Nondo, Chali

Article

Is there a relationship between information and communication technologies infrastructure, electricity consumption and total factor productivity? : evidence from a panel of African countries

International Journal of Energy Economics and Policy

Provided in Cooperation with:
International Journal of Energy Economics and Policy (IJEEP)

Reference: Nondo, Chali (2018). Is there a relationship between information and communication technologies infrastructure, electricity consumption and total factor productivity? : evidence from a panel of African countries. In: International Journal of Energy Economics and Policy 8 (4), S. 207 - 218.

This Version is available at:
http://hdl.handle.net/11159/2156

IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2018, 8(4), 207-218.

EJ EconJournals

Is There a Relationship between Information and Communication Technologies Infrastructure, Electricity Consumption and Total Factor Productivity? Evidence from a Panel of African Countries

Chali Nondo*

Department of Business Administration, Massachusetts College of Liberal Arts, USA. *Email: chali.nondo@mcla.edu

ABSTRACT

This study examines the short-run and long-run relationships among information and communication technologies (ICTs), electricity consumption, and total factor productivity (TFP) growth for a panel of 26 African countries. The long-run relationship is determined using the three standard panel causality tests. As a whole, empirical results provide clear evidence that ICT, electricity consumption and TFP have a long run equilibrium relationship. However, results also show lots of variation on the impact of electricity consumption and ICT access on TFP. Panel estimations reveal that electricity consumption has a statistically positive impact on TFP growth in 22 countries, but has a negative effect in four countries. Similarly, the sign of the effect of ICT on TFP growth varies across countries, being positive in some and negative in others. Additional insights from the empirical estimations show presence of a two-way causality between electricity consumption and TFP and a unidirectional causality running from ICT to TFP. Overall, results suggest that bridging the infrastructure gap is a vital step for African countries to take towards sustaining economic growth.

Keywords: Information and Communication Technologies, Electricity Consumption, Total Factor Productivity, Panel Granger Causality
JEL Classifications: C14, C32, O3, Q4

1. INTRODUCTION

Since the mid 1990's, the Sub-Saharan African region has been enjoying significant economic progress. The World Bank asserts that Africa is the world's second fastest growing region after East Asia. In spite of showing signs of economic resilience, the general increase in income levels across Africa has not been moving in tandem with growth in physical infrastructure and demand, respectively. Accordingly, Africa is plagued by the serious problem of inadequate and deteriorated physical infrastructure in transportation, power, communication, water, sanitation, and other key sectors (Ndulu, 2007; Yepes et al., 2008). As a consequence, the lack of quality and adequate infrastructure has put severe constraints on member countries' abilities to improve productivity, sustain economic growth, accelerate the structural economic transformation, as well as help in the fight against poverty.

While the provision of infrastructure is not the panacea to the economic and social woes confronting Africa, infrastructure is the means through which various services and goods are produced and delivered. In the theoretical literature, public infrastructure is a key ingredient for productivity growth and efficiency enhancement because of its complementary relationship with other factors of production (Aschauer, 1989; Barro and Sala-i-Martin, 1995; Lucas, 1988). The basic idea is that technological progress is embodied in new capital goods, and therefore, investment in new capital is necessary to promote productivity growth (Solow, 1957). The hypothesis that investments in public infrastructure produce strong economic benefits and fosters total factor productivity (TFP) growth has significant implications for African countries that have poor and a small stock of physical infrastructure.

Many development institutions and other specialized government agencies have unequivocally warned that Africa's deficient infrastructure stock hampers economic activities and weakens human development efforts (IMF, 2013; World Bank, 2009). It is therefore not surprising that despite the recent improvements in the African region's growth, most African leaders have reiterated the need for more capital funding for infrastructure development. The World Bank investment climate surveys point out that the limited and poor quality of infrastructure in Africa acts as a major barrier to business growth and development - and adversely undermines productivity growth (Escribano et al., 2010; 2008; Calderón, 2008). Consequently, expanding affordable access to information and communication technologies (ICT) and power infrastructure has become a priority for policy makers because they are important drivers of productivity, social development, and economic development.

While the provision of infrastructure is not the panacea to the economic and social woes confronting African economies, inarguably, critical infrastructure such as energy and ICTs play an essential role in the performance of economies. From the above, electricity and ICTs, as two of the most recognized and important general-purpose technologies (hereafter referred to as GPTs) can help African countries leapfrog development challenges. Lipsey et al. (1998. p. 5) define a GPT as "a technology that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many Hicksian and technological complementarities."

Indeed, bountiful evidence exists on the productivity-enhancing benefits that stem from extensive use of ICTs and electricity consumption. The seminal article by Schurr and Netschert (1960) on the electricity-productivity nexus show that the electrification of the U.S. industry promoted the mechanization and automation of production processes, and this in turn contributed to growth in labor and TFP growth. Other researchers (Berndt, 1978; Berndt and Wood, 1984; David and Wright, 1999; Jorgenson, 1984; Schön, 2000; Schurr, 1984) have corroborated their findings. Recently, Tugcu (2013) produce empirical evidence on the short and long-run Granger causal relationship between disaggregate energy consumption and TFP growth in the Turkish economy. Tugcu find a bidirectional relationship between disaggregate energy consumption and TFP growth in the Turkish economy, both in the long and short-run. In a similar fashion, Ladu and Meleddu (2014) use data from 21 Italian regions to examine the causal relationship between energy consumption and TFP. Similarly, results show that energy consumption and TFP growth have a bidirectional relationship, both in the short and long run.

The empirical literature also contains compelling evidence on why ICT access is important for the overall economy, including promoting productivity, entrepreneurship, innovation, and social development (Beil et al., 2005; Cronin et al., 1993; Dutta, 2001; Sadorsky, 2012; Stiroh, 2002). Lee et al. (2005), a threshold of ICT capital must be attained before the effect of ICT on output growth becomes measurable. These productivity gains arise because both electricity and ICTs have broad applications in the informal and formal sectors of the economy, first as production inputs and second through the spillover effects (Lipsey et al., 2006; Moser and Nicholas, 2004). Taking into account that electricity and ICT are GPTs and thus form part of the physical stock for production, their use has the concomitant effect of enabling firms to reach their fullest productive potential through innovation and adoption of newer technologies.

Whereas most past studies establish determinants of TFP growth, ICT penetration or impacts of ICT and electricity on GDP, there is remarkably no empirical evidence on the causal direction for Africa. Therefore, this study attempts to fill this void by investigating whether an increase in electricity understand the dynamic long-run relationship between infrastructure development and TFP growth, this study employs the panel Granger causality test by pooling data on 26 African countries over a 15-year time period. Specifically, we investigate the causal relationship among electricity consumption, ICT penetration and TFP growth. This study addresses two related questions:

1. Does an increase in ICT penetration rates and electricity consumption Granger cause the long run growth of TFP in Africa?
2. Do cross-country differences in TFP growth explain changes in ICT penetration rates and electricity consumption?

In light of the direct and indirect benefits of the contributions of electricity and ICT infrastructure to productivity growth and GDP growth, the importance of this study cannot be overemphasized. Conceptually, electricity may affect TFP growth through the technical and efficiency channels. First, because electricity enters the production function as an input, and as such, a steady supply of electricity promotes utilization of productive resources (capital and labor) and this, in turn, provides a guarantee for sustained output production. For this reason, the extent to which firms efficiently and intensely use factors of production crucially depends on the supply of quality electricity. Similarly, the use of ICT services plays a significant role in promoting the efficiency of capital's contribution to output and productivity growth.[1]

The empirical analysis begins with examination of the stationarity of the variables using panel unit root tests. The next empirical tests focus on investigating the long run equilibrium relationship using the methodologies proposed by Pedroni (1997). For the causal relationship, the Engle and Granger (1987) two-step procedure is used to examine the relationship among the variables estimation. Another notable feature in the estimation is the ability to circumvent the problem of multicollinearity among the ICT variables; obviously, inclusion of individual ICT indicators in the regression analysis may lead to multicollinearity problem and therefore, we use the principal component analysis (PCA) to construct one composite indicator for ICT.

The framework of the remainder of this paper is as followed. In Section 2, we provide an overview of electricity and ICT infrastructure in Africa; Section 3 briefly describes the estimation techniques, while Section 4 presents the data we use in our study.

1 Agénor and Moreno-Dodson (2007) provide an extensive discussion on the channels through which infrastructure affects productivity. Overall, it is recognized that while infrastructure development may stimulate productivity growth and output, economic growth and productivity growth can also stimulate the demand and supply of infrastructure services.

The empirical results are shown in Section 5 and finally, Section 6 concludes the paper.

2. ICT AND ELECTRICITY TRENDS IN AFRICA

Because of the recognized importance of infrastructure in the development process, many African governments have intensified efforts over the last decade to increase public infrastructure investment. The World Bank's Africa Infrastructure Country Diagnostic (2008) estimates that Africa will need to invest up to U.S. $93 billion annually until 2020 for both public investment and maintenance (World Bank, 2014). The region's greatest infrastructure challenges lie in the power sector, where the number of households with access to electricity is not only the lowest compared to any developing region, but the power supply is also highly unreliable and expensive. While the African region is endowed with abundant fossil fuels and renewable energy resources, it's installed generating power capacity stands only at 1.2 terawatts - and yet, under ideal conditions has the potential to produce 10 terawatts or more (World Bank, 2015). Consequently, approximately 620 million people (75% of the population) across Africa do not have access to electricity.

Africa's electric power generation is so dire that some countries have electrification rates of <10% (Figure 1). Figure 1 also shows that there are marked differences in access to electricity among the African countries. As can be seen in Figure 1, the share of people lacking access to electricity is higher among SSA countries, whereas North African countries have the largest share of the population with access (<1% of the population do not have access). Data from the IEA indicate that in 2012, in countries such as Chad, Burundi, Chad, Rwanda, Sierra Leone, Central African Republic, Malawi, Uganda, Niger, Burkina Faso, and Ethiopia, more than 90% of the population did not have access to electricity. Figure 2 presents some power generation trends across different regions in 10-year periods, from 1985 to 1994, 1995–2004, and from 2005 to 2014. As can be seen, while other parts of the world saw a significant increase in electric power generation over the years, Africa has made very little progress in increasing installed electricity power generation. There is also some evidence that suggests that electric power consumption (kWh per capita) has declined, and this trend is attributed to old infrastructure, poor maintenance, and increasing energy demand, among other factors (IEA, 2012).

Although ICTs have recorded unprecedented growth rates across the world, the full potential of ICTs, including access and their benefits have not spread evenly across the African continent

Figure 1: Population without access to electricity

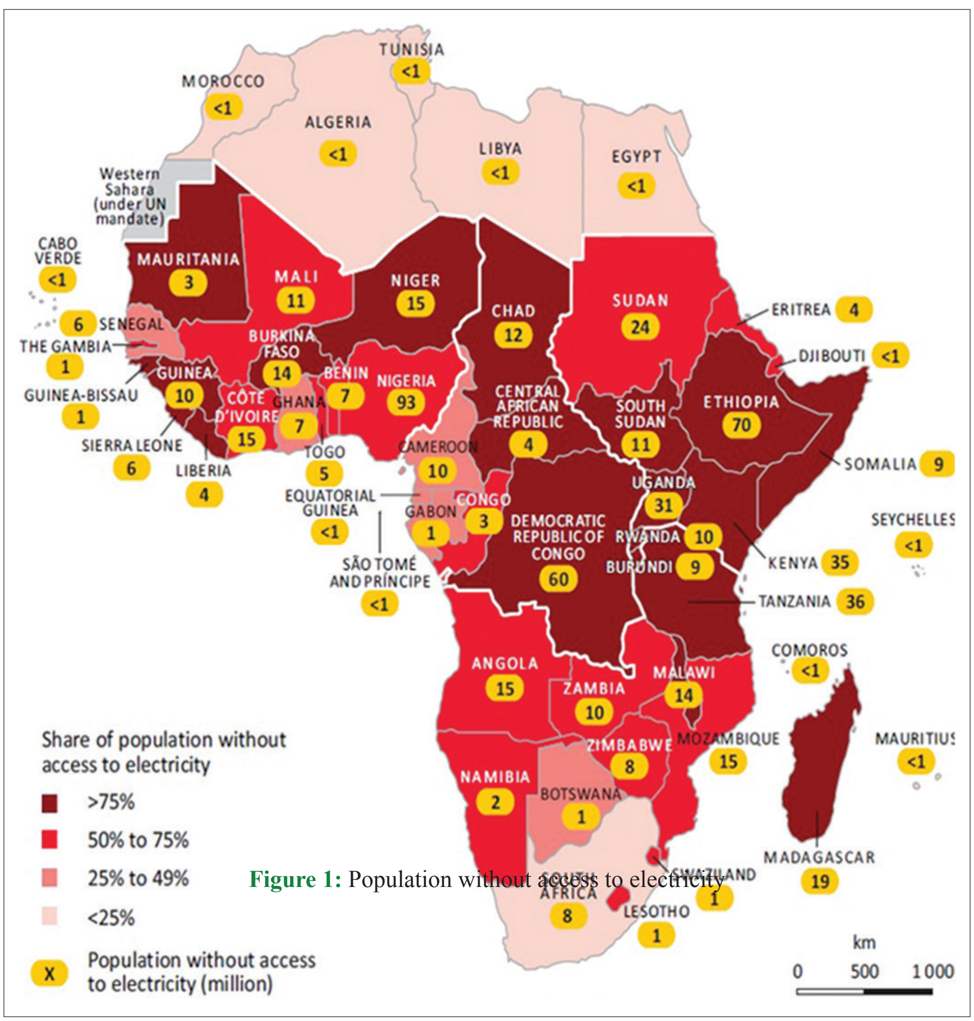
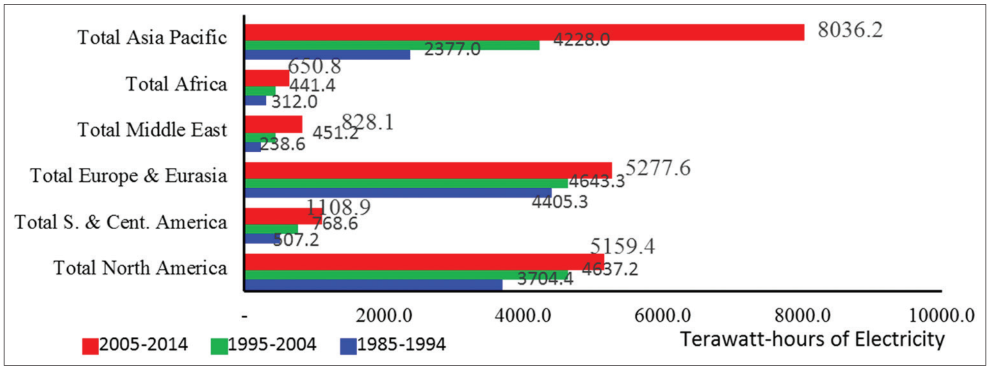


Figure 1: Population without access to electricity

Source: International energy agency (IEA, 2012)

Figure 2: Average electricity generation, 1985–2014

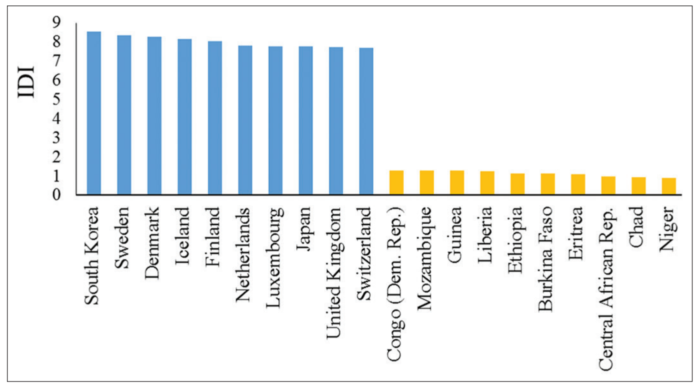


Source: Authors' own calculation based on data from the IEA (2013)

(Gebremichael and Jackson, 2006). According to the international telecommunications union 2015 ICT development index (IDI), which compares ICT development across countries, Africa lags considerably behind in ICT access. While African countries have made some positive progress in increasing the stock of ICT infrastructure, compared to other regions of the world the pace of expansion has been slow, and therefore, the digital divide may continue to widen (Foster and Briceño-Garmendia, 2010).

Figure 3 shows the IDI values for a sample of countries for the period 2010–2011. As shown below, the countries that rank high in the ICT IDI development belong to high-income countries, while African countries are at the bottom of the rung of the ICT IDI. In general, the African ICT IDI is the lowest of all regions. In terms of accessibility, Figure 4 illustrates that except in mobile phone access, the African continent has not made significant progress in fixed phone and internet access. In 2011, the share of the population using mobile phones reached a peak of 71%, compared to 1.1% penetration rate of fixed telephone lines and 0.4% for fixed broadband (Figure 4). Based on these trends, it is apparent that increasing ICT access should be one of the priorities for African countries.

Figure 3: 2010 information and communication technologies development index for sample countries



Source: Authors' own calculation based on data from the international telecommunications union (2012)

3. METHODOLOGY

The empirical analyses are accomplished by using the three standard causality tests: (1) Panel unit root tests; (2) panel cointegration tests; and (3) panel error correction model (ECM). A series of panel unit tests are employed to investigate the stationarity of the variables. Panel data techniques have the advantage of increasing the statistical power when testing for stationarity of a series compared to time series techniques (Levin et al., 2002).

The first-panel unit root test conducted is the Levin et al. (2002) test, popularly known as the LLC test. The LLC test is an augmented Dickey–Fuller (ADF) based test and assumes homogeneity in the dynamics of the autoregressive coefficients for all panels while imposing heterogeneity in the error variances. The null hypothesis is that each cross-section series in the panel contains a unit root, whereas the alternative is that at least one of the cross-section series is stationary. The test involves fitting an augmented ADF regression for each panel and the optimal number of lags is based on the method suggested by LLC. The LLC conventional ADF test for a single-equation is shown below.

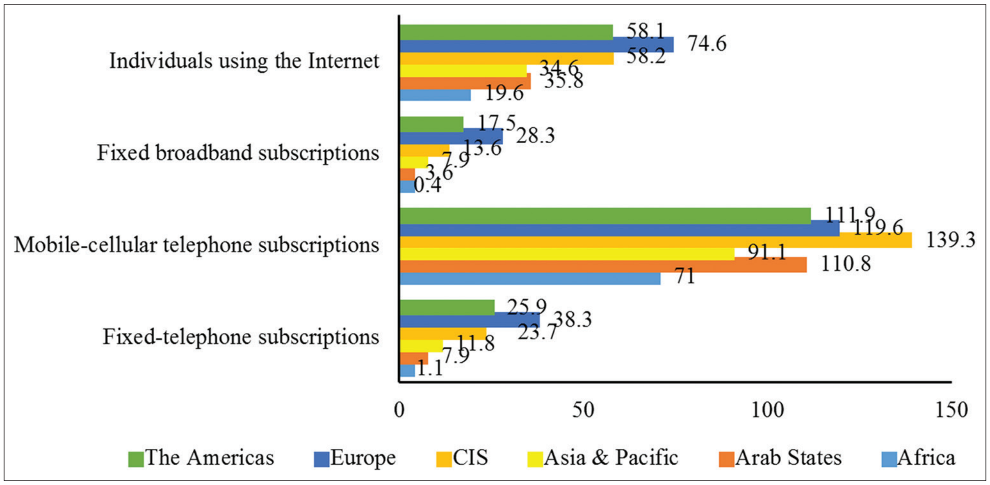
$$\Delta X_{it}=\alpha_i+\beta_i X_{i,t-1}+\varepsilon_{it} \quad (1)$$

Where Δ is the first difference operator, X_{it} is the series of observations (electricity consumption, TFP growth and per capita GDP) for country i for t=1, 2,…,T t ime periods, ε_{it} is the disturbance term, with a variance of σ^2, and γ_{it} is the deterministic component. The LLC unit root null hypothesis is that $\beta_1 = \beta_2 = \beta = 0$ against the alternative of $\beta_1 = \beta_2 = \beta < 0$, with the test based on the test statistic.

The second unit root test implemented is the Im et al. (2003) test, denoted IPS test, which unlike the LLC test, relaxes the assumption of homogeneity of the autoregressive coefficients across the panels. The IPS also combines information from the time series dimension and the cross section dimension. To this end, the IPS test allows to vary across the panels under the alternative hypothesis. Formally, the null hypothesis is that $\beta_1 = \beta_2 = \beta = 0$, against the alternative of $\beta < 0$, for some *i*.

The third unit root test performed in the Hadri test, which is a residual-based Lagrange multiplier test. The Hadri test statistic is one-sided and has the null hypothesis of no unit root (stationary) in any of the series in the panel. Since the Hadri test is based on

Figure 4: Information and communication technologies penetration rates per 100 people, 2011



Source: Authors' own calculation based on data from the International Telecommunications Union, 2013)

the residuals from the individual OLS regressions, estimates are obtained by regressing on a constant (or a constant plus trend) as shown in equation (2).

$$y_{it}=\alpha_i+\lambda_{it}+\varepsilon_{it} \quad (2)$$

3.1. Panel Cointegration

After determining that the variables are integrated of order one, the second step of the empirical analysis involves examining whether there is a long-run relationship among the integrated variables. We employ Pedroni's (1999; 2004) panel cointegration techniques. These methods allow for heterogeneity among individual members of the panel and are thus an improvement over conventional cointegration tests, which assume that the vectors of cointegration are homogenous. Equation (3) presents the cointegration panel model of TFP growth for the heterogeneous panel of countries.

$$LTFP_{it}=\alpha_{it}+\delta_{it}+\beta_1 LENC_{1it}+\beta_2 LICT_{2it}+\varepsilon_{it} \quad (3)$$

Where LENC, LTFP, and LICT are the natural logarithms of the observable variables of electricity power consumption per capita, TFP and information communication technologies, respectively; t=1, …T are time periods; *i*=1,…, N are panel members; denotes country-specific effects, δ_t is the deterministic time trends. Finally, β_1 and β_2 are the parameters of the model to be estimated, and ε_{it} is the estimated residual from the panel regression. The structure of the estimated residual follows:

$$\varepsilon_{it}=\rho_i\varepsilon_{it-1}+\mu_{it} \quad (4)$$

The estimated residual indicates the deviation from the long-run relationship. With the null of no cointegration, the panel cointegration is primarily a test of unit roots in the estimated residuals of the panel. Pedroni (1999) shows that there are seven different residual statistics for the cointegration test: (1) The panel *v*; (2) panel ρ - statistic; (3) Panel (PP)-statistic; (4) panel ADF-statistic; (5) group ρ-statistic; (6) group PP-statistic; and (7) group ADF-statistic. The first four statistics are known as panel cointegration statistics and are based on the within-dimension approach. The within-dimension imposes a common (ρ_i=ρ) coefficient by pooling the autoregressive coefficients across different members for the unit root tests on the estimated residuals. The within-dimension tests the following hypotheses: H_0: ρ = 1 $\forall_i$ against the alternate H_1: ρ_i = ρ < 1.

The last three statistics are group-panel test statistics and are based on the between-dimension approach. Unlike the within approach which imposes a common coefficient under the alternate hypothesis, the between- dimension allows for heterogeneous coefficients by averaging the individually estimated coefficients of each country. The hypotheses for the between-dimension approach are stated as $H_{0\rho}$ = 1 for all *i*, against the alternate hypothesis of H_1: ρ < 1. In the presence of a cointegrating relationship, the residuals are expected to be stationary. The panel *v*-test is a one-sided test, with the null of no cointegration being rejected when the test has a large positive value. The other tests reject the null hypothesis of no cointegration when they have large negative statistics.

After establishing that the variables are cointegrated, we proceed to use the panel fully modified ordinary least squares (FMOLS) to estimate the long-run cointegrating relationship among TFP growth, electricity consumption, and ICT for a heterogeneous panel of countries. The FMOLS technique accounts for both serial correlation and endogeneity problems and thus provides asymptotically unbiased estimates than simple OLS estimation (Pedroni, 2004). Another advantage of the FMOLS is that the FMOLS technique allows for heterogeneity among individual members of the panel while estimating the long-run relationship.

3.2. Panel Granger Causality Tests

To test for Granger causality in the short-run and long run, we employ a two-step estimation procedure. The first step involves the estimation of the residuals from the long-run model (Equation 4), while the second step involves fitting the estimated residuals as a right-hand variable in a dynamic error ECM.[2] We specify the dynamic ECM as follows:

2 The lag length in the dynamic panel error correction model is based on the Akaike and Schwarz Bayesian Information criteria and both criteria indicate that two lags as the optimal lag length.

$$\begin{aligned}\Delta \ln TFP_{it} &= \alpha_1 + \beta_1 ECT_{it-1} + \beta_2 \Delta \ln TFP_{it-1} + \beta_3 \Delta \ln TFP_{it-2} \\ &+\beta_4 \Delta \ln ENC_{it-1} + \beta_5 \Delta \ln ENC_{it-2} \\ &+\beta_6 \Delta \ln ICT_{it-1} + \beta_7 \Delta \ln ICT_{it-2} + \varepsilon_{1t}\end{aligned} \quad (5)$$

$$\begin{aligned}\Delta \ln ENC_{it} &= \alpha_1 + \delta_1 ECT_{it-1} + \delta_2 \Delta \ln TFP_{it-1} + \delta_3 \Delta \ln TFP_{it-2} \\ &+\delta_4 \Delta \ln ENC_{it-1} + \delta_5 \Delta \ln ENC_{it-2} \\ &+\delta_6 \Delta \ln ICT_{it-1} + \delta_7 \Delta \ln ICT_{it-2} + \varepsilon_{2t}\end{aligned} \quad (6)$$

$$\begin{aligned}\Delta \ln ICT_{it} &= \alpha_1 + \varphi_1 ECT_{it-1} + \varphi_2 \Delta \ln TFP_{it-1} + \varphi_3 \Delta \ln TFP_{it-2} \\ &+\varphi_4 \Delta \ln ENC_{it-1} + \varphi_5 \Delta \ln ENC_{it-2} \\ &+\varphi_6 \Delta \ln ICT_{it-1} + \varphi_7 \Delta \ln ICT_{it-2} + \varepsilon_{3t}\end{aligned} \quad (7)$$

Where, Δ denotes the difference operator; ECT is the lagged error correction term derived from the long-run cointegrating relationship. β_1, δ_1, and φ_1 represent the coefficients that capture how lnICT, lnTFP, and lnENC respond to deviations in the long run, ε_t is the independently and normally distributed error term, $i = 1, 2, \ldots, 26$ represents the number of countries and t = 1, 2, …15 time periods. lnENC is the log of per capita electricity consumption, lnTFP is the log of TFP growth, and lnICT is the log of ICTs. The Wald test is used to determine the optimal lag length.

Within this dynamic ECM, we examine whether the relationship among TFP, ENC, and ICT is weak Granger causality, long-run Granger causality, or strong Granger causality. Accordingly, the weak Granger causality is determined using the F-Wald test, and mainly examines the joint significance of the lagged dependent variables in equation (5), (6) and (7). We use the following hypothesis to test for the short-run or weak Granger causalities: H_0: $\beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$ for all i in equation (5); H_0: $\delta_2 = \delta_3 = \delta_6 = \delta_7 = 0$ for all in equation (6), and H_0: $\varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = 0$ for all in equation (7).

After testing for short-run causality, we test for the long-run causality by first examining the significance of the coefficients of the error correction terms (β_1, δ_1, and φ_1). In order to examine the long-run Granger causality among TFP, ICT, and ENC, we test the following hypotheses H_0: $\beta_1 = 0$ for all i in equation (5), H_0: $\delta = 0$ for all i in equation (6), and H_0: $\varphi_1 = 0$. If $\beta_1 = \delta_1 = \varphi_1 = 0$ for all i then we conclude that there is no Granger causality in the long run. If, however, all the adjustment coefficients are negative and significant, this suggests that long-run Granger causality runs in both directions among the variables (TFP, ENC, and ICT).

Finally, we perform the strong Granger causality test by testing for the joint significance of both the lagged terms and the error correction term. The following hypotheses are tested:

H_0: $\beta_1 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$ for all i in equation (5), H_0: $\varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = 0$ for all i in equation (6), and $H_0 = \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = 0$ for all in equation (7). This test is referred to as the strong Granger causality test and is used for determining the variables that bear the burden of short-run adjustment to re-establish long-run equilibrium, following a shock to the system. A result of no causality in either direction indicates that the variables have a neutral effect on each other.

3.3. Malmquist TFP Index

The non-parametric DEA estimates the Malmquist index through the calculation of distance functions under both constant and variable returns-to-scale technologies. These indexes follow the work of Malmquist's (1953) quantity index who constructed indexes by comparing two quantity vectors to an arbitrary indifference curve using radial scaling. The output distance function represents the maximum feasible expansion of the output vector while holding the input vector constant. Equation (8) shows the output oriented Malmquist Productivity Index specification introduced.

$$M_i^{t+1}\left(y_i^{\,t}, y_i^{\,t+1}, x_i^{\,t}, x_i^{\,t+1}\right) = \left[\frac{D_i^t\left(y_i^{\,t+1}, x_i^{\,t+1}\right)}{D_i^t\left(y_i^{\,t}, x_i^{\,t}\right)} * \frac{D_i^{t+1}\left(y_i^{\,t+1}, x_i^{\,t+1}\right)}{D_i^{t+1}\left(y_i^{\,t}, x_i^{\,t}\right)}\right]^{1/2} \quad (8)$$

Where, y_t is the output vector and x^t is the input vector in period t; the terms x_i^t and y_i^t represent the inputs used and outputs produced by the i[th] DMU during the period t. The notation D^t denote the output distance function that measures the efficiency of converting inputs x_i^t into outputs y_i^t during the time period t. Similarly, $D_i^{t+1}(x_i^{t+1},\ y_i^{t+1})$ denote the output distance function between the observations at period t+1 in relation to the technology at period t+1. The notation M in equation (8) represents the value of the Malmquist index of the most recent data point $(x_i^{t+1},\ y_i^{t+1})$ relative to the earlier production point $(x_i^t,\ y_i^t)$. A value of M in equation (8) > 1 is an indication of positive productivity growth between the two-time periods, t and t+1. On the other hand, when M < 1 this indicates a decline or regress in TFP, and finally, a value equal to one indicates that productivity has not changed. The distance functions are calculated under constant returns to scale. Färe et al. (1989) shows that equation (8) is the geometric mean of two output-oriented indices as shown in equations (9) and (10), respectively.

$$M_i^t = \frac{D_i^t\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^t\left(y_i^t, x_i^t\right)} \quad (9)$$

$$M_i^{t+1} = \frac{D_i^{t+1}\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^{t+1}\left(y_i^t, x_i^t\right)} \quad (10)$$

The values for $D^t(y^t,x^t)$, $D^t(y^{(t+1)},x^{(t+1)})$, $D^{(t+1)}(y^t,x^t)$, and $D^{(t+1)}(y^{(t+1)},x^{(t+1)})$ are obtained by solving linear programs (11), (12), (13) and (14) shown below:

$$\begin{aligned}&D^t[y_i^t, x_i^t]^{-1} = \max\theta \\ &st \\ &-\theta y_i^t + \lambda Y^t \geq 0 \\ &x_i^t - \lambda X^t \geq 0 \\ &\lambda \geq 0\end{aligned} \quad (11)$$

$$D^t[y_i^{t+1}, x_i^{t+1}]^{-1} = \max\theta$$
$$st$$
$$-\theta y_i^{t+1} + \lambda Y^t \geq 0$$
$$x_i^{t+1} - \lambda X^t \geq 0$$
$$\lambda \geq 0 \qquad (12)$$

$$D^{t+1}[y_i^t, x_i^t]^{-1} = \max\theta$$
$$st$$
$$-\theta y_i^t + \lambda Y^{t+1} \geq 0$$
$$x_i^t - \lambda X^{t+1} \geq 0$$
$$\lambda \geq 0 \qquad (13)$$

$$D^{t+1}[y_i^{t+1}, x_i^{t+1}]^{-1} = \max\theta$$
$$st$$
$$-\theta y_i^{t+1} + \lambda Y^{t+1} \geq 0$$
$$x_i^{t+1} - \lambda X^{t+1} \geq 0$$
$$\lambda \geq 0 \qquad (14)$$

Where X and Y are inputs and outputs, respectively, for all DMUs; θ provides information on the technical efficiency score for the i^{th} country, and λ provides information on the peers of the (inefficient) i-th country (Coelli et al., 1998). Like Färe et al. (1994), we decompose TFP into technical change or technological progress (TECH) and efficiency change (EFFCH), which captures the catch-up effect. If these two indices are higher than one, it means that there are improvements in both technical efficiency and technological progress. On the other hand, if the indices are lower than one, it means that there are decline in both technical efficiency and technology.

4. DATA TYPES AND SOURCES

As already mentioned, the focus of this paper is on examining the Granger causality relationship among TFP, ICTs, and electricity consumption in 26 African countries. Data used in this study are pooled annual time series for electric power capita (ENC), measured in kWh per capita, ICT penetration is represented by mobile phone subscriptions per 100 people (CELL), fixed telephone subscriptions per 100 people (LANDL), and internet access per 100 people (INTER). All data come from the World Bank, World Development Indicators. Table 1 report the sample countries included in this study. This group of countries is selected on the basis of data availability. Annual observations are collected for the sample period 1996–2011.

Since an issue of great interest is the Granger causality relationship among ICT, ENC, and TFP, we use panel data on 26 countries covering the period 1996–2011 to estimate TFP using the data envelopment analysis (DEA) Malmquist productivity index approach. In the DEA-malmquist estimation, we use capital stock and the actual number of people employed (labor) as inputs, and real GDP as the output variable. We compute the capital stock data by applying the perpetual inventory method. Investment data (gross capital formation) and the stock of labor comes from the World Bank, World Development indicators. To compute the Malmquist productivity index, we adopt Färe et al.'s (1994) application of the non-parametric DEA-malmquist technique on panel data to calculate the cross-country TFP for 26 African countries.

Table 2 presents summary descriptive statistics associated with the analysis. All variables enter the model in log form.

Table 3 presents the correlations among the panel variables, and it is evident that there is a positive correlation among all the variables. An econometric issue that arises is the high correlation between mobile phones and fixed lines. High correlation between the variables may present multicollinearity problems; therefore, we construct a composite ICT index by combining mobile phone, fixed line and internet penetration rates using the PCA.

5. RESULTS AND DISCUSSIONS

Table 4 presents summary estimates of TFP, including the decomposed measures of technical change and efficiency change for the period 1996–2011. DEA-Malmquist results indicate that for the sample countries, TFP improved by an average of 0.50% over the period 1996–2011. The increase in TFP was bolstered by technological change improvement of 0.74%. The decomposition of TFP into technological progress (technical change) and efficiency change (catch-up effect) shows that technological progress largely explained the modest growth in Africa's TFP growth. Overall, 7 of the 26 countries in the sample experienced

Table 1: List of countries in the sample

Angola	Algeria	Egypt	Sudan
Benin	Morocco	Gabon	Tanzania
Botswana	Mozambique	Ghana	Togo
Cameroon	Namibia	Kenya	Tunisia
Democratic Rep. of Congo	Niger	Libya	Zambia
Congo, Rep.	Senegal	Mauritius	Zimbabwe
Cote d'Ivoire	South Africa		

Table 2: Summary of descriptive statistics

Summary statistics	Electric	Internet	Fixed telephone	Mobile phone	TFP
Mean	753.546	3.574	4.455	21.299	1.005
Median	290.842	1.111	1.510	6.627	1.003
Maximum	5061.000	52.000	31.503	180.445	1.564
Minimum	29.560	0.000	0.006	0.000	0.567
SD	1050.026	6.342	6.079	29.923	0.097

SD: Standard deviation

Table 3: Correlation matrix for panel variables

Variable name	Electr	Internet	TFP	Fixed lines	Mobile phones
Electr	1.0000	0.3130	0.0278	0.6331	0.3906
Internet	0.3130	1.0000	0.0140	0.5064	0.8883
TFP	0.0278	0.0140	1.0000	0.0461	0.0271
Fixed Lines	0.6331	0.5064	0.0461	1.0000	0.8651
Mobile phones	0.3905	0.8883	0.0271	0.8651	1.0000

deterioration in TFP over the period 1996–2011. Previous studies have also demonstrated both theoretically and empirically, that technological progress is the main driver of long-run growth.

Table 5 presents summary results of the panel unit root tests based on the IPS, LLC and Hadri panel tests for the series LTFP, LENC, and LICT. The unit root statistics reported are for the level and first differenced series, including constant and a constant with a time trend. As can be seen from Table 5, except for IPS test all the panel unit root tests confirm that the series are stationary in both the level and first differenced form. Therefore, the null hypothesis regarding the presence of panel unit root is rejected at 1% level, 5% level, and 10% level, respectively. Based on the above, there is substantial evidence that suggests that the variables are integrated of order one across countries.

Table 4: TFP decomposition for sample countries (annual average, 1996–2011)

Country	ΔTFP	TEC	EFFCH
Algeria	0.995	1.004	0.991
Angola	1.011	1.008	1.003
Botswana	1.017	1.017	1.000
Cameroon	0.995	0.995	1.000
Congo, Dem. Rep.	1.022	1.045	0.978
Congo, Rep.	0.965	1.000	0.965
Cote d'Ivoire	1.005	1.009	0.996
Egypt, Arab Rep.	1.008	1.008	1.000
Gabon	0.978	0.991	0.987
Ghana	1.015	0.998	1.016
Kenya	1.002	1.013	0.989
Morocco	1.007	1.007	1.000
Mozambique	1.013	1.001	1.012
Namibia	0.986	0.986	1.000
Senegal	1.000	1.000	1.001
South Africa	1.005	1.005	1.000
Sudan	1.032	1.032	1.000
Tanzania	1.020	1.023	0.997
Togo	0.973	0.999	0.974
Tunisia	1.027	1.027	1.000
Zambia	1.045	0.992	1.054
Zimbabwe	0.998	1.003	0.995

Having confirmed that the variables are integrated of order one, the next step involves establishing the presence of cointegration among the variables. Table 6 reports the results of the panel cointegration tests. The first four rows shown in Table 6 represent the computed test statistics for the within-dimension - which pool the autoregressive coefficient across different countries. The within-dimension estimates with an individual intercept show that the panel rho-statistic, panel pp statistic, and the panel ADF statistic reject the null of no cointegration at the 5% and 1% significance levels, respectively.

By the contrast, the within-dimension estimates with an individual intercept and trend show that only the panel PP and panel ADF provide strong evidence of the presence of cointegration among the panel series indicate. All test statistics for the between dimension estimates with an individual intercept reject the null hypothesis of no cointegration. Except for the Group rho test statistic, all the test statistics for the between-dimension, with an individual intercept and trend reject the null hypothesis of no cointegration at the 1% significance level. Overall, the cointegration results shown in Table 6 provide evidence of a long-run steady state relationship among electricity consumption, ICT, and TFP for a cross-section of countries after allowing for country-specific effects. All variables enter the models in log form, and this allows interpretation of results in terms of elasticities.

Since Table 6 confirms presence of a long-run equilibrium relationship among the variables, we estimate the long-run equilibrium relationship using the FMOLS. Table 7 provide results of the panel FMOLS. All variables are expressed in natural logarithms. Based on the group-mean FMOLS estimation

Table 5: Panel unit root results

Variables	LLC		IPS		Hadri	
	Constant	Constant+trend	Constant	Constant+trend	Constant	Constant+trend
lnTFP	−6.78*	−9.80	−12.61***	−2.81**	0.79	8.28***
ΔlnTFP	−23.46***	−21.84***	−21.04***	−6.84***	1.08	7.27***
lnENC	−2.36*	−6.23*	3.11	−1.99*	12.71**	9.40**
ΔlnENC	−16.54***	−15.87***	−11.86***	−10.85***	3.50***	6.88***
lnICT	−12.85***	−12.06***	−5.76***	−0.51	14.17***	10.58***
ΔlnICT	−7.54***	−5.07***	−2.49**	−2.24*	7.51***	7.35***

ln denotes the natural logarithm of the variable under consideration. Δ means the first difference of the variable under consideration. ***Indicates significant at 1% level, ** denotes significant at 5% level (P<0.05) and * indicates significant at 10% level (P<0.1) based on MacKinnon critical value

Table 6: Panel cointegration test results

Dimension	Test statistics	Individual intercept	Individual intercept and constant trend
Within dimension	Panel rho-stat	−3.019**	−0.536
	Panel v-stat	−0.039	−3.002
	Panel PP stat	−11.724***	−14.609***
	Panel ADF stat	−11.540***	−13.079***
Between dimension	Group rho stat	−2.079*	0.866
	Group PP stat	−18.060***	−22.524***
	Group ADF Stat	−16.242***	−15.401***

***, **, and * indicates rejection of the null hypothesis of no co-integration at 1%, 5%, and 10% levels of significance, respectively

Table 7: FMOLS estimates (dependent variable is TFP)

Country	lnENE	lnICT	Country	lnENE	lnICT
Algeria	0.452***	0.388***	Morocco	0.598***	0.405***
Angola	0.170*	0.155*	Mozambique	0.035	0.288**
Benin	0.113*	0.225**	Namibia	0.358**	0.393***
Botswana	0.374***	0.246**	Niger	−0.519	0.171*
Cameroon	0.116*	0.081*	Senegal	0.185**	0.249**
Congo, Dem. Rep.	−0.422	0.233**	South Africa	0.165*	0.351***
Congo, Rep.	−0.11	0.265**	Sudan	0.002	−0.298
Cote d'Ivoire	0.172*	−0.288	Tanzania	0.004	0.087
Egypt, Arab Rep.	0.363***	0.247**	Togo	−0.112	0.281**
Gabon	0.189*	−0.338	Tunisia	0.438***	0.269**
Ghana	0.132*	0.155*	Zambia	0.096*	0.082
Kenya	0.103*	0.416***	Zimbabwe	0.171*	0.132*
Libya	0.418***	0.268**	Panel FMOLS	0.430**	0.331**
Mauritius	0.299**	0.220**			

Shown above are estimated coefficients for the panel of 26 countries. *and **indicate the significance at the 10% and 5% level, respectively. FMOLS: Fully modified ordinary least squares

technique (Table 7), there is strong evidence of a positive relationship running from electricity consumption to TFP for the panel of countries. It follows that, a 1% increase in electricity consumption improves TFP by 0.430%. Table 7 also reports the long-run elasticities of TFP growth with respect to electricity consumption and ICT for each of the 26 countries in the sample.

Empirical results indicate that out of 26 countries in the sample, electricity consumption has a statistically significant impact on TFP growth in 19 countries. As shown in Table 7, there is a significant positive relationship (1% level of significance) between electricity consumption and TFP growth for Algeria, Botswana, Egypt, Morocco, and Tunisia - with Morocco having the highest elasticity of electricity consumption with respect to TFP. On the other hand, countries that exhibit a positive relationship at the 5% level of significance between electricity consumption and TFP include Mauritius, Namibia, and Senegal. By contrast, Angola, Benin, Cameroon, Cote d'Ivoire, Gabon, Ghana, Kenya, South Africa, Zambia, and Zimbabwe have a positive relationship at the 10% significance level. However, the coefficients for electricity consumption for Democratic Republic of Congo, Congo Republic, Mozambique, Niger, Sudan, Tanzania, and Togo are not statistically significant at any level. These results do not come as a surprise given the incessant power outages that have plagued these countries.

With regard to the long-run relationship between ICT and TFP growth, the panel test results indicate the presence of a positive relationship (5% significance level) between ICT access and TFP growth. Panel results suggest that a 1% increase in ICT access stimulates TFP growth by 0.331%. Country-specific coefficients for the ICT variable are positive for 22 countries—and thus confirm a positive relationship running from ICT to TFP growth. However, three countries (Cote d'Ivoire, Gabon, and Sudan) exert a negative effect on TFP—and the coefficients are not statistically significant. Similarly, Zambia's coefficient for ICT in spite of being positive does not attain any statistical significance. Table 7 further shows that although the results confirm that ICT penetration positively affects TFP growth, its contribution to the TFP growth among the sample countries varies. From the group of countries in the sample, Kenya has the highest elasticity of ICT access relative to TFP, while Gabon has the lowest elasticity of ICT access.

Having determined that the three variables have a long-run relationship, we perform the Granger causality tests by employing the two-step panel ECM proposed by Engle and Granger (1987). The optimal lag structure is determined using the Schwarz information criterion (SIC). Table 8 presents results for the panel Granger causality.

Short-run causality is determined by the statistical significance of the partial F-statistics associated with the right hand side variables. Long-run causality is revealed by the statistical significance of the respective error correction terms using a t-test (presented are the P-values).

Panel granger causality tests shown in Table 8 indicate that there is a short-run causal relationship running from electricity consumption (ENE) to TFP. On the other hand, there is no evidence of short-run transitory relationship running from TFP to electricity consumption. The fact that TFP has no statistical effect on electricity consumption may suggest that TFP levels are low in the short-run and thus not sufficient to stimulate an increase in electricity consumption. The above findings confirm that electricity consumption is a key determinant of TFP. As such, the short-run unidirectional causality running from electricity consumption to TFP suggests that African countries' energy crisis - that manifests in the form of power outages, blackouts, and use of other inefficient forms of energy may retard productivity growth. This hypothesis corroborates Nondo et al. (2012) and Kahsai et al.'s (2012) assertion that African countries must increase the supply of reliable electric power as well as expand electricity generation by tapping into other sources of energy, such as renewables.

In the long-run, the coefficient of the ECT term in the electricity consumption equation is also negative, thereby confirming that electricity consumption has a permanent long run relationship with TFP growth. Similarly, the strong causality test (joint short-run and long-run) supports the existence of a strong bidirectional relationship between electricity consumption and

Table 8: Panel Causality Results for 26 African Countries

Dependent variables	Short-run causality F-test			Long-run causality t-test	Test for short-run and long-run causality (strong causality) F-test		
	Δ (lnTFP)	Δ (lnICT)	Δ (lnENE)	ECT (−1)	Δ (lnTFP) ECT (−1)	Δ (lnICT) ECT (−1)	Δ (lnENE) ECT (−1)
Δ(lnTFP)	-	F=0.43	F=2.42**	−0.038*	-	4.02**	2.83*
Δ(lnICT)	F=5.61*	-	F=0.81	−0.016*	1.33	-	3.23**
Δ(lnENE)	F=0.34	F=0.70	-	−0.099*	3.18*	5.37*	-

TFP growth. The implication is that an increase in electricity consumption is associated with an increase in the TFP level. This finding confirms Schurr and Netschert (1960) and Berndt (1978) hypothesis that availability of electricity stimulates TFP growth. Theoretically, high levels of TFP may stimulate high electricity consumption because this may provide signals of growth in the economy (GDP) and thereby induce higher demand for electricity consumption. Another plausible explanation is that energy intensity in Africa is known to be very high and this stems from inefficient use of energy sources and old production technologies, among others. For instance, estimates by the IEA indicate that due to inadequate energy infrastructure, 35% of the indirect costs incurred by Sub-Saharan African firms stem from energy costs that come from backup electric generators. Also, firms that opt not to undertake these additional investments still incur costs in the form of lost production that results from idling equipment (IEA, 2014).

Table 8 also shows that there is no short-run transitory relationship between ICT and TFP growth. The above findings clearly suggest that ICT access has a limited impact on Africa's TFP growth in the short-run and this could be attributed to insufficiently low levels of ICT access, particularly in the area of broadband Internet usage. These findings corroborate with previous studies (Dewan and Kraemer, 1998; Gruber and Koutroumpis, 2010) which contend that developing countries do not experience significant returns from ICT development due to low penetration rates. Similarly, Nyirenda-Jere and Biru (2015) point out that many African countries have internet penetration rates below the 20% threshold level required for countries to reap the economic benefits of broadband investment.[3] Nonetheless, the long-run and strong causality tests reveal a unidirectional causality running from ICT to TFP, and thus underscores the important role that ICT is poised to play in stimulating TFP growth through the promotion of technological progress, labor productivity, and positive network externalities.

Additional insights from the causality tests indicate that there is no transitory relationship running either from electricity consumption to ICT or from ICT to electricity consumption. The insignificant short run relationship between ICT and electricity consumption is expected given that ICT development in Africa are not sufficiently developed, except for the fact that cell phones remain the predominant form of ICT - and these do not necessarily result in an increase in the demand for electricity consumption. For the same reason, the fact that power is widely unavailable, unreliable, and unaffordable makes it difficult for households and businesses to adopt ICT technologies. Stated differently, an increase in the use of ICTs inextricably depends on the availability of a steady supply of electric power. A further examination of Table 8 shows that the joint F-test for the short-run and long-run relationship is significant at the 5% level. This confirms the presence of a strong two-way Granger causality between the ICT access and electricity consumption and a unidirectional causality from ICT to TFP. This means that African countries will be able to capture higher TFP growth by increasing broad-based ICT access.

3 For instance, while a country such as morocco has broadband internet penetration rates in excess of 50%, majority of countries have penetration rate below 10%, with countries such as Niger and chad having penetration rates <2%.

6. CONCLUSION

This study provides a formal analysis of the short-run and long-run causality relationship among ICT access, electricity consumption, and TFP for a panel of 26 African countries over the period 1996–2011. The analysis shows that in the long-run there is a bidirectional relationship between ICT and electricity consumption, a unidirectional relationship running from ICT to TFP, and a two-way relationship between electricity consumption and TFP growth. The existence of a two-way relationship between electricity consumption and TFP is indicative of the productivity-enhancing role that electricity plays, particularly by encouraging technological progress and technical efficiency. This means that countries that have a reliable supply of electric power are bound to increase TFP. Likewise, an increase in TFP in the long-run may provide the impetus for the growth of the economy (GDP), and thereby induce higher demand for electricity consumption. Effectively, this may result in increasing expenditure in the power generation sector by way of upgrades, new construction, and maintenance. Based on the above, it seems reasonable to conclude that in order for African countries to sustain economic growth and promote broad-based development, the ubiquitous and incessant power shortages must be addressed.

Further, empirical results do not show presence of a short-run transitory relationship between electricity and ICT access; however, in the long-run, there is existence of a bidirectional causality. The presence of a bidirectional relationship confirms the important role that electric power plays in facilitating the use of a bundle of ICTs. Conversely, evidence indicates that an increase in ICT access induces demand for TFP and electricity consumption in the long-run. These findings imply that African governments must devise and implement strong policies that will provide more resources and support to the expansion of ICT infrastructure.

REFERENCES

Agénor, P., Moreno-Dodson, B. (2007), Public Infrastructure and Growth: New Channels and Policy Implications. World Bank Policy Research Working Paper No. 4064.

AICD (Africa Infrastructure Country Diagnostic). (2008), AICD Power Sector Database. Washington, DC: World Bank.

Aschauer, D.A. (1989), Is public expenditure productive? Journal of Monetary Economics, 23(2), 177-200.

Barro, R., Sala-I-Martin, X. (1995), Economic Growth. New York: McGraw-Hill.

Beil, R., Ford, G.S., Jackson, J.D. (2005), On the relationship between telecommunications investment and economic growth in the United States. International Economic Journal, 19(1), 3-9.

Berndt, E.R. (1978), Aggregate energy, efficiency, and productivity measurement. Annual Review of Energy, 3, 225-273.

Berndt, E.R., Wood, D.O. (1986), Energy price shocks and productivity growth in U.S. and U.K. manufacturing. Oxford Review of Economic Policy, 2(3), 1-31.

Calderón, C. (2008), Infrastructure and Gro[wt]h in Africa. Policy Research Working Paper, No. WPS 4914. Washington, DC: World Bank.

Coelli, T.J., Rao, D.S.P., Battese, G.E. (2002), An Introduction to Efficiency and Productivity Analysis. 6th ed. Boston, MA: Kluwer Academic Publisher.

Cronin, F., Parker, E.B., Colleran, E.K., Gold, M.A. (1991), Telecommunications infrastructure and economic growth: an analysis of causality. Telecommunications Policy, 15(6), 529-535.

David, P.A., Wright, G. (1999), Early Twentieth Century Productivity Growth Dynamics: An Inquiry into the Economic History of Our Ignorance. University of Oxford Papers in Economic History, No. 33.

Dewan, S., Kraemer, K.L. (1998), International dimensions of the productivity paradox. Communications of the ACM, 41(8), 56-62.

Dutta, A. (2001), Telecommunications and economic activity: An analysis of granger causality. Journal of Management Information Systems, 17(4), 71-95.

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

Escribano, A., Luis, G.L, Jorge, P. (2008), Impact of Infrastructure Constraints on Firm Productivity in Africa. Working Paper 9, Africa Infrastructure Country Diagnostic, Washington, DC: World Bank.

Escribano, A., Luis, G.L., Jorge, P. (2010), Assessing the Impact of Infrastructure Quality on Firm Productivity in Africa: Cross-Country Comparisons Based on Investment Climate Surveys from 1999 to 2005. Policy Research Working Paper; No. 5191. Washington, DC: World Bank.

Foster, V., Briceno-Garmendia, C. (2010), Africa's Infrastructure: A Time for Transformation. Washington, DC: World Bank.

Färe, R., Grosskopf, S., Norris, M., Zhang, Z. (1994), Productivity growth, technical progress, and efficiency change in industrialized countries. American Economic Review, 84(1), 66-83.

Gebremichaela, M., Jackson, J.W. (2006), Bridging the gap in sub-saharan Africa: AH holistic look at information poverty and the region's digital divide. Government Information Quarterly, 23(2), 267-280.

IEA (International Energy Agency). (2014), Africa Energy Outlook: A Focus on Energy Prospects in Sub-Saharan Africa. World Energy Outlook Special Report, International Energy Agency, Paris Cedex 15, France.

Im, K.S., Pesaran, M.H., Shin, Y. (2003), Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115(1), 53-74.

IMF (International Monetary Fund). (2013), Sub-Saharan Africa: Keeping the Pace. Washington, DC: Regional Economic Outlook, International Monetary Fund.

ITU (International Telecommunications Union). (2013), ITU Yearbook of Statistics 2013. 39th ed. Available from: http://www.itu.int/en/ITU-D/Statistics/Pages/publications/yb2013.aspx <http://www.itu.int/en/ITU-D/Statistics/Pages/publications/yb2013.aspx>.

ITU (International Telecommunication Union). (2012), Measuring the Information Society: The ICT Development Index. Geneva, Switzerland: Place des Nations CH-1211.

Jorgenson, D.W. (1984), The role of energy in productivity growth. American Economic Review, 74(2), 26-30.

Kahsai, M.S, Nondo, C., Schaeffer, P.V., Gebremedhin, T.G. (2012), Income level and the energy consumption—GDP nexus: Evidence from Sub-Saharan Africa. Energy Economics, 34(3), 739-746.

Ladu, M.G., Meleddu, M. (2014), Is there any relationship between energy and TFP?' A panel cointegration approach for Italian regions. Energy, 75(1), 560-567.

Lee, S.Y.T., Gholami, R., Tong, T.Y. (2005), Time series analysis in the assessment of ICT impact at the aggregate level–lessons and implications for the new economy. Information and Management, 42(7), 1009-1022.

Levin, A., Lin, C.F., Chu, C.S.J. (2002), Unit root tests in panel data: Asymptotic and finite sample properties. Journal of Econometrics, 108(1), 1-24.

Lipsey, R.G, Carlaw, K.I., Bekar, C. (2006), Economic Transformations: General Purpose Technologies, and Long Term Economic Growth. Oxford: Oxford University Press.

Lipsey, R.G., Bekar, C., Carlaw, K.I. (1998), What Requires Explanation? In: Helpman, E., editor. General Purpose Technologies and Economic Growth. Cambridge, Mass.: MIT Press. p15-54.

Lucas, R. (1988), On the mechanics of endogenous growth. Journal of Monetary Economics, 22, 3-42.

Moser, P., Nicholas, T. (2004), Was electricity a general purpose technology? Evidence from historical patent citations. American Economic Review, 94(2), 388-394.

Ndulu, B.J. (2007), Challenges of African Growth. Opportunities, Constraints, and Strategic Directions. Washington, DC: World Bank.

Nondo, C., Kahsai, M.S., Schaeffer, P.V. (2012), Energy consumption and economic growth: Evidence from COMESA countries. Southwestern Economic Review, 39(1), 107-120.

Nyirenda-Jere, T., Biru, T. (2015), Internet Development and Internet Governance in Africa. Internet Africa. Internet Society. Available from: http://www.internetsociety.org/sites/default/files/Internet%20development%20and%20Internet%20governance%20in%20Africa.pdf.

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

Pedroni, P. (2004), Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econometric Theory, 20(3), 597-625.

Sadorsky, P. (2012), Information communication technology and electricity consumption in emerging economies. Energy Policy, 48(1), 130-135.

Schurr, S.H. (1984), Productive efficiency and energy use: An historical perspective. Annals of Operations Research, 2(1), 229-238.

Schurr, S.H., Netschert, B.C. (1960), Energy in the American Economy, 1850–1975: An Economic Study of Its History and Prospects. Baltimore, MD.: Johns Hopkins University Press.

Schön, L. (2000), Electricity, technological change and productivity in Swedish industry 1890-1990. European [R]eview of Economic History, 4(2), 175-194.

Solow, R. (1957), Technical change and the aggregate production function. Review of Economics and Statistics, 39(3), 312-320.

Stiroh, K.J. (2002), Information technology and the U.S. productivity revival: What do the industry data say? American Economic Review, 92(5), 1559-1576.

Tugcu, C.T. (2013), Disaggregate energy consumption and total factor productivity: A Cointegration and causality analysis for the Turkish economy. International Journal of Energy Economics and Policy, 3(3), 307-314.

World Bank. (2009), Infrastructure and Growth in Africa. The World Bank, Policy Research Working Paper 4914. Washington, DC: World Bank.

World Bank. (2011), World Development Indicators Database. Washington, DC: World Bank. Available from: http://www.data.worldbank.org/data catalog.

World Bank. (2014), Regional Infrastructure in Sub-Saharan Africa: Challenges and Opportunities. Washington, DC: World Bank.

World Bank. (2015), Africa's Pulse: An Analysis of Issues Shaping Africa's Economic Future. Washington, DC: World Bank. Available from: http://www.documents.worldbank.org/curated/en/258281467991904972/pdf/99988-2nd-REVISED-WB-AfricasPulse-Fall2015-vol12-v19-print.pdf.

Yepes, T., Pierce, J., Foster, V. (2008), Making Sense of Sub-Saharan Africa's Infrastructure Endowment: A Benchmarking Approach. Working Paper No. 1, Africa Infrastructure Country Diagnostic. Washington, DC: World Bank.