 87				
Panel method: Pooled estimation				
Cointegrating equation deterministic: C				
Coefficient covariance computed using default method				
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG (GCF)	0.217213	0.067822	3.202665	0.0019
LOG (IVW)	–0.242656	0.108861	–2.229049	0.0286
LOG (CPI)	0.119245	0.080180	1.487214	0.1408
R-squared	0.947632	Mean dependent var		1.834318
Adjusted R-squared	0.944400	S.D. dependent var		0.287948
S.E. of regression	0.067897	Sum squared resid		0.373414
Long-run variance	0.010581			

electricity consumption by 0.35% in DOLS and 0.24% in FMOLS model.

The effects of GCF variations on electricity consumption can be explained in two scenarios which depends on the type of capital stock and rate of utilization. The first is the case of industrialized and developed countries where the new acquired capital stock is replacing the existing ones and more energy efficient, this was the case of china since 1978 that experienced a gradual decline in energy consumption despite increasing industrial growth and attributed this to energy efficiency (Dan, 2002). The second is for developing countries which are on starting phase of industrialization and where the new accumulated capital stock is not replacing the existing ones but it is new that is going to start to consume energy or not energy efficient.

Considering the level and the process of industrialization of the three countries under study since 1990s, they are developing countries which was in their starting phase of industrialization in general. This implies that most the accumulated fixed capital were intended to start consuming electricity not to replace the existing ones. This support our results where the increase in GCF increases the consumption of electricity. The figures also show that the three countries experienced a positive rate of increase in industrial growth since 2010. According WDI 2020, for Kenya the annual growth rate of industrial value added as percentage of GDP was 8.7% in 2010 and 7.2% in 2015, while for Rwanda it was 8.4% and 9% and 9% for Tanzania for the same period, this follows the same path during the period of the study.

The results of this study show also that the increase in Industry Value Added per work reduces the consumption of electricity. The literature clearly points out that the main sources of productivity is the adapted technology and labor efficiency. This implies that the increase in technology and labor efficiency will results in the increase in IVW and in turn reduces electricity consumption. The obtained results can be explained by the different polices adopted in East African Countries to involve modern information and technologies in the process of production as well as in changes of model of education towards Technical and Vocational Training (TVT) schools.

Table 8: Variance inflation factors for DOLS

Variance Inflation Factors		
Sample: 1990 2019		
Included observations: 90		
	Coefficient	Uncentered
Variable	Variance	VIF
Log (GCF)	0.006141	6.450296
Log (IVW)	0.009025	2.728364
Log (CPI)	0.014185	7.201838

5.4. Testing the Robustness of the Model

5.4.1. Test for multicollinearity and serial correlation

Variance inflation factor (VIF) can be used to test for multicollinearity.

$$VIF_j = 1/(1-R_j^2) \tag{6}$$

The equation (6) shows that VIF_j is a function of R_j^2, this means that as the correlation between independent variables becomes high, VIF also becomes high. The objective is to have smaller VIF. The value 10 is chosen, below or above which to conclude that multicollinearity is a "problem" for estimating coefficients.

The results in the Tables 8 and 9 shows that for all independent variables, the Variance Inflation Factors are low compared to the value 10, this implies that there is no serious multicollinearity among the variables to warrant model re-specification.

For serial correlation, Tables 10 and 11 report that the Q-statistics are not significant, indicating insignificant serial correlation in the residuals. Thus, the estimated coefficients are not biased and are consistent and robust that can thus be used for hypothesis tests and forecasting.

6. CONCLUSION AND POLICY RECOMMENDATIONS

The objective of this paper is to investigate the effects of industrialization, technology and labor efficiency on electricity consumption in East African Region especially in Rwanda, Kenya and Tanzania over the period 1990–2019. This study adopts a three-stage approach, consisting of panel unit root, panel cointegration tests and estimating the long run cointegration relationship in a panel context, to study the dynamic relationships between Electricity consumption, Industrialization, technology and labor efficiency. For this study industrialization is represented by Gross capital formation (GCF) while technology and labor efficiency are represented by Industry Value Added per Worker (IVW), Consumer Price Index (CPI) has been used to represent the general level of price changes in the country, including changes in electricity prices.

Table 9: Variance inflation factors for FMOLS

Sample: 1990 2019		
Included observations: 87		
	Coefficient	Uncentered
Variable	Variance	VIF
Log (GCF)	0.004600	4.621025
Log (IVW)	0.011851	1.412859
Log (CPI)	0.006429	5.320561

Table 10: Serial correlation test for DOLS results

Sample (adjusted): 1992 2018						
Included observations: 81 after adjustments						
Autocorrelation	**Partial Correlation**		**AC**	**PAC**	**Q-Stat**	**Prob***
.|**|	.|**|	1	0.224	0.224	4.2144	0.070
.*|.|	.*|.|	2	–0.127	–0.187	5.5921	0.061
.*|.|	.|.|	3	–0.083	–0.009	6.1922	0.103
.|*.|	.|*.|	4	0.174	0.190	8.8287	0.066
.|.|	.*|.|	5	0.015	–0.106	8.8483	0.115
.*|.|	.*|.|	6	–0.190	–0.140	12.099	0.060
.*|.|	.|.|	7	–0.100	0.009	13.012	0.072
.|.|	.*|.|	8	–0.004	–0.069	13.014	0.111
.|.|	.|.|	9	–0.011	–0.029	13.024	0.162
.|.|	.|.|	10	–0.063	–0.003	13.403	0.202
.|.|	.|.|	11	–0.064	–0.058	13.791	0.245
.|.|	.|.|	12	0.052	0.055	14.058	0.297

*Probabilities may not be valid for this equation specification

Table 11: Serial correlation test for FMOLS results

Sample (adjusted): 1992 2019						
Included observations: 84 after adjustments						
Autocorrelation	**Partial Correlation**		**AC**	**PAC**	**Q-Stat**	**Prob**
**|.|	**|.|	1	–0.248	–0.248	5.3672	0.071
.|.|	.*|.|	2	–0.016	–0.083	5.3895	0.068
.|*.|	.|*.|	3	0.137	0.120	7.0522	0.070
**|.|	.*|.|	4	–0.215	–0.164	11.215	0.064
.|*.|	.|*.|	5	0.181	0.110	14.226	0.084
.|.|	.|.|	6	–0.015	0.027	14.247	0.077
.|.|	.|.|	7	–0.062	–0.010	14.604	0.061
.|.|	.*|.|	8	0.011	–0.074	14.615	0.067
.|.|	.|*.|	9	0.043	0.084	14.791	0.097
.|.|	.|.|	10	0.046	0.069	14.998	0.132
.*|.|	.*|.|	11	–0.135	–0.134	16.814	0.113
.|.|	.*|.|	12	–0.009	–0.088	16.823	0.156

We used four different panel unit root tests including Levin, Lin and Chu (hereafter referred to as LLC); Im, Pesaran, and Shin, (hereafter referred to as IPS); ADF - Fisher Chi-square and PP - Fisher Chi-square. The results of the tests reveal that generally, the variables are non-stationary at "level" and stationary at first-differences and integrated with order one denoted as I(1).

We also used different panel cointegration tests namely, Pedroni (1999, 2004), Johansen Fisher and error correction-based panel cointegration tests to analyze the long run relationship among the variables. To ascertain the robustness of the model, Johansen Fisher and error correction-based panel cointegration tests have been applied. The results of both tests reveal that all variables are cointegrated with at most one cointegrating equation, thus EC, GCF, IVW and CPI have a long run relationship, while the Wald test confirms that no short run causality from independent variables to dependent variable.

Estimation of the long run relationship between the variables used FMOLS and DOLS models and the results report that GFC coefficient is positive and statistically significant at 1% significance level, the IVW is negative and statistically significant at 1% significance level while CPI is positive and not statistically significant. The results imply, that increase in industrialization is associated with increase in electricity consumption, while the increase in technology and labor efficiency decreases electricity consumption. It was also noted that increase in the Consumer Price Index, which was used as a proxy to capture the effects of general increase in electricity prices does not statistically affect electricity consumption in the countries under study.

For policy decision-making the results seem to indicate that to avoid significant over or under production of electricity compared to the demand, East African Countries need to take into consideration the current level and the future expected gross Capital formation which represents the investment in gross capital in the sector, including investment in energy efficient capital, in the short, medium and long term planning of electricity supply and production to meet demand. In addition, the countries need to promote the efficient use of innovative technology as this could improve energy conservation, while enhancing labor efficiency to reduce cost of production in the industrial sector to catalyze industrial development.

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