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ORIGINAL ARTICLE

Total factor energy efficiency and economic development in Africa

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Abstract This paper presents an energy efficiency assessment of 46 African countries and analyzes possible bidirectional relationship between energy efficiency and economic development within a three-stage framework. In the first stage, energy efficiency is measured within a total factor framework using the slack-based measure with undesirable output and sub-regional comparisons are done. The second stage assesses the determinants of energy efficiency in Africa by way of a bootstrapped truncated regression. The third stage tests the reverse causal relationship between energy efficiency and economic development using 2-stage least squares. The results showed African countries to be on average, 56% energy efficient within the study period. Other African sub-regions could adopt the energy efficiency policies of North Africa as benchmark to improve energy efficiency. Economic development and technological progress are found to have significant positive effects on energy efficiency of African countries, while higher energy prices lead to higher inefficiency. Also, a bi-causal relationship is found to exist between total factor energy efficiency and economic development, giving support to the concept of sustainable development and confirming the International Energy Agency's assertion on the positive macroeconomic impacts of energy efficiency. African countries are therefore, encouraged to invest in energy efficiency technologies and policies to drive sustainable economic development.

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Introduction

The accessibility and utilization of energy are vital for almost all major economic activities, as such, energy is the driving force of life on earth (Mahmood and Kanwal 2017). Consequently, energy remains the major ingredient for economic development and prosperity (Chontanawat et al. 2008; Asafu-Adjaye 2000; Apergis and Payne 2009; Belloumi 2009; Costantini and Martini 2010; Mehrara 2007; Pao and Tsai 2011; Yuan et al. 2008; Lee and Chang 2007; Huang et al. 2008). Due to the indispensable nature of energy, global energy consumption in 2017 amounted to 14,050 million tonnes of oil equivalent (Mtoe), compared with 10,035 Mtoe in 2000 (International Energy Agency 2017). Meanwhile, Africa's energy consumption increased by 2.9% in 2017, faster than the world's average of 2.2% (BP 2017). It has been predicted that Africa may become a worldwide motor of growth in the future (Koskimäki

2012). This implies that energy use is expected to surge in the continent. African regional energy consumption remains heavily dominated by oil, gas, and coal. Hydro accounts for 6.5% while nuclear and renewables combined only represent 2.0% (BP 2017).

It is worth noting that, in the wake of environmental concerns, energy generation and consumption have been linked with emission of harmful atmospheric gasses (Zhang and Cheng 2009). Energy production and use, for instance, account for about two-thirds of the world's greenhouse gas (GHG) emissions (IEA 2015; Li and Hu 2012). Economies are therefore faced with either resorting to more use of renewable energy or ensuring energy efficiency where less energy is consumed to produce the maximum economic output possible (Gerrard 2011). Thus, renewable energy and improvements in energy efficiency are now part of the top global concerns towards achieving sustainable development as evidenced in the sustainable development goals (Stuggins et al. 2013). This is a concern for Africa especially given that the continent is facing an upsurge in energy consumption, mainly from unrenewable sources, which is projected to grow even further (Arouri et al. 2014; Pielli 2014). Apart from the environmental concerns driving energy efficiency, studies have uncovered that efficient energy use could drive economic growth (Xiaoli et al. 2014; Rajbhandari and Zhang 2018; Hu and Kao 2007; Hu and Wang 2006; Zhang et al. 2011; Honma and Hu 2008). Additionally, the International Energy Agency (2017) asserts that energy efficiency can enable economic growth, reduce emissions, and improve energy security and that right efficiency policies could enable the world to achieve more than 40% of the emissions cuts needed to reach its climate goals without new technology. To ensure energy efficiency, some African countries have set up regional intergovernmental organizations (IGOs) to draft energy efficiency policies to ensure efficient energy use. The Regional Center for Renewable Energy and Energy Efficiency (RCEEE), ECOWAS Centre for Renewable Energy and Energy Efficiency (ECREEE), East African Centre for Renewable Energy and Energy Efficiency (EACREEE), and SADC Centre for Renewable Energy and Energy Efficiency (EACREEE) are all examples of the bodies set up in this regard. It is important to examine the success thus far achieved by the IGOs in ensuring energy efficiency in order to set benchmarks for the low performers. Additionally, it is imperative that policy makers understand how energy efficiency translates into economic development as well as identify the areas of maximum potential for energy efficiency improvement.

The academic literature has focused on the relationship between energy consumption and economic development while a broader assessment of the macroeconomic effect of energy efficiency policy is lacking (Rajbhandari and Zhang 2018), especially for Africa. Yet, understanding the link between energy efficiency and economic development will help economies to account for the costs and benefits of energy efficiency measures (Vivid Economics 2013). The need to examine the causal relationship between the energy efficiency and economic development in the short and long runs is stressed by Mahmood and Kanwal (2017). This will enable a better understanding of the sustainability of economic development in Africa. The environmental impacts of energy generation and consumption such as global warming and environmental degradation are those aspects which make causality between economic development and energy efficiency a researchable debate (Mirza and Kanwal 2017). Energy efficiency studies on Africa are lacking, despite the fact that energy efficiency is a critical priority towards achieving sustainable energy supply and sustainable development (Ohene-Asare and Turkson 2018). The few studies, for instance (Ohene-Asare and Turkson 2018), consider selected sub-regions such as ECOWAS; however, considering all the sub-regions will help to provide both country-specific benchmarks as well as regional benchmarks for the various regional organizations in charge of energy efficiency policies. Additionally, this study further assesses the effect of economic development on energy efficiency and the reverse causality between energy efficiency and economic development.

The objectives of the study are three-folds: first, to contribute to the energy efficiency literature by evaluating the total factor energy efficiency (TFEE) of African countries and sub-regions while considering carbon dioxide emissions; second, to contribute to the economic development literature by investigating the impact of economic development on TFEE in Africa; and lastly, to contribute to the second stage regression in efficiency literature by investigating the possible bidirectional link between energy efficiency and economic development. The next section presents the relevant literature, followed by methods and models in the "Methods and models" section. The data and variables are presented in the "Data and variables" section while the final section presents analysis, discussions, and conclusions.

Literature review

Measuring energy efficiency

The concept of energy efficiency has become central to the energy policies of various economies (Ang 2006; Zhou et al. 2008; Patterson 1996; Bosseboeuf et al. 1997). During the 1970s, energy efficiency received much focus due to the 1973 world oil crises (Honma and Hu 2009; Zhou and Ang 2008). With energy prices increasing substantially within the period, policymakers and economies became interested in how effectively energy resources were being used and how to ensure the possible maximum amount of outputs were produced given level of energy inputs (Ang 2006). This attention to energy efficiency was further emphasized in the late 1980s with growing concerns of global warming, which is said to result from burning of fossil fuel (Zhang et al. 2011; Chang and Hu 2010; Li and Lin 2014; Ang 2006; Bosseboeuf et al. 1997). To put this into context, the International Energy Agency (IEA) in 2014 noted that the production and use of energy contribute to two-thirds of the world's CO_2 emissions (IEA 2015). In this sense, energy efficiency is seen as the main channel through which economies can attain emission targets set by the Kyoto Protocol (Honma and Hu 2009; Ang 2006). Energy efficiency is also seen as a means of attaining industrial competitiveness and energy security (Singh 2016). Traditionally, energy efficiency can be defined as the use of less energy to produce the same amount of some useful output (Ang 2006). Mathematically, Patterson (1996) defines energy efficiency as the ratio of some useful output to a process to the energy input into the process. That is $\frac{\text{Useful output}}{\text{Energy input}}$.

Given the multi dimensionality and importance of energy efficiency, various indicators have been developed for its measurement (Ang 2006; Patterson 1996). Energy efficiency indicators are, however, mainly classified into simple single factor indices and composite indices (Apergis et al. 2015). Traditional single factor indices include the energy-GDP ratio (energy intensity index) and the GDP-energy ratio (energy productivity) and are based on a relative measure of output to energy inputs only (Apergis et al. 2015; Chang and Hu 2010; Li and Hu 2012). This has been the basis for criticism of the single factor indices. It is argued that single factor indices do not consider other inputs of production such as capital and labor, implying that all attainable outputs are a result of energy consumption alone (Zhang et al. 2011). However, energy alone cannot produce any output and hence must be combined with other inputs (Zhang et al. 2011). Moreover, these measures tend to overestimate energy efficiency due to the substitution effects between inputs and fail to measure the underlying technical efficiency (Chang and Hu 2010; Hu and Wang 2006). Therefore, estimating energy efficiency using the partial factor indicators could present misleading results (Honma and Hu 2008, 2009; Hu and Kao 2007; Hu and Wang 2006). The preferred approach then, is to measure energy efficiency within a total factor framework, which considers other inputs of production (Hu and Wang 2006). To this effect, Hu and Wang (2006) proposed the TFEE while considering labor and capital as additional inputs in the production process. This measure of energy efficiency does exactly what the partial factors fail to consider. That is, it takes into consideration the complementarity or substitutability of inputs, measures the underlying technical efficiency, and has the possibility to disaggregate the energy inputs. Given its advantages over the single factor indices, the current study adopts the DEA-based TFEE measure to study energy efficiency in Africa.

Literature on energy efficiency with the TFEE in Africa

Studies emphasize that energy is an important part of everyday life. However, the use of energy to produce desirable output also results in the emission of harmful gasses that affect the local and global climate and contributes highly to the global warming, one of the dreaded concerns of the world today (Mardani et al. 2017). Consequently, models that address energy efficiency issues have become crucial. In a survey paper, Mardani et al. (2017) have reviewed a number of models in the data envelopment analysis (DEA) literature that address energy efficiency. The TFEE framework was developed based on the DEA nonparametric efficiency and productivity assessment approach. Based on the earlier work of Farrell (1957), DEA is a linear programming methodology introduced by Charnes et al. (1978) and extended by Banker et al. (1984) used to evaluate the relative efficiencies of decision-making units which employ similar inputs to produce similar outputs (Zhou et al. 2008). The TFEE indicator, developed within this framework, has been employed in a number of energy efficiency assessments. Nonetheless, scanty work on energy efficiency and productivity exists on Africa. Some of the few studies include Ramanathan (2005) who analyzed the energy consumption and carbon emission performance of Middle East and North African (MENA) countries. Using the Malmquist productivity index, the study employed fossil fuel energy consumption and carbon dioxide as inputs and GDP and non-fossil fuel energy consumption (electricity and non-conventional energy sources) as the outputs. Although the study recognized the drawback of using CO_2 as an input, this does not appear to be the only drawback of the study. First, under any energy consumption performance study, one will mainly like to reduce the amount of all energy sources consumed as done in studies such as Honma and Hu (2008, 2009), therefore, employing non-fossil fuel energy consumption as on output to be maximized defeats the whole purpose of analyzing energy consumption performance. Moreover, other traditional factors of production, such as labor and capital, were not considered inputs, suggesting that fossil energy consumption alone can produce GDP, which is not the case (Hu and Wang 2006). Nonetheless, the study found Sudan, Bahrain, and Oman to be efficient while Saudi Arabia was the least efficient. The study also found a progress in productivity from 1992 to 1996 for 5 out of the 17 countries.

Also, Zhang et al. (2011) analyzed the TFEE of developing countries using window analysis and Tobit model to analyze the relationship between energy efficiency and per capita income. The study found Botswana to be among the most efficient countries selected, with Kenya being the worst performer with an average TFEE of 0.329 within the entire period. However, the environmental effect of energy generation and use was not considered by the study (IEA 2015; Li and Hu 2012). Note also that the sample consisted of countries spread across the different world regions, hence using the window analysis, without recognizing the possible heterogeneities among the countries and regions could lead to biased energy efficiency estimates (Battese et al. 2004). The Tobit model estimation reported a U-shaped relationship between TFEE and income per capita. Yet, applying the second stage Tobit regression in efficiency assessment could result in serial correlation and biases (Simar and Wilson 2007, 2011, 2015).

Similarly, Ohene-Asare and Turkson (2018), using the TFEE framework, examined the energy efficiency and energy productivity changes of 15 ECOWAS member states over the period 1990–2014. While considering undesirable outputs, the study found that states in the sub-region differ in the nature and levels of energy efficiency and sources of inefficiency. Their study further found that technical changes outside direct state control were the major source of energy productivity growth in the sub-region. Considering the rising concerns on the harmful by-products in the consumption of energy, it is ideal that the study considered undesirable output in the efficiency assessment (Sueyoshi and Goto 2012a, b; Ismail et al. 2013). The study is, however, limited to one African sub-region and does not present the full picture of the continent as a whole. A study on Africa as a whole will allow for inter-country benchmarking for the countries as well as inter-regional benchmarking for the regions. The inter-regional benchmarking will assess how well the regional energy policies are helping countries in their respective regions to achieve energy efficiency. Additionally, since energy efficiency is claimed to be closely related to economic development, it would be more informative to further investigate how the situation is for the African continent in the presence of undesirable output.

Energy efficiency and economic development

Empirical studies on the economic development-energy efficiency relationship point to a positive relationship between the two variables and also indicate a long-run U-shaped relationship. However, some of these studies (Honma and Hu 2008; Hu and Wang 2006) have made this conclusion not based on any statistical test, but rather based on graphical analysis, where the mean per capita income scores are matched against the mean energy efficiency scores. For example, Hu and Wang (2006) analyzed the TFEE of Chinese administrative regions and based on the graphical relationship between the two variables concluded on a U-shaped relationship, similar to the environmental Kuznets curve hypothesis. In a similar analysis but on 47 Japanese prefectures, Honma and Hu (2008) also found a U-shaped relationship between energy efficiency and economic development, concluding that energy efficiency eventually increases with economic growth. The studies help in understanding the energy efficiency-economic development relationship although could not determine whether this relationship is statistically significant or not. Studies such as Hu and Kao (2007); Xiaoli et al. (2014); Rajbhandari and Zhang (2018); and Zhang et al. (2011) have tested this relationship via a second stage analysis.

In their analysis of APEC economies, Hu and Kao (2007) used a random effects panel model to examine the relationship between energy saving target ratio and economic development, proxied by the GDP per capita and reported an inverted U-shaped relationship between the variables pointing that developing economies should pay more attention to energy savings issues. Xiaoli et al. (2014), studying the TFEE of China's provincial industrial sectors, investigated the factors that affect TFEE using a Tobit model, with economic development considered one of the explanatory variables. Using income per capita as a proxy for economic development, they reported a positive relationship between TFEE and economic development. Similarly, Zhang et al. (2011) investigated the relationship between energy efficiency and economic development, proxied by GDP per capita and also found a statistically significant positive relationship between TFEE and per capita income squared, also depicting a U-shaped relationship. A common feature and limitation of these studies is that by using the Tobit model, possible serial correlation problem of the independent variables as identified by Simar and Wilson, 2007, 2011, 2015) is likely to be ignored.

Apart from the positive relationship between energy efficiency and economic development, Rajbhandari and Zhang (2018), in their recent study, found bidirectional causality between energy efficiency and economic growth. Using a panel data for 56 high and middle-income countries from 1978 to 2012, the study found long-run Granger causality from economic growth to lower energy intensity. Additionally, the study found a long-run bidirectional causality between lower energy intensity and higher economic growth. This finding suggests that beyond the environmental benefits of energy efficiency, it could be a driver of economic development IEA (2014) . This study extends the investigation by considering the possible reverse causality between energy efficiency on economic development of African countries where energy is measured in a total factor framework.

Methods and models

The SBM of Tone (2001 and 2003) which accounts for non-radial slacks and undesirable outputs is employed in the estimation of TFEE while the truncated bootstrapped regression and two-stage least squares are used to assess the impact of ED on EE and investigate the ED-EE nexus in that order.

The undesirable SBM

DEA models fall under two main classifications: radial and non-radial. Radial models by their nature focus on the proportional reduction of all inputs (input efficiency) or increase in outputs (output efficiency) given the output or input levels respectively (Cook and Zhu 2005; Fried et al. 2008; Cooper et al. 2011). The radial input (output)-oriented models only focus on ensuring input (output) efficiencies, consequently ignoring non-radial slacks in their estimation, a crucial shortcoming when undesirable outputs are considered (Apergis et al. 2015). The SBM, a variant of the DEA models, is a non-radial model that accounts for input excesses and output shortfalls in its estimation of efficiency, and hence has greater discriminatory power, an advantage it possesses over the radial models. Moreover, it is not affected by the statistics of the whole data set, and is unit invariant and monotone decreasing with respect to input excesses and output shortfalls (Tone 2001; Gómez-Calvet et al. 2014). Therefore, the non-radial and non-oriented models are the best at capturing the whole measures of efficiency within the framework of undesirable outputs (Apergis et al. 2015). The objective of the non-radial non-oriented model with undesirable outputs is to simultaneously reduce inputs and undesirable outputs while increasing good outputs.

Following Tone (2003), to formularize the SBM given the technology set T, where there are n DMUs (j: 1,…, n), assume that the DMUs use m (i: 1,…,m) common inputs to produce s_1 desirable outputs (r: 1,…,s_2) and s_2 undesirable outputs (r: 1,…,s_2), and the non-oriented SBM model in the presence of undesirable outputs is formulated as:

$$p^* = \min \left[\frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{S_i^-}{X_{io}}}{1 + \frac{1}{S_1 + S_2} \left(\sum_{r=1}^{S_1} \frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2} \frac{S_r^b}{y_{r0}^b} \right)} \right] \quad (1)$$

Subject to:

$$\begin{aligned}&\sum_{j=1}^{n}\lambda_j x_{ij}+s_i^-=x_{io};i=1,2,\ldots,m,\\&\sum_{j=1}^{n}\lambda_j {y^g}_{rj}-s_r^g=y_{ro};r=1,2,\ldots,s_1,\\&\sum_{j=1}^{n}\lambda_j {y^b}_{rj}+s_r^b=y_{ro};r=1,2,\ldots,s_2,\\&\lambda_j\geq 0,(\forall j);\ \ s_i^-\geq 0,(\forall i);\ \ s_r^+\geq 0,(\forall r)\end{aligned} \tag{2}$$

where s_i^- and s_r^b represent excesses in input and undesirable outputs respectively, s_r^g represents shortfalls in desirable outputs, and λ_j are intensity variables whose values will be determined by the optimal solution to the linear programming problem. The objective function, Eq. (3), is monotone decreasing with respect to all s_i^-, s_r^g, and s_r^b, and $\rho*$ satisfies $0<\rho*\leq 1$. Note that the optimal solution satisfies $\lambda^*, s_i^{-*}, s_r^{g*}, s_r^{b*}$ such that a DMU is only efficient if $\rho* = 1$, in which case, all the input and output slacks are equal to zero.

Using the Charnes-Cooper transformation (Charnes and Cooper 1962), Eq. (3) can be linearized to the equivalent linear programming problem:

$$\tau^*=\min\left(t-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}\right) \tag{3}$$

Subject to:

$$\begin{aligned}&t+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)=1\\&\sum_{j=1}^{n}\lambda_j x_{ij}+s_i^-=x_{io}t; \qquad i=1,2,\ldots,m,\\&\sum_{j=1}^{n}\lambda_j y_{rj}^g-s_r^g=y_{ro}t; \qquad r=1,2,\ldots,s,\\&\sum_{j=1}^{n}\lambda_j y_{rj}^b+s_r^b=y_{ro}t; \qquad r=1,2,\ldots,s,\\&\lambda_j\geq 0,(\forall j);\ \ s_i^-\geq 0,(\forall i);\ \ s_r^g\geq 0,\ \ s_r^g\geq 0,(\forall r);\mathrm{t}>0\ \ j=1,2,\ldots n.\end{aligned} \tag{4}$$

where the $e\lambda = 1$ constraint is added if VRS.

It is noteworthy also that $\rho*$ is a measure of technical efficiency which aims at minimizing inputs to generate both desirable and undesirable outputs. Yet, energy efficiency assessment focuses on the energy input. Hence, using the optimal weights from solving the model in Eq. (1) or (3), the target energy input for a DMU can be estimated as target energy input$_o$= $e_0 - s_i^{-*}$, where s_i^{-*} is the optimal input excess in Eq. (1) or (3) corresponding to the constraints for the energy input e which is one of the m inputs earlier defined. From this, the energy efficiency measure of Hu and Wang (2006) is computed as the ratio of target energy input to actual energy input (Chang and Hu 2010; Ohene-Asare and Turkson 2018):

$$\mathrm{TFEE}=\frac{\text{Target energy input}_{(i,t)}}{\text{Actual energy input}_{(i,t)}} \tag{5}$$

and

$$\begin{gathered}\text{Target energy input}\leq\text{actual energy input}\\0<\mathrm{TFEE}\leq 1\end{gathered} \tag{6}$$

From Eq. (6), the TFEE score always lies between 0 and 1, where a DMU is efficient and given the score of 1 if the target energy input equals the actual energy input and inefficient and given a score less than 1 if the target energy input is less than the actual energy input. The level of inefficiency is then defined by how large a difference there is between the target and the actual energy input levels.

Scale elasticity in DEA

In estimating efficiency in DEA, one has to specify a type of returns to scale (RTS) underlying the production technology. Specifying either constant returns to scale (CRS) or variable returns to scale (VRS) is a crucial question for any efficiency analysis since adopting a wrong technology assumption may distort results or lead to statistical inconsistencies (Simar and Wilson 2002). To this effect, Simar and Wilson (2002) propose tests for RTS based on bootstrap algorithms. In doing so, the following hypotheses are tested:

- H_0 = the production technology is globally CRS
- H_a = the production technology is VRS

To test the above hypotheses, the mean of ratios test by Simar and Wilson (2002) is adopted. The test statistic is defined as

$$\hat{S}=n^{-1}\sum_{i=1}^{n}\left(\frac{D_n^{\mathrm{CRS}}(x,y)}{D_n^{\mathrm{VRS}}(x,y)}\right) \tag{7}$$

where H_0 is rejected when $\hat{S}$ is significantly less than unity. To statistically test the hypothesis, since the distribution of the test statistic is unknown, bootstrapping procedures are used to generate p values and critical values. Hence, H_0 is rejected if the p value is less the chosen significant level (Simar and Wilson 2002).

Alternatively, reject H_0 if the test statistic is less than the critical value.

The SZAL for DEA efficiency analysis

Despite the existence of a number of statistical tests for efficiency differences of various groups, this study adopts the Li test. The Li test, proposed by Qi Li (1996) and adapted by Simar and Zelenyuk (2006) into the DEA context (hereafter referred to as SZAL), does not strictly require the choice of a dependent or an independent sample, unlike other tests such as Mann-Whitney *U* test or Kruskal-Wallis the Friedman test. Also, other tests only test the central tendencies and assume that the true efficiency estimates are observed when they are in fact unknown. The SZAL test addresses these issues (Epure et al. 2011; Li 1996; Simar and Zelenyuk 2006) by applying kernel density estimations and bootstrapping procedures to compare the entire distributions of efficiency scores between different groups. Given the efficiency estimates of two groups expressed as two density functions $f(\alpha)$ and $f(\beta)$, the following hypotheses are tested:

H_0: $f(\alpha) = f(\beta)$
H_a: $f(\alpha) \neq f(\beta)$

That is, testing the null hypothesis that the two distributions are drawn from the same sample against the alternative that the two distributions are different. The null hypothesis is rejected when the *p* value associated with the SZAL test statistic is less than 5%.

The bootstrapped truncated regression models

In order to investigate the impact of economic development and some contextual variables on efficiency scores, we adopt the second stage bootstrap truncated regression model of Simar and Wilson (2007, 2011) which, unlike other models, is able to resolve issues of bias and serial correlations. Generally, the second stage truncated regression model is specified as:

$$\phi_j = \alpha + \beta Z_j + \varepsilon_j, \quad j = 1, \ldots, n \tag{8}$$

where ϕ_j represents the bootstrapped TFEE score of the particular country, *j*, obtained from solving model (4), and Z_j is a vector of environmental variables which are expected to influence TFEE.

To test the relationship between economic development and TFEE, the following specific model is adopted:

$$\begin{aligned}\mathrm{TFEE}_{i,t} = {} & \beta_1 \mathrm{GNIPC}_{i,t} + \beta_2 \mathrm{GNIPC}^2{}_{i,t} + \beta_3 \mathrm{TECH}_{i,t} \\ & + \beta_4 \mathrm{ECONSTR}_{i,.t} + \beta_5 ENEPR_{i,t} \\ & + \beta_6 \mathrm{POP}_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}\end{aligned} \tag{9}$$

where TFEE is the TFEE score attained from bootstrapping the non-oriented SBM and GNIPC is the gross national income per capita used as a proxy for economic development. GNIPC^2 is included in the model to capture the nonlinear relationship between TFEE and economic development as found by Chang and Hu (2010) and Xiaoli et al. (2014). GNIPC is preferred to gross domestic product (GDP) as a measure of economic development because although GDP is a good measure for economic growth, economic development goes beyond just acceleration in economic growth (Todaro and Smith 2011). The authors adopt the World Bank's approach which classifies economies based on their level of GNI per capita.

The remaining variables are control variables and defined as follows:

TECH measures the level of technology, and is proxied by the capital-labor ratio which is found by dividing the level of capital by the economic active population. Following Apergis et al. (2015) and Xiaoli et al. (2014), this variable is expected to have a positive relationship with TFEE.

ECONSTR is defined as the ratio of industrial added value to GDP and is a proxy for the economic structure of the country and is expected to have a negative effect on TFEE (Xiaoli et al. 2014; Hu and Kao 2007).

ENEPR is a proxy for energy prices including crude oil (petroleum), natural gas, and coal price with 2005 as the base year, and αi represents firm-specific fixed effects, λt captures time effects, $\mathcal{E}_{i,t}$ is the error term, and the subscripts *i*,*t* represents a particular insurer *i*, at time *t*.

POP is the population of a country measured in millions.

Reverse causality between TFEE and economic development

Following the views of IEA and Singh (2016), a reverse causality between energy efficiency and economic development is tested by way of a structural model of a two-equation system and estimated using the two-stage least squares (2SLS) approach.

$$\mathrm{TFEE}_{i,t} = \beta_1 \mathrm{GNIPC}_{i,t} + \delta Z_{2i,t} + \alpha_{1i} + \lambda_{1t} + \varepsilon_{1i,t} \tag{10}$$

$$\mathrm{GNIPC}_{i,t} = \beta_1 \mathrm{TFEE}_{i,t} + \omega Z_{2i,t} + \alpha_{2i} + \lambda_{2t} + \varepsilon_{2i,t} \tag{11}$$

where $Z_{2i,\ t}$ is a vector of explanatory variables which affect GNIPC. These are SAVR, the savings rate measured as the ratio of gross savings of a country to GDP; POP, the population of a country measured in millions; TECPR, technological progress measured by the capital-labor ratio as a proxy for the technology level; and HCI, human capital measured as the index of human capital per person, based on years of schooling.

Data and variables

Data on 46 African countries were used for the study based on the availability of data. The study covers the period 1980–2011. For TFEE estimation, three inputs and two outputs (desirable and undesirable) were used. Capital, measured by capital stock at current purchasing power parities (in mil. 2005 US$); labor, by number of persons engaged (in millions); and energy, by total primary energy consumed (quadrillion bitumen) are considered to produce two outputs, real GDP (desirable), measured in constant 2005 US$ and CO_2 (undesirable), by emissions from the consumption of petroleum (million metric tons). Data for labor, capital, and real GDP were sourced from the Penn World Tables 8.1 and complemented with data from the World Development Indicators (WDI). Energy and CO_2-related data was collected from the US Energy Information Administration. Due to the non-availability of data for some countries for some years, this study relies on an unbalanced panel data. The summary statistics on the pooled data are presented in Table 1. There are five regional groupings within the continent including the Arab Maghreb Union (AMU), East African Community (EAC), Economic Community of Central African States (ECCAS), Economic Community of West African States (ECOWAS), and South African Development Council (SADC) and these are shown in the summary statistics. The sample includes 4 AMU, 4 EAC, 8

Table 1 Summary statistics of input and outputs by regional groupings

Regional group		Labor	Capital	Energy	Real GDP	CO_2
AMU	Count	128	128	128	128	128
	Mean	9.26986	173,377	0.65917	110,545	40.9359
	SD	6.53837	178,235	0.80707	107,573	47.5299
EAC	Count	232	232	232	232	232
	Mean	9.29295	33,967.2	0.04724	20,581.1	2.55647
	SD	8.96325	38,284.9	0.05008	19,374.7	2.72604
ECCAS	Count	218	218	218	218	218
	Mean	2.60319	30,460.5	0.04159	16,053.5	4.2844
	SD	2.43875	38,605.2	0.04829	18,336	5.18859
ECOWAS	Count	473	473	473	473	473
	Mean	5.03617	33,491.4	0.07967	19,116.8	7.11332
	SD	8.8294	60,819.7	0.19614	48,511.9	20.8279
SADC	Count	342	342	342	342	342
	Mean	5.56019	74,941	0.45721	43,794.5	36.3936
	SD	5.43669	168,970	1.25543	97,267.1	106.852
	Count	1393	1393	1393	1393	1393
POOLED	Mean	5.88205	56,126.5	0.21425	33,341.1	16.2083
	SD	7.535341	115,466.5	0.712411	70,737.11	58.2521

Count number of observations, *SD* standard deviation, *min* minimum value, *max* maximum value

ECCAS, 15 ECOWAS, and 11 SADC countries. It should be noted that countries with no or multiple regional affiliations are grouped based on their position on the map.

Observations from Table 1 show that on the average, Northern Africa, represented by the AMU, employs more inputs with the exception of labor, than the other African regional groups. Moreover, these inputs are seen to be transformed into more outputs. Even with carbon dioxide emissions, AMU tops the other regions (M = 40.94, SD = 47.53), followed by SADC (M = 36.39, SD = 106.85), ECOWAS (M = 7.11, SD = 20.83), ECCAS (M = 4.28, SD = 5.29), and lastly, EAC (M = 2.56, SD = 2.73). This observation may be due to the fact that AMU countries are rich in oil. From the statistics, it is evident that countries that consume more fuel emit more harmful gasses which give a cause for alarm as energy consumption is projected to grow into the future. Meanwhile, in terms of labor employed on average, East Africa which is the second to the lowest in real GDP output tends to have the highest. A one-way independent ANOVA performed on the variables based on regional integration showed differences in all variables at 0.1% significance level for the groups.

Given the pooled statistics, it can be observed that the standard deviations are quite high in relation to the means for both outputs and inputs, suggesting that African state energy sectors vary in the sizes. To confirm this observation, the returns to scale test in DEA was conducted and the results show that firms in the industry operate on variable returns to scale. To conduct this test, a null hypothesis that the technology underlying the African energy sector is CRS was tested against the alternate hypothesis of a VRS technology (Simar and Wilson (2002). The results presented in Table 2 provide support for the rejection of the null hypothesis at the 0.1% level, thereby giving support to the alternative hypothesis. Thus, the African energy sectors vary in sizes, providing a statistical justification for the adoption of VRS in all DEA efficiency estimations in this study.

Table 2 Test of returns to scale

Test statistic	Critical value	p value
0.7722	0.8869	0.0005

Analysis and discussions

Analysis of TFEE of African countries

In this section, we assess the level of TFEE of African countries. The TFEE of each African country under study was estimated using the undesirable SBM under VRS. Table 3 reports the average yearly TFEE of African countries for generalization purposes. The TFEE was estimated based on each year-specific frontier rather than a pooled frontier, due to the differences between variables for the various years. To avoid making wrong inferences, both the geometric (GM) and arithmetic (AM) means are reported. It can be inferred from Table 3 that over the study period, African countries on average achieved a TFEE score of 65%, as suggested by the arithmetic mean and its accompanying low standard deviation. The implication therefore is that African countries employ more energy to produce less GDP while producing higher amounts of CO_2.

This suggests that on average, African countries can reduce their energy consumption and CO_2 emissions levels while simultaneously increasing real GDP by 35%. This inefficiency level is further exacerbated when taking into consideration the geometric mean value of 56%. This suggests a high level of energy saving potential for African countries. Koskimäki (2012) recommends four policy areas with energy saving potential for Africa including energy using products, buildings, energy efficiency in transport, and efficiency in cities and communities. Figure 1 shows the trends in average levels of TFEE of African countries over the study period. From Fig. 1, it can be seen that average TFEE levels have been on a downward trend since 2008, from an average level of 49% in 2008 to 28% in 2011 as measured by the geometric mean. This seems to coincide with the global economic crunch, suggesting that the economic crisis may have had some sort of influence on TFEE of African countries. In the oil market, the recession caused demand for energy to shrink in late 2008, with oil prices collapsing from the July 2008 high of $147 to a December 2008 low of $32. Also, the decreasing TFEE for the period could be as a result of less attention to energy issues, with much focus on the financial sector during the period.

Though not displaying a smooth trend, TFEE appears higher in the earlier years than the latter years with the highest level of TFEE (73%) achieved in 1986 and the lowest of 28% in 2011. Moreover, the average TFEE

Table 3 Yearly average TFEE of African countries

Year	Count	TFEE			Year	Count	TFEE		
		GM	AM	SD			GM	AM	SD
1980	42	0.68	0.75	0.04	1996	46	0.54	0.63	0.05
1981	43	0.68	0.74	0.04	1997	46	0.57	0.67	0.05
1982	42	0.64	0.71	0.04	1998	46	0.54	0.64	0.05
1983	43	0.69	0.76	0.04	1999	46	0.52	0.62	0.05
1984	44	0.67	0.73	0.04	2000	46	0.57	0.66	0.05
1985	44	0.67	0.75	0.04	2001	46	0.58	0.67	0.05
1986	43	0.73	0.79	0.04	2002	47	0.60	0.68	0.04
1987	43	0.69	0.75	0.04	2003	47	0.56	0.64	0.04
1988	43	0.6	0.69	0.05	2004	47	0.52	0.62	0.05
1989	44	0.6	0.67	0.04	2005	47	0.50	0.60	0.05
1990	45	0.61	0.68	0.04	2006	48	0.47	0.57	0.05
1991	45	0.58	0.67	0.05	2007	48	0.47	0.56	0.05
1992	46	0.62	0.71	0.05	2008	48	0.49	0.58	0.05
1993	46	0.54	0.64	0.05	2009	48	0.48	0.58	0.05
1994	46	0.51	0.62	0.05	2010	48	0.37	0.45	0.04
1995	46	0.51	0.62	0.05	2011	48	0.28	0.37	0.05
					Average		0.56	0.65	0.05

levels suggest that although all the input and output variables have been increasing over the study period, with all the variables attaining maximum levels in 2011, these input levels are not been efficiently transformed into outputs. This suggests that the increase in energy consumption of 43.38% between 2000 and 2012 as pointed out earlier has not translated into economic growth (GDP) as it should.

Next, the energy efficiency of African countries over the period is reported. Table 4 presents the average TFEE score for each country for the period 1980–2011.

The table reveals that Gabon, Egypt, and South Africa were on the frontier for the entire period, while Comoros, Equatorial Guinea, and Sao Tome and Principe were also on the frontier for the years they appeared in the study, thereby attaining an average TFEE of 1 for the entire period under study. These countries are therefore, the best performing TFEE African countries, and can be said to have the best level of technology and production process in transforming inputs into outputs. Out of the 46 countries considered in the study, 17 countries had an average TFEE below 50%, with the worst performing

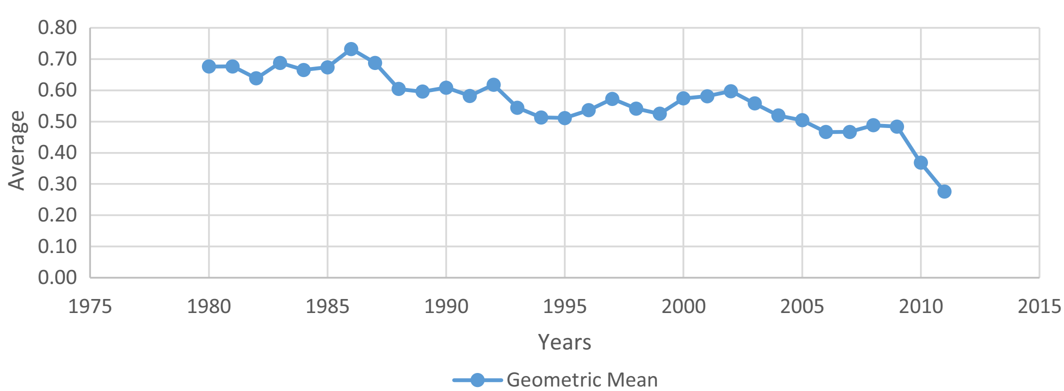


Fig. 1 Trends in average levels of TFEE

Table 4 Average energy efficiency of African countries

Country	Group	TFEE				
		GM	AM	Number of times efficient	Out of	Rank
Angola	ECCAS	0.50	0.54	5	32	29
Benin	ECOWAS	0.43	0.49	5	32	32
Botswana	SADC	0.79	0.83	15	32	18
Burkina Faso	ECOWAS	0.36	0.37	0	32	39
Burundi	EAC	0.44	0.48	4	30	35
Cameroon	ECCAS	0.58	0.63	7	32	23
Cape Verde	ECOWAS	0.85	0.89	20	26	13
Central African Republic	ECCAS	0.39	0.41	1	32	36
Chad	ECCAS	0.97	0.98	30	32	7
Comoros	EAC	1.00	1.00	10	10	1
Congo	ECCAS	0.55	0.61	8	32	25
Côte d’Ivoire	ECOWAS	0.47	0.49	1	32	34
D.R Congo	SADC	0.19	0.23	0	32	45
Djibouti	EAC	0.83	0.88	26	32	14
Egypt	AMU	1.00	1.00	32	32	1
Equatorial Guinea	ECCAS	1.00	1.00	23	23	1
Ethiopia	EAC	0.92	0.95	30	32	11
Gabon	ECCAS	1.00	1.00	32	32	1
Gambia	ECOWAS	0.83	0.87	24	32	15
Ghana	ECOWAS	0.71	0.77	18	32	20
Guinea	ECOWAS	0.56	0.63	8	32	24
Guinea-Bissau	ECOWAS	0.45	0.49	3	28	31
Kenya	EAC	0.67	0.74	14	32	21
Lesotho	SADC	0.80	0.86	24	32	16
Liberia	ECOWAS	0.30	0.31	0	32	41
Madagascar	SADC	0.35	0.39	0	32	37
Malawi	SADC	0.25	0.26	0	32	43
Mali	ECOWAS	0.51	0.53	0	32	30
Morocco	AMU	0.87	0.91	26	32	12
Mozambique	SADC	0.18	0.19	0	32	46
Namibia	SADC	0.69	0.73	5	22	22
Niger	ECOWAS	0.28	0.30	1	32	42
Nigeria	ECOWAS	0.36	0.54	14	32	28
Rwanda	EAC	0.51	0.58	9	32	27
Sao Tome and Principe	ECCAS	1.00	1.00	6	6	1
Senegal	ECOWAS	0.37	0.39	0	32	38
Sierra Leone	ECOWAS	0.53	0.61	9	32	26
South Africa	SADC	1.00	1.00	32	32	1
Sudan	AMU	0.92	0.96	30	32	10
Swaziland	SADC	0.79	0.83	18	32	17
Togo	ECOWAS	0.32	0.34	0	32	40
Tunisia	AMU	0.96	0.98	31	32	8

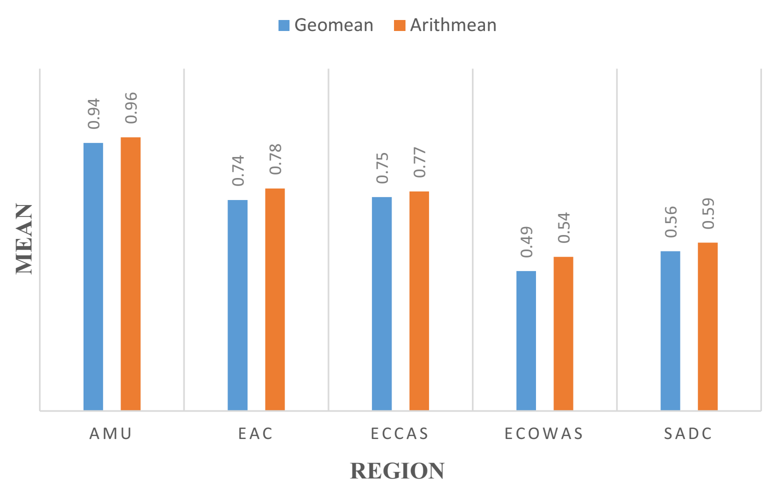
Table 4 (continued)

Country	Group	TFEE GM	AM	Number of times efficient	Out of	Rank
Uganda	EAC	0.77	0.82	21	32	19
United Republic of Tanzania	SADC	0.46	0.49	2	32	33
Zambia	SADC	0.24	0.25	0	32	44
Zimbabwe	SADC	0.96	0.97	30	32	9
Sub-regional	AMU	0.94	0.96			1
	EAC	0.74	0.78			2
	ECCAS	0.75	0.77			3
	ECOWAS	0.49	0.54			5
	SADC	0.56	0.59			4

Rank is from 1 to 46, where 1 is the most efficient and 46 is the least efficient country

countries being DR Congo and Mozambique with average TFEE levels of 19% and 18% respectively. These countries show more room for energy savings, which can be achieved by adjusting technology levels and production processes to the levels demonstrated by the frontier countries. Meanwhile, comparing the group TFEE scores, North African countries appear the best performers under TFEE with an average TFEE of 94% with West African countries being the worst performers with average TFEE of 49% for the study period. A test of differences in distributions using nonparametric Kruskal-Wallis test produced a chi-square value of 206.375 and a *p* value of 0.0001, suggesting that the difference in the average TFEE levels between the regional groups is significant at 0.1%. Given this, the high level of performance of North African countries suggests that they are able to leverage on their high average levels of energy consumption and capital stock to produce real GDP and CO_2 in an efficient manner. However, same cannot be said for Southern African countries, which enjoyed the second highest levels of the inputs and outputs but are fourth in terms of TFEE performance. Although Central African countries on average have the lowest levels of inputs and outputs, the TFEE ranking suggests that they have the third best technology level of transforming inputs into outputs. A further exploration is done using the SZAL for pairwise comparisons based on the distributions of TFEE scores but for easy conceptualization, the scores of the sub-regions are graphically presented in Fig. 2.

Fig. 2 Energy efficiency scores of African sub-regions



The SZAL test for differences in regional grouping

From Table 4, it is seen that the AMU is the best performing African region in terms of TFEE with average TFEE levels of 94%, while ECOWAS countries are identified as the worst performers, with average TFEE levels of 49% over the study period. To test the significance of these differences, pairwise comparisons of the distributions of TFEE between the various African regional groups using SZAL are presented in Table 5.

The results show significant differences in the distribution of TFEE scores between all the pairwise African regional groupings. Thus, one can confidently conclude that AMU countries are the most total factor energy efficient countries given that they have the highest average TFEE scores for the period, followed by EAC, ECCAS, SADC, and lastly, ECOWAS as the least energy efficient. Consequently, Africa sub-regions could benchmark the energy efficiency policies adopted by the AMU as well as the measures adopted to ensure enforcement of energy efficiency policies in order to improve energy efficiency in Africa as whole.

Energy efficiency and economic development

We next employ a truncated regression model to investigate the impact of economic development on TFEE while controlling for other variables. From Table 6, it is shown that income per capita (GNIPC) has a positive and highly significant effect on TFEE as reported by Xiaoli et al. (2014) in their study on energy efficiency of China. In a related study, Chang and Hu (2010) also found a positive relationship between income per capita and total factor energy productivity index in China. This suggests that highly developed countries are likely to be more energy efficient than their less developed counterparts. These highly developed countries have the necessary structures to ensure high energy savings. These include policies on energy efficiency, use of renewable energy, and investment in energy-saving technologies.

However, the coefficient of the squared GNIPC indicates that this relationship is actually an inverted U-shape, given its significant negative coefficient. Thus, TFEE initially increases with economic development, reaches a maximum point, then in the long term, decreases with development. The current average of GNIPC of African countries ($3828.123) is to the left of the peak value of the estimated equation (using the first differential). This shows that there is potential for performance improvement with increased GNIPC up to $24,055.12. Thereafter, an inverse effect can be expected of economic development on energy efficiency. As found by Rakshit and Mandal (2020), even high-income economies are still experiencing more energy efficiency improvement compared with middle and low-income economies. This might be so because most of the high-income economies have probably not reached their

Table 5 Pairwise comparisons with SZAL test

Group pairs		SZAL	
		Test statistic	*p* value
AMU	-EAC	19.7121	0.0000***
AMU	-ECCAS	37.7287	0.0000***
AMU	-ECOWAS	32.9933	0.0000***
AMU	-SADC	26.7796	0.0000***
EAC	-ECCAS	3.5212	0.0002***
EAC	-ECOWAS	8.4943	0.0000***
EAC	-SADC	6.0920	0.0000***
ECCAS	-ECOWAS	3.4497	0.0003***
ECCAS	-SADC	4.4565	0.0000***
ECOWAS	-SADC	3.5043	0.0002***

Table 6 Truncated bootstrapped regression output

TFEE	Coefficient	
GNIPC	6.11E-05	***
	(9.04E-06)	
GNIPC2	− 1.27E-09	***
	(3.63E-10)	
TECH	2.28E-06	**
	(8.69E-07)	
ECSTR	− 1.23E-03	
	(0.000978)	
ENEPR	− 2.06E-03	***
	(0.000254)	
POP	1.19E-03	.
	(0.000722)	
INTERCEPT	5.25E-01	***
	(0.036947)	

Coefficients have been bootstrapped. Standard errors are in parenthesis

.***** , , and represent significance at 10%, 1%, and 0.01% respectively peak. The World Bank atlas classification method, for instance, classifies low-income countries as those with GNI per capita of $995 or less in 2017; middle-income economies as those with GNI per capita of between $995 and $12,055; and high-income economies with GNI per capita of $12,056 or more.

Contrary to our observation, however, Zhang et al. (2011) in their study of developing countries found a significant negative relationship between TFEE and economic development, and a long-run U-shaped relationship. This attributed to initial growth of industries which decreases energy efficiency to a certain point after which energy efficiency begins to improve. The result of this study, therefore, points out to African economies to be mindful of energy efficiency issues in their pursuit of development. This suggests the need of development through sustainable energy use. One way of achieving this could be through the use of clean and renewable energy such as solar, which have little negative environmental impacts.

Technological progress, proxied by the capital-labor ratio, is reported to have a significantly positive influence on TFEE. Similar results were also found by Apergis et al. (2015), Xiaoli et al. (2014), and Fang et al. (2013). Wu (2012) hypothesized that the improvement capital–labor ratio reduces inefficient energy use, because new capital utilizes energy-saving technology. Thus, countries that are more capital intensive are more energy efficient than labor-intensive countries. Meanwhile, in contrast with Xiaoli et al. (2014), energy prices are reported to have a negative and significant relationship with TFEE, implying that African countries tend to use more energy to produce less GDP in times of high global energy prices. This is surprising since the oil crisis in 1973 is cited as one of the main reasons for the interest in energy efficiency by both researchers and economies (Honma and Hu 2009; Zhou et al. 2008). This result, however, calls for governments to ensure energy prices are affordable since lower prices relate to higher efficiency. Hence, more government deregulation is needed in the energy sector. Population is found to have a significant weak positive relationship with TFEE of African countries. This means that as population grows, more useful economic output is produced with less energy. Economic structure proxied by the industry value added to GDP ratio has a negative but insignificant relationship with TFEE levels of African countries. This contradicts the findings of Xiaoli et al. (2014) and Lan-Bing Li and Hu (2012) who find a negative but significant relationship for their studies in China, and Hu and Kao (2007) who found a positive and significant relationship between the industry structure and energy saving target ratio (ESTR) of APEC economies (Note that a high ESTR indicates low TFEE). This could be as a result of the differences in structure and government policies between the African and developed economies, and the availability of technology.

Reverse causality between TFEE and economic development

Finally, we investigate the bi-directional nexus between TFEE and economic development (GNIPC). The reverse link is tested using the 2SLS approach. The 2SLS is used to address situations where two variables are considered to be endogenous. The results from both stages of the 2SLS are presented in Table 7.

With exception of the significance level of technological progress, the results from the first stage show the same signs and significance levels as that of the bootstrapped truncated regression; hence, particular emphasis here is placed on the second stage results. The results show a positive and statistically significant link between TFEE and GNIPC. This means that being energy efficient has some contribution to economic development of African countries. The finding affirms that of Rajbhandari and Zhang (2018) who found a bidirectional causality between energy efficiency and economic growth. This also supports the IEA's assertion on the socioeconomic aspect of the multiple benefits of energy efficiency and is also in line with the concept of sustainable development. The IEA (2014) explained that being more energy efficient means less expenditure on energy-related products, leaving funds for other macroeconomic investments such as capital accumulation. Moreover, energy efficiency may translate into economic development through reduction in energy poverty (caused as a result of high energy prices), thereby leaving funds for households to invest in education and even small business startups which will eventually provide income for the family. In terms of sustainable development, the effects of energy efficiency may be realized through the reductions of carbon emissions and the mitigating of global greenhouse warming and replacing old technologies with energy efficient ones lacking (Rajbhandari and Zhang 2018). Hence, this finding is very crucial since it provides a reason for investing in energy efficiency.

Table 7 2-stage least squares regression output

Stage one				Stage two			
TFEE		COEF.		GNIPC		COEF.	
	GNIPC	9.21E-05	***		TFEE	6597.194	***
		(0.000014)				(759.6471)	
	GNIPC2	− 3.34E-09	***		SAVR	42.01607	**
		(6.77E-10)				(12.20981)	
	ECSTR	− 0.0009			HC	2111.697	***
		(0.001065)				(413.2945)	
	TECH	3.45E-07			POP	− 12.35224	
		(1.09E-06)				(11.19322)	
	ENEPR	− 0.0023	***		TECH	.0813611	***
		(0.000219)				(.0087459)	
	INTERCEPT	0.559601	***		INTERCEPT	− 5882.396	***
		(0.041451)				(689.2535)	
	R-squared	0.5296			R-squared	0.6984	
	F-stat	56.94			F-stat	197.10	
	$p > F$	0.0000			$p > F$	0.0000	

Standard errors are in parenthesis

** and *** represent significance at 1% and 0.01% respectively

In line with the classical theories of development, human capital, savings rate, and technological advancement are all significant and have positive impacts on economic development. The positive and significant coefficient of the rate of savings indicates that for African countries to develop, these countries must mobilize savings and then transform these savings into investments as put forth by the Harrod-Domar models. The relationships between human capital and technological advancement and economic development are supported by the Solow growth model which recognizes technological change and increases in the quality and quantity of labor as factors necessary for development. Since development is mainly defined as growth plus change, change in levels of technology is key to economic development of African countries. Growth in the levels of technology provides an avenue for more productivity to be achieved and hence ensures sustainability of economic growth. This therefore requires that African countries be open to foreign direct investments, since this will provide an avenue for capital accumulation. In terms of human capital, when people are more educated, they become more productive. This result is supported by Yao et al. (2013) in their analysis of the relationship between population and economic development in China.

Conclusions and recommendations

We have assessed the energy efficiency of 46 African countries in a total factor framework, in the presence of undesirable output and subsequently investigated the link and reverse causality between total factor energy efficiency and economic development. The study makes the following contributions: It is one of the few energy efficiency studies to consider total factor energy efficiency; it also studies all sub-regions on the African continent; it is one of the first to investigate energy efficiency—economic development nexus in Africa and lastly it provides benchmarks for energy efficiency improvement in Africa to policy makers. Before efficiency estimations, the scale elasticity property in the energy sector in Africa was tested.

The findings and conclusions of the study are summarized as follows:

a. African countries are on average 56% energy efficient over the study period. This implies that African countries are 44% energy inefficient. Hence, African countries can simultaneously increase outputs and reduce inputs and CO_2 levels by 44%, showing more room for energy savings. The most energy efficient countries are Gabon, Egypt, South Africa, Comoros, Equatorial Guinea, and Sao Tome and Principe with Mozambique being the least energy efficient country. Energy efficiency in Africa has been on a decreasing trend since 2009. Policies that focus on the provision of renewable energy technologies are recommended to reduce reliance unsustainable energy sources. Additionally, policy areas with energy saving potential for Africa could include energy using products, buildings, energy efficiency in transport, and efficiency in cities and communities.

b. Northern African countries are the most energy efficient with average efficiency levels of 94% with West African countries being the least efficient with average efficiency levels of 49%. North African countries, therefore, have the most energy efficient production process. It was found that regional groupings have statistically significant impact on TFEE. AMU sub-region is recommended as benchmarks for other African sub-regions to improve their energy efficiency policies and enforcement towards improving energy efficiency in Africa.
c. Economic development is found to statistically impact positively on energy efficiency; however, the second derivative of the GNIPC suggests the relationship to be an inverted U-shape. African countries in the pursuit of development should pay attention to energy efficiency and sustainability issues such as global warming and energy security. As Africa's average GNIPC is currently at the left side of the peak, more improvement in energy efficiency is expected with increased economic development.
d. Countries that are more capital intensive are more energy efficient than labor-intensive countries. Also supported is the need for government deregulations in the energy sector to lower energy prices.
e. There exists a reverse causality between energy efficiency and economic development. Energy efficiency is found to have a positive and statistically significant effect on economic development. This finding is very much in line with the concept of sustainable development. Investments and appropriate policies on energy efficiency are keys for sustainable economic development of African countries.

This study has some limitations that could be addressed in future studies. Future research can use global Malmquist-Luenberger productivity index (Oh 2010); global Malmquist index (Pastor and Lovell 2005); Biennial Malmquist index (Pastor et al. 2011), or the overall Malmquist index (Afsharian and Ahn 2015) which can address infeasibility of mixed period efficiency and unbalanced panel data. Further studies can also consider the disaggregating energy input into its various sources such as electricity, coal, and gasoline other than using a composite measure of primary energy consumed in order to reveal the energy resources that are most and least efficiently used. Future studies can also disaggregate the TFEE to assess the contribution of each input and output variable to the TFEE score.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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