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Energy efficiency-economic growth nexus: What is the role of income inequality?

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ABSTRACT

The Sustainable Development Goal (SDG) 7 stresses the importance for economies around the world to double their efforts in improving energy efficiency. Energy efficiency improvements have been found to trigger economic growth, albeit empirical evidence to support this claim remains mixed. In a world of widening inequality, how income inequality dynamics affect the growth and energy efficiency nexus is critical, yet empirical research investigating the role of income inequality is lacking. This study addresses this concern by examining the moderating role of income inequality in the economic growth – energy efficiency nexus. The study is based on an unbalanced yearly panel dataset for 51 African countries from 1991 to 2017. We measure energy efficiency using the stochastic frontier analysis technique and apply the two-step generalized method of moments (GMM) technique to examine the direct and indirect effects (moderating through income inequality) of energy efficiency on economic growth. We conduct several robustness checks to ensure consistent estimates of the parameters. We find that, directly, improving upon energy efficiency triggers economic growth, but this is compromised in economies with high-income inequality. The estimated conditional total effect of energy efficiency on economic growth is lower for countries with higher income inequality compared to countries with lower income inequality. By implication, reducing income inequality could be one effective channel through which energy efficiency can trigger economic growth.

1. Introduction

The aim of this study is to examine the effect of energy efficiency (EE) improvements on economic growth, considering the moderating role of income inequality in 51 African countries. Africa is the world's second fastest-growing region with an average real GDP growth rate of 4.5% over the period 2000–2019 (AUC/OECD, 2021). The continent is projected to grow at an average growth rate of 4.2% by 2025 (AUC/OECD, 2021). This comes against the backdrop of increasing energy demand and environmental problems like high traffic emissions and pollution from the use of unclean cooking fuels in Africa (Fayiga et al., 2018). Energy demand has increased by about 50% since 2000, reaching 752 million tonnes of oil equivalence in 2014 and more than 810 million tonnes of oil equivalence in 2018 (IEA, 2019). Estimates show that Africa's energy demand will further increase by 85% from 2010 to 2040 (IEA, 2013). However, public and private investment[1] in energy supply infrastructure in Africa is inadequate to meet the rising demand, creating energy deficit. Consequently, about 595 million people in Africa have no access to electricity irrespective of their income levels (IEA, 2019). The energy deficit, access and the environmental quality situation requires, among other things, Africa to manage the level of energy consumption through technological innovation, energy conservation and efficient demand management techniques (Ali et al., 2020). To this end, the United Nations Sustainable Development Goal (SDG) 7 requires countries around the world to double their efforts in energy efficiency (EE) improvements.

Although Africa's EE improvements are below the global average[2] of 1.7%, the UN progress report on SDG7 reports of consistent improvements in EE in Africa, averaging 1.3%, between 2010 and 2017 (IEA et al., 2020). Studies by Adom (2019), Jebali et al. (2017) and Chang

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[1] In 2018, only $100billion representing 5.5% of global total energy investment was in the energy sector. Of this, $70billion, $13billion and another $13billion were invested into fossil fuel, renewable energy and electricity networks respectively (IEA, 2019).

[2] The most improved region, Asia, averages 3.3% between 2010 and 2017.

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(2016) also corroborate this. The IEA's multiple-benefits approach to EE policy asserts that analysing the impact of EE should go beyond the traditional effects of reduced energy demand and lower greenhouse emissions to estimating its impact across different spheres and on the whole economy (IEA, 2019b). Sustainable energy policies, like EE, are more likely to succeed if they maximise, where they exist, positive synergies with other socio-economic outcomes like economic growth (Ahuja and Tatsutani, 2009). Literature on the macroeconomic effects of EE in Africa remains limited (Ohene-Asare et al., 2020), especially after the promulgation of the SDGs. Consequently, evidence on the question of whether the improvements in EE draw any positive synergies with economic growth in Africa remains scanty. Against the background of rising income inequality in Africa, how income inequality dynamics affect EE-economic growth nexus is critical, yet empirical research investigating the role of income inequality is also lacking. The motivation of this study is to fill these gaps. Empirical evidence on the growth-inducing effect of EE would emphasize whether environmental protection measures are detrimental to economic growth or otherwise[3] and could provide an incentive for policy makers to adopt more EE measures. This is important because Africa needs strong economic growth to attain SDG8 and, at the same time, the continuous upsurge in Africa's energy consumption, especially from non-renewable sources (Ohene-Asare et al., 2020), poses challenges to the environment for which EE measures become necessary for sustainable economic growth. Understanding the growth-inducing effects of EE would also help policy makers to fully account for the benefits and costs of EE measures. Ultimately, our study contributes to the quest of the United Nations to identify and enhance, where they exist, positive synergies among the Sustainable Development Goals (SDGs).

The classical, neoclassical, endogenous growth, new endogenous growth and catch-up theories of economic growth provide the theoretical link between economic growth and EE, albeit implicitly. Growth theories stress the importance of technological progress to output expansion or economic growth (Lakhera, 2016). Lipsey et al. (2005) have concluded that most economic growth is due to general-purpose technologies, which could involve efficient production, transmission and utilisation of energy to do useful work (Ayres and Warr, 2009). Technological progress improves the quality of inputs, reduces cost significantly, and maximises output. Since energy is an input in the production process, technological progress or investment in innovation improves the quality of energy inputs, reduces the associated cost, and frees up resources to employ other factors of production to increase output.

However, the conventional view (advocated by neoclassical and endogenous growth theories) downplays the significance of EE as a key driver of economic growth. According to this view, energy cost is an insignificant share in the total cost (Sorrell, 2009). Therefore, EE improvements can only produce a mild impact on economic growth. One possible explanation could be that most of these growth theories did not consider energy as an explicit input in the production process, but the events unfolding after the 1970s have changed this view about energy. Smulders and de Nooij (2003) provided a theoretical model of the link between energy conservation policies and economic growth. They found that energy conservation policies reduce per capita income. However, a reduction in energy input through induced technical change can facilitate improvement in energy-related technology and partially mitigate the cost of energy conservation policies. Thus, contrary to the hypothesis of Porter and van der Linde (1995) (which states that well-designed environmental policies, including EE, can trigger innovation and produce a Pareto optimal situation by fostering productivity, competitiveness, profits and hence economic growth), induced technical innovation cannot lead to a 'win-win' situation.

In contrast to the conventional view, the ecological economics view asserts that, over the past two decades, the increasing availability of high-quality energy inputs has been the key driver of economic growth (Compton, 2011). Ayres and Warr (2009) explicitly state that EE improvements have been one of the major (or perhaps the major) drivers of economic growth since the industrial revolution. These anti-conventional view assertions could be strongly rooted in the Porter and van der Linde (1995) *hypothesis*.

Empirically, there seems to be some level of consensus on the positive effects of EE on economic growth in developed economies (Razzaq et al., 2021; Marques et al., 2019; Bataille and Melton, 2017; Rajbhandari and Zhang, 2018), where to some extent, successful decoupling of economic growth and the environment has occurred. Rajbhandari and Zhang (2018) found that lowering energy intensity (signifying improvements in EE) is associated with long-run economic growth in high-income countries. Bataille and Melton (2017) found that, in Canada, improvements in total EE increased GDP by 2 percent. However, the evidence looks mixed and scanty for developing economies. For example, while Akram et al. (2021), Ohene-Asare et al. (2020), Heun and Brockway (2019), Cantore et al. (2016), Bayar and Gavriletea (2019), Go et al. (2019), Hu et al. (2019) and Rajbhandari and Zhang (2018) all found the effect of EE on economic growth to be positive, other studies such as Pan et al. (2019), Mahmood and Kanwal (2017) and Sinha (2015) failed to establish any meaningful effect of EE improvements on economic growth for developing economies. Notably, only Ohene-Asare et al. (2020) exclusively covered 46 African countries.

The controversy in the case of developing economies could be explained in two ways. First, since, in developing economies, a huge amount of production and consumption of energy is needed to meet developmental goals (Esen and Bayrak, 2017), Dercon (2012) asserts that environmentally friendly growth policies (such as EE) are more of a threat than an opportunity to promote growth and development. Khazzoom (1980) has criticised the pollution- (and energy-) reducing effect of EE, noting that EE is not cost-effective in reducing pollution since improvements in EE, which reduce the implicit cost of energy, also trigger higher energy demand and hence higher pollution; something referred to in the literature as the *rebound effect*. Thus, the rebound effect, which can be an exogenous response to EE improvements or induced by a policy, can negate the gains achieved from EE (Gillingham et al., 2016).

Second, in most developing economies, the burden of energy cost is very high, especially on the poor, who form a significant number of the total population in developing economies (Njiru and Letema, 2018). Therefore, EE improvements can trigger significant cost savings on energy, which can free up resources for other productive activities. However, some of these activities may be energy intensive, and this could also raise concerns about a possible rebound effect. For instance, energy cost savings invested in energy-intensive productive activities like food and related support activities can cause an increase in energy consumption and pollution especially with the massive use of unclean cooking fuels in Africa (Fayiya et al., 2018; Conti et al., 2016). Investment of energy cost savings in other energy-intensive productive industries like paper manufacturing, printing, basic organic and inorganic chemicals, etc (Conti et al., 2016, pg. 113) could also produce similar effects. The overall effect on energy consumption and pollution would depend on the size of the rebound effect (Adom and Adams, 2020). Nevertheless, Porter and van der Linde (1995) emphasized that savings made on energy cost can trigger investment in technological innovation and improve productivity in the economy. Of course, operating through the supply side, EE can improve productivity as producers deploy more energy efficient production techniques.

From the above, empirical evidence on the effect of EE on economic growth remains controversial. There are two possible reasons that can explain the sources of this controversy in the literature. The first

[3] This debate re-emerged in 2017 when President Trump of the United States of America (USA) rolled back some environmental regulations of the Clean Air Act of the USA, arguing they compromise business interests and, for that matter, economic growth.

concerns how EE is measured. Most of the studies on the subject used the popular energy intensity indicator (i.e., energy consumption per GDP) as a measure of EE. However, especially at the macro level, this has been criticised since changes in energy intensity could reflect environmental factors, changing energy price, population density and changing economic structure (Adom et al., 2018; Zhang and Adom, 2018). Thus, interpreting lower energy intensity to mean improvement in EE, as it is currently done in the literature, may be flawed since this could mean something different from technological progress. Other studies used proxies like the reduction in fossil-fuel energy waste (Sinha, 2015), thermodynamic efficiency[4] (Heun and Brockway, 2019), total factor energy production efficiency (Pan et al., 2019) and intended energy reductions (Barker et al., 2009) to measure EE. Ohene-Asare et al. (2020) estimated the total factor EE using Data Envelopment Analysis (DEA), which can lead to less precise EE scores. However, none of these approaches is capable of decomposing energy efficiency into transient and persistent components. We applied the stochastic frontier analytic (SFA) technique to estimate EE.[5]

Second, EE decision is endogenous, as it is driven by economic, political, social and institutional factors. This creates potential identification problems. Liu et al. (2020) showed that, at least, there is a reverse causality from economic growth to EE indicating a possible endogeneity of EE. In developing economies, where poverty rates are high, widespread income inequalities could impede investment decisions in EE. The high upfront cost of investment in energy-efficient equipment is very difficult to bear for low-income households (Simcock et al., 2017). Galvin and Sunikka-Blank (2018) assert that widespread inequalities in income affect household energy consumption behaviours, such as investing in EE. Liu et al. (2020), in a recent study, estimated the effects of income inequality on EE (estimated using data envelope analysis) for 33 Belt and Road Initiative (BRI) countries. Their results revealed an inverted U-shaped effect of income inequality on EE for middle- and low-income BRI countries and a U-shaped effect for high-income BRI countries. Thus, although inequalities in income could influence EE behaviours, the mode of transmission is not clear.

Increased income inequality can provide an outlet for innovative assets and processes that promote EE. For example, a sizeable market is required to meet the demand for pollution-free goods and innovative manufacturing processes. Since these products are costly, richer households will advance towards the development of this market. Thus, increased income inequality in this case would complement the economic growth–inducing effect of EE. On the other hand, it is possible that increased income equality can either complement or compromise the growth-inducing effect of EE. Given that the poor consume poor quality goods, a redistribution of income away from the rich towards the poor implies that the consumption of goods by the poor would increase more than the proportion of reduction in the consumption of the rich. This is possible because the poor would spend on poor-quality goods, which are mainly less expensive. Since energy-efficient appliances and solutions are costly, the poor will reach out for less energy-efficient products, and this would compromise the growth-inducing effect of EE. However, increased income equality would complement the growth-inducing effect of EE if it enables the poor to reach out for innovative energy-efficient appliances and solutions. This is possible, especially in an environment where policy interventions, like restrictions on the importation of energy-inefficient products and heightened education or sensitization on the adoption of EE encourage the substitution of less energy-efficient solutions for more energy-efficient ones. Clearly, income (in)equality can influence the nature of the relationship between EE and economic growth, as it can complement or compromise the growth-inducing effect of EE. Certainly, omitting income inequality from the model could cause bias in the estimates. However, empirical studies in the literature provides little information about how income inequality affects the direction and strength of the EE-economic growth nexus.

This study makes two contributions to the literature on the economic growth–EE nexus. First, we provide a new empirical evidence on the rather scanty literature on the growth-inducing effects of EE in Africa using an approach that robustly addresses the endogeneity problem of EE. We apply the GMM technique, which relies on lag instruments of endogenous variables to improve the identification of the causal effect of EE unlike previous studies. Second, and perhaps the main contribution, this study makes the first attempt to empirically investigate the effect of income inequality on the growth-induced effect of EE. We condition the effect of EE on the level of income inequality. This helps to distinguish between the direct and the moderated effects of EE on economic growth. This also opens up new insights and informs policy makers in Africa to design the necessarily income distribution policy interventions to complement the growth-inducing effect of EE. Income inequality is identified as a decisive force that translates into marked differences in energy consumption and emissions (Oswald et al., 2020). This is largely because different purchasing power makes people use different goods and services with different energy requirements and EE. Yet, income inequality has received limited research, policy, and political attention until it became the overarching goal of the United Nations' 2030 Agenda for Sustainable Development in September 2015 (Odusola et al., 2019, pg.3). Africa is the most unequal region in the world (Gomis et al., 2020. pg70). Income inequality in Africa, is not only high and rising, but also variable ((Odusanya and Akinlo, 2020; Odusola et al., 2019; Anderson and McKay, 2004, AUC/OECD, 2018), amidst the reported improvements in EE in Africa (IEA et al., 2020). Based on the available Gini coefficients (as the measure of within-country income inequality) in 2014, 10 out of the 19 extremely unequal countries[6] globally are in Africa (Odusola et al., 2019, pg.157). Compared to the other developing countries' average Gini coefficient of 0.39, Africa's average is 0.43 with a range between 0.31(Egypt) and 0.65 (South Africa – the world's most unequal country) (Odusola et al., 2019, pg.54). Consequently, Africa's Agenda 2063 aims at strong, sustainable and inclusive growth that curbs inequality to further poverty alleviation (AUC/OECD, 2018). This makes a case to examine the role of income inequality dynamics in any economic growth-inducing process of the continent. In addition, we control for many related socio-economic factors to improve the identification of the causal effect from EE to economic growth.

We find that improving EE directly triggers economic growth, but its effect is negatively moderated downwards by widespread income inequality. The results show that the total growth effect of EE is higher for economies with minimal income inequality but lower for economies with maximum income inequality. By implication, higher income inequality could impose significant constraints on the growth-induced effect of EE improvements. Thus, reducing income inequality could facilitate investment decisions in EE and hence lead to economic growth. Section 2 discusses the data and method. Section 3 presents and discusses the results. Section 4 concludes with policy recommendations.

2. Methods and data

2.1. Measurement of energy efficiency

This study uses the Stochastic Frontier Approach (SFA) to estimate the energy efficiency scores. Compared with the non-parametric DEA, the SFA is superior in dealing with measurement errors, data uncertainty and atypical (outlier) observations in the data, which are embedded in the EE scores obtained based on DEA (Mutz et al., 2017). SFA is also able

[4] Similar to energy conversion efficiency: it is the aggregate primary-to-useful exergetic efficiency (Heun and Brockway, 2019).

[5] See Section 2.1 on the reasons for the choice of SFA over DEA.

[6] South Africa, Namibia, Botswana, Central Africa Republic, Comoros, Zambia, Lesotho, Eswatini, Guinea Bissau and Rwanda.

to handle omitted variable bias problem unlike the DEA (Hu et al., 2019). Lastly, by accounting for the random error term, the SFA can decompose energy efficiency scores into short-term and long-term components, which is not possible with DEA.

There are three stages involved in measuring EE: (*i*) defining a normative benchmark, (*ii*) observing the actual state of the world, and (*iii*) reporting the degree of deviation of the observed state of the world from the normative benchmark (Malghan, 2019). Our estimate of EE follows the approach of Filippini and Hunt (2011). Filippini and Hunt (2011) proposed the estimation of a single conditional energy input demand frontier function (see Equation (1)), where the dependent variable is energy demand, the optimal energy use is denoted by the energy demand frontier, $f(p_{it}, y_{it}, x_{it}; \theta)e^{v_{it}-u_{it}}$, where '*e*' is the Euler's mathematical constant; and the deviation from the optimal energy use (a measure of energy inefficiency) is denoted by u_{it}. 'v_{it}' is the noise term that is two-sided and normally distributed, while u_{it} is non-negative half-normally distributed. Thus, the error-term (ε_{it}) in this model is a two-composite error term with a noise term and an inefficiency term, '*p*' is the price of energy, '*y*' is the income measured as real GDP per capita (*Y*), '*x*' captures other factors that affect energy demand, and θ represents the energy demand elasticities. Following the works of Adom (2019b), Filippini and Hunt (2011), Zhang and Adom (2018), and Adom et al. (2018), we include in the 'x' vector population density (*Popden*), human capital development (*Hcdi*), urbanization (*Urbnzn*), a financial development index (F*indev*), foreign direct investment (*FDI*), share of industry output (*indsha*) in GDP and temperature (*Temp*).

We assume a Cobb-Douglas energy demand function, $f(p_{it}, y_{it}, x_{it}; \theta) = Ap_{it}^{\theta_p} y_{it}^{\theta_y} x_{it}^{\theta_x}$, and take the logarithmic transformation, which produces Equation (2), where the dependent variable, e_{it}^d, is energy demand and $\varepsilon_{it} = v_{it} - u_{it}$.

$$e_{it}^d = f(p_{it}, y_{it}, x_{it}; \theta)e^{v_{it}-u_{it}} \quad \text{where} \quad \theta_p < 0 \quad \text{and} \quad \theta_y > 0 \tag{1}$$

$$lne_{it}^d = \alpha + \theta_p lnp_{it} + \theta_y lny_{it} + \theta_x lnx_{it} + v_{it} - u_{it} \tag{2}$$

Technical EE (ef_{it}) is computed as the exponential of negative u_{it}. That is,

$$ef_{it} = \exp(-u_{it}) \tag{3}$$

Since the inefficiency term is non-negative, Equation (3) is bounded between 0 and 1, where 1 represents a fully energy-efficient country and 0 otherwise. Filippini and Zhang (2016), Kumbhakar et al. (2014), Alberini and Filippini (2018), and Adom et al. (2018) have emphasized the importance of decomposing the EE index into a time-varying component (referred to as transient EE in the literature) and time-invariant component (referred to as persistent EE). As noted in these studies, this distinction has important implications for policy design by showing the major source of inefficiency, and the intensity with which a government should adopt policies with a long-term orientation vis-a-vis those with a short-term orientation. Very high persistent energy inefficiency relative to transient energy inefficiency means that energy inefficiency will persist for the country over time, if there is no change in government policy (Kumbhakar et al., 2014). However, if the residual energy inefficiency is very high relative to the persistent energy inefficiency, then it means that inefficiency is caused by something, which is unlikely to repeat in the next period. Accordingly, we can further define the inefficiency term as the sum of the transient (τ_{it}) and persistent (u_i) components (see Equation (4)). Substituting Equation (4) into Equation (2) produces Equation (5).

$$u_{it} = \tau_{it} + u_i \tag{4}$$

$$lne_{it}^d = \alpha + \theta_p lnp_{it} + \theta_y lny_{it} + \theta_x lnx_{it} + v_{it} - \tau_{it} - u_i \tag{5}$$

Overall EE is evaluated as the product of transient and persistent EE. The fixed effect model proposed by Schmidt and Sickles (1984) estimates time-invariant EE, considering country-specific effects as inefficiency. Therefore, it suffers from model misspecification. The true fixed effects model by Greene (2005) and Chen et al. (2014) rather assumes the time-varying efficiency term. While their method controls for country-specific effects, it ignores the persistent part of EE. Thus, studies that apply the fixed effect and true fixed effect models to independently estimate persistent and transient EE, respectively, suffer from some biases.

Consequently, this study adopts the Kumbhakar et al. (2014) approach to decompose EE into transient and persistent components while still controlling for unobserved country-specific heterogeneity. The adopted approach decomposes the error component into four sub-components: the country's latent heterogeneity [ϑ_i] (Greene, 2005), which has to be separated from the inefficiency term, the transient technical inefficiency (τ_{it}), the persistent technical inefficiency (u_i) and the noise term (v_{it}). Thus, Equation (5) can be written as Equation (6).

$$lne_{it}^d = \alpha + \theta_p lnp_{it} + \theta_y lny_{it} + \theta_x lnx_{it} + v_{it} - u_i - \vartheta_i - \tau_{it} \tag{6}$$

The Kumbhakar et al. (2014) method is a four-step approach. Based on Hausman test, the first step involves the estimation of fixed or random effects panel model (see Table A.1 in Appendix A). The second step involves estimating the time-varying (transient) EE. The third step involves estimating the time-invariant (persistent) EE using the stochastic frontier model. The final step is to estimate the overall EE as a product of the transient and the persistent EE (Kumbhakar et al. (2015). Schmidt and Sickles (1984) propose a test of skewness to determine the type of stochastic frontier to construct for the estimation of EE. The test is based on the null hypothesis of no skewness versus the alternative hypothesis of positive or negative skewness (see Adom and Adams, 2020a). For a cost-type stochastic frontier, the residuals after the OLS estimation of the energy demand function should be positively skewed. On the other hand, for a production-type stochastic frontier, the distribution of OLS residuals should be negatively skewed. The results of the test, reported in Table 1, support the latter one.

2.2. Specification of the empirical growth model

This study adopts the theoretical underpinning of Howarth (1997) summarized in a functional form as Equation (7) where y* is the steady-state output per worker, *s* is the share of output devoted to capital investment, *ef* is energy efficiency and *g* is population growth. Thus, we specify the baseline economic growth model as Equation (8), where y_{it} is the dependent variable (i.e. real GDP per capita); ef, s and g are the regressors representing energy efficiency, capital formation and population growth, respectively, with β_{ef}, β_s and β_g being the respective economic growth elasticities of the regressors, and ε_{it} is the error term. The subscripts *i* and *t* represent individual countries and time in years, respectively. Basically, equation (8) shows that economic growth is endogenously determined by energy efficiency, capital formation and population growth.

$$y^* = f(s, ef, g) \tag{7}$$

$$lny_{it} = \alpha + \beta_{ef} lnef_{it} + \beta_s lns_{it} + \beta_g lng_{it} + \varepsilon_{it} \tag{8}$$

The distribution of income in any economy affects economic growth and EE. Income inequality can either complement or compromise the growth-inducing effect of EE, as discussed earlier in this study. This suggests that income inequality may have a moderating role with EE in Equation (8). Therefore, we also include income inequality (*IE*) and its

Table 1
Skewness test of energy demand function (Equation (6)).

Skewness	Pr(Skewness)	Kurtosis	Pr(Kurtosis)	Joint Chi-square test
−0.6606	0.0000	2.7677	0.1754	48.47***

***p < 0.01, **p < 0.05, *p < 0.1.

interaction with EE ($lnef_{it}*lnIE_{it}$) in the model to analyze the conditional (i.e. moderated by income inequality) effects of EE on economic growth.

EE may also be correlated with both time-invariant and time-varying factors that affect economic growth. For example, tax and pricing regimes as well as globalization may affect EE. A higher tax regime may not only disincentivise production and hence reduce economic growth, but also impose income constraints that would discourage investments in EE technologies (Adom and Adams, 2020b). This may also apply to higher pricing regimes in an economy. Globalization induces not only a scale effect, which promotes economic growth, but also a technical effect that advances EE improvements. Including both time-varying (τ_t) and time-invariant (δ_i) country-specific effects, together with income inequality and its interaction with EE, globalization (*TOP*), CPI (consumer price index) inflation (*INF*) and labour force participation rate (*LAB*) in the model would condition out the effects of these variables[7] and make the parameter of EE more likely to be identified.

Further, we include the lagged dependent variable (y_{it-1}) to form a dynamic panel model to cater for conditional growth convergence. The implication of this convergence assumption is that low-income countries should grow faster in order to catch up and reach higher income levels. Another issue of concern is reverse causality from economic growth to EE (Liu et al., 2020). Following Cantore et al. (2016), the lag of EE (ef_{it-1}) is included in the model to eliminate possible reverse causality problems as a further robustness check. Given that oil production is a key driver of economic growth, the authors included a country-specific dummy for oil-producing countries (*OPC*) in the model. In addition, we control for the effect of the global financial and economic crisis in 2008–2009, using time dummies for these years.

The resultant empirical model estimated is equation (9), where y and y_{t-1} are the dependent and lagged dependent variables, respectively. The variables ef, ef_{t-1}, IE, TOP, INF, LAB, OPC, s and g are the regressors, respectively, with Φ, β_{ef}, β_{ef1}, β_{IE}, ρ, β_s, β_g, β_{TOP}, β_{INF}, β_{LAB}, β_g and β_D being the respective parameters to be determined, and ε_{it} is the error term. The subscripts i and t represent individual countries and time in years, respectively, while τ_t and δ_i are the time-varying and time-invariant specific-country effects, respectively.

$$lny_{it} = \alpha + lny_{it-1} + \beta_{ef} lnef_{it} + \beta_{ef1} lnef_{it-1} + \beta_{IE} lnIE_{it} + \rho lnef_{it}*lnIE_{it} + \beta_s lns_{it} + \beta_g lng_{it} + \beta_{TOP} lnTOP_{it} + \beta_{INF} INF_{it} + \beta_{LAB} lnLAB_{it} + \beta_D OPC_i + \delta_i + \tau_t + \varepsilon_{it} \tag{9}$$

This list of control variables, however, is not exhaustive to condition out all unobserved factors that might correlate with EE. Thus, the endogeneity of EE can still be an issue. As indicated by Bond et al. (2001), economic growth regressions typically involve endogenous regressors and variables measured with errors. This is because some of the variables, like the initial level of efficiency, that should be included in the growth regressions are not observed. The plausibility of approximations in specifying a production function, data assumptions and the representativeness of samples introduces conceptual and data problems in the estimation task (Bond et al., 2001). This leads to endogeneity, measurement error and omitted variable problems in economic growth regressions.

2.3. Econometric strategy

Due to the above reasons, this study primarily relies on the generalized method of moments (GMM) estimator to deal with further endogeneity, serial correlation and incidental parameter problems (Ozcan and Ozturk, 2019: pp.103–4). In addition, the GMM estimator is most appropriate in dealing with heteroscedasticity when one or more regressors are endogenous. The GMM estimator remains more asymptotically efficient and consistent than OLS[8] or Instrumental Variable[9] (IV) estimators in the presence of the twin problems of heteroscedasticity and endogeneity. In this situation, GMM makes use of orthogonality conditions to enable efficient estimation (Baum et al., 2003).

This study mainly applies four variants of the GMM estimator to estimate Equation (9), following Bond et al. (2001) to determine whether the difference GMM or system GMM is a more appropriate model to be estimated. This determination of aptness requires the estimation of pooled ordinary least squares (OLS) and panel fixed effects (FE) regressions. Estimating the autoregressive distributed lag of the dynamic panel model with OLS will cause a dynamic panel bias. Thus, the autoregressive term in the OLS regression will positively correlate with the error term, thereby leading to an upward bias in the coefficient of the lagged dependent variable. Similarly, a panel FE regression that relies on within-group transformation does not remove the dynamic panel bias either. The lagged dependent variable as a regressor will have a negative correlation with the error term after the transformation. Consequently, the autoregressive coefficient will suffer from a downward bias. The actual estimates of the true coefficient of the lagged dependent variable using GMM should lie between or near the downward and upward biased estimates (Bond et al., 2001). In addition, good GMM estimates of this coefficient should be less than unity to be dynamically stable so that growth converges to equilibrium values over time (Roodman, 2009). The dynamic stability of the autoregressive coefficient also serves as a further robustness check of the aptness of the specified model. If the difference GMM estimate of the autoregressive coefficient is below or close to the downward-biased estimate, a system GMM is deemed superior in estimating the model. Otherwise, the difference GMM is preferred (Bond et al., 2001).

The difference GMM approach involves taking first-differences of a dynamic panel model regression equation to eliminate unobserved time-invariant individual specific effects and instrumenting for the right-hand-side variables in the first-differenced equations with the lagged levels of the series. The system GMM, in addition to the above, simultaneously instruments for the level equations using lags or even levels of the first differences of the regressors. The number of lags (moment conditions) used depends on the regressors. For the autoregressive term as an additional regressor and for the endogenous variables, a minimum of two lags is used. For each of the predetermined regressors, at least one moment condition should suffice. For strictly exogenous regressors, a minimum of zero lags (Roodman, 2009) is required.

The use of a higher number of lags would lead to weak instruments and instrument proliferation. Instrument proliferation can overfit the endogenous variables in the model, leading to a loss of power. In such instances, it is vital to ensure that valid overidentifying restrictions are tested and satisfied. The Hansen test for joint validity of instruments or overidentifying restrictions must then be satisfied. The test relies on the null hypothesis that overidentifying restrictions are valid. The minimum rule of thumb to check instrument proliferation is to ensure that the number of instruments does not exceed the number of groups (countries) in the panel (Roodman, 2009). Roodman (2009) further cautioned that accepting the validity of the overidentifying restrictions with a Hansen p-value above 0.25 is a source of concern because it can be an indication that instrument proliferation has affected and possibly invalidated the

[7] The sources of data for these variables and how they are computed is explained in Section 2.6.

[8] In the presence of heteroscedasticity, the OLS estimator becomes inefficient but the GMM estimator remains efficient. The presence of endogeneity together with heteroscedasticity even makes the efficiency of heteroscedastic OLS (HOLS) too unattainable unlike with GMM (Baum et al., 2003).

[9] In the presence of heteroscedasticity, the standard IV estimator is consistent but inefficient, and produces invalid inference since estimates of the standard errors are inconsistent (Baum et al., 2003). The GMM estimator still remains efficient under this condition.

Hansen test. Consequently, the overidentifying restrictions may appear valid with large p-values but actually invalid due to instrument proliferation. For these reasons, this study primarily minimizes the number of lags in the GMM instrumentation.

In addition, GMM estimators assume that time-varying errors in the level equations are serially uncorrelated. This assumption is satisfied if there is a negative first-order autocorrelation, AR(1), of the first-differenced residuals and there is no AR(2) correlation of the first-differenced residuals (Roodman, 2009). The validity of using two or more lag periods of the dependent variable as GMM instruments depends on the absence of serial autocorrelation in the errors of the level equations. Therefore, this condition must be satisfied for the validity of all GMM models.

In order to improve the efficiency of the GMM estimator, linear moment conditions in GMM can be augmented with nonlinear (quadratic) moment conditions (Ahn and Schmidt, 1995). Mindful of heteroscedasticity, the study augmented the moment conditions of the difference GMM with nonlinear moment conditions to explore the effects on the model estimates.

Though asymptotically efficient, the estimation of the optimal weighting matrix for a two-step GMM estimator may depend on the choice of the initial weighting matrix, especially in finite samples. Consequently, the robustness of the coefficient estimates and of the overidentification tests in empirical work might lead to the choice of only the most favoured results by GMM estimators. To address this problem, Hansen and Lee (2018) suggested the use of iterated GMM to remove the arbitrariness in choosing the initial weighting matrix. In iterated GMM, the weighting matrix and coefficient estimates are constantly updated until a convergence is reached (Kripfganz, 2019)[10]. This may make the coefficient estimates more robust. This study also applies the iterated GMM estimator to estimate the effect of EE on economic growth.

On the conditional effects of EE on economic growth, we evaluate the total effect of EE using the median, mean, minimum and maximum income inequality values. Further, we compute the conditional marginal effects for each country to deal with possible heterogeneities that might exist in the data. We also follow Baron and Kenny (1986) and Anderson et al. (2014) to analyze the interaction of EE and income inequality. We check for the moderation hypothesis of income inequality and also conduct two sample tests to assess the differential validity of the moderating effect of income inequality. We split the sample between countries that have lower versus higher than the average level of income inequality in one breath, and also by the threshold classification of income inequality according to the United Nations where Gini values below 40% define low income inequality, and those above 40% are considered as high income inequality (Teng et al., 2011). Then, we assess the differential validity (Baron and Kenny, 1986; Andersson et al., 2014) of the moderating effect of income inequality by testing for the statistical significance of the difference in means of the estimated total effect of EE. Finally, we test for the validity of the difference in mean income inequality between countries that have a lower versus higher than the average estimated total effect of EE on economic growth.

2.4. Empirical strategy

In order to estimate Equation (9), empirically, we address a number of issues to attest the robustness of the estimated total effect of EE on growth. First, we test for heteroscedasticity as Baum et al. (2003) emphasized that testing for the presence of heteroscedasticity in the disturbance terms is imperative for GMM to be used. The Breusch-Pagan's, Koenker's and White's tests confirmed the presence of heteroscedasticity of unknown form (see results in Table 2 and Table A.3). Moreover, a Phillips-Perron unit root test was also conducted to assess the stationarity of the series. This test corrects for heteroscedasticity and autocorrelation of unknown forms in determining the stationarity of the series. It is also asymptotically robust (Zivot, 2003). The results of the Phillips-Perron unit root test are in Table A2 of Appendix A.

Table 2
Heteroscedasticity test (on residuals of Equation (9)).

Name of test	Assumption	Null Hypothesis	df	Chi-sq. test
Breusch-Pagan/ Godfrey/ Cook-Weisberg	Normality distribution of regression errors	Constant variance	13	60.66***
Koenker	No Normality	Homoscedastic Disturbance	99	437.584***
White	No Normality	Homoscedastic	100	133.64**

***p < 0.01, **p < 0.05, *p < 0.1.

The second issue is whether to use one-step or two-step GMM estimators. This study adopts two-step GMM estimators, rather than one-step, in line with conventional asymptotics. The former has a smaller asymptotic variance than the latter (Hwang and Sun, 2018). It is also more asymptotically efficient and produces valid inferences with Bond and Windmeijer's (2005) corrected standard errors. The one-step estimators are less efficient asymptotically, although they produce valid inferences without corrected standard errors (Bond and Windmeijer, 2005; Kripfganz, 2019).

Third, considering the adverse effects of using further lags in GMM instrumentation, the number of lags has been restricted to a maximum of three. Moreover, the first-differencing of the dynamic panel model makes the lagged dependent variable potentially endogenous (Roodman, 2009) because the first lagged term in the first-differenced autoregressive term (y_{it-1}) correlates with the first lagged error term (ε_{it-1}) of the first-differenced error term[11]. Consequently, we classify the lagged dependent variable and EE as endogenous regressors and instrumented them with a minimum of 2 lags and a maximum of 3 lags. Zero to a maximum of three lags were used for the exogenous regressors as instruments. As a further robustness check, a sensitivity analysis of the coefficient estimates with respect to the choice of the number of lags[12] was also carried out. We adjust the lags of the endogenous variables, holding the lags of the other variables constant. Then, we adjust the lags of the exogenous variables, holding the lags of the other variables constant. We follow this adjustment procedure for both the differenced and the level equations. This is meant to report whether changes in the lags would affect the direction of the effects of EE.

Fourth, this study also carries out sample sensitivity analysis as a further robustness check of the direction of the effect of EE on growth. Following Adom et al. (2019), countries from North Africa were excluded from the full sample to create a sub-sample comprising only sub-Saharan Africa (SSA) countries. The excluded countries were Algeria, Morocco, Libya, Egypt and Tunisia. The World Bank classifies these countries mainly as upper middle-income economies (World Bank, 2018). The exclusion of these countries could reduce the potential influence of outliers in the sample. In addition, the sensitivity of the estimation to changes in the time series was also carried out to check whether the direction of the effect of EE on economic growth remained robust. The rationale was to deal with potential business cycle issues. Four different sub-samples were generated from the full sample data period. The first three and the last three years were dropped to form the

[10] We used the community-contributed Stata program "xtdpdgmm" written by Sebastian Kripfganz for the GMM estimations.

[11] For any ARDL(1), $y_{it} = \alpha + \Phi y_{it-1} + \beta x_{it} + \varepsilon_{it}$; $y_{it-1} = \alpha + \Phi y_{it-2} + \beta x_{it-1} + \varepsilon_{it-1}$. $y_{it} - y_{it-1} = (y_{it-1} - y_{it-2}) + \beta(x_{it} + x_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1})$ implies $\Delta y_{it} = \Delta y_{it-1} + \beta \Delta x_{it} + \Delta \varepsilon_{it}$ where Δ is the difference operator. Hence the y_{it-1} in Δy_{it} correlates with ε_{it-1}in $\Delta \varepsilon_{it}$.

[12] Roodman (2009, pg. 156) admonishes researchers to aggressively test results against the number of lags or instruments used.

first sub-sample. Then, the middle three years were also excluded from the full sample and the rest formed the second sub-sample. We exclude the first three and the last five years to create the third sub-sample and reverse the order of exclusion to create the fourth sub-sample. The estimations were repeated for each of these sub-samples.

Next, we apply the Andrews-Lu Model and Moment Selection Criteria (MMSC) to assess the best model among those estimated in the previous steps as a further robustness check for our model specification. With the MMSC, the model with the lowest values for the Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hann-Quin information criterion (HQIC) is selected as the model that fits the data best (Andrews and Lu, 2001).

Finally, we perform the Pesaran (2004, 2015) residual cross-sectional dependence test on the panels. The test investigates the presence of mean correlation between panel units. The null hypothesis for this test is cross-sectional independence. A high mean correlation and/or the presence of cross-sectional dependence in the disturbances should be addressed since this can make the estimates less efficient and inconsistent. We address cross-sectional dependence problems using an alternative estimator, the augmented mean group (AMG). As indicated in Eberhardt and Teal (2020), the validity of the identification strategy of GMM estimators partly depends on the assumptions of common technology, stationarity of the series and cross-sectional independence (Pesaran and Smith, 1995). The stationarity of the series assumption is assessed by the results of the Phillips-Perron unit root test on the specification of the series (see Table A.2 in Appendix A). To address the other assumptions, we employ the augmented mean group (AMG) estimator developed by Eberhardt and Teal (2008). The AMG estimator involves a two-stage procedure. In the first stage, we augment a pooled regression model with first-differenced year dummies. We retrieve the coefficients of the year dummies as the estimated cross-group average to represent the evolution of unobserved common factors across all panel groups.

In the second stage, we augment the group-specific regression models with the estimated common dynamic effect by subtracting this effect from the dependent variable. Thus, a common dynamic process is imposed on each group with a unit coefficient. The AMG coefficients are then estimated as the average of group-specific estimates, as is the case in Pesaran and Smith (1995) mean group regressions. Monte Carlo simulations conducted by Eberhardt and Bond (2009) show that the inclusion of the common dynamic effect enables the identification of the regression coefficients and solves endogeneity problems arising from unobserved common factors. The inclusion of the common dynamic process also addresses cross-sectional dependence in the group-specific regressions (Bond and Eberhardt, 2013). The common dynamic effect is interpreted to denote similar factors that affect all groups but to different extents for each group (Eberhardt and Teal, 2020). Moreover, the differential impact of the common dynamic process on individual groups also implicitly relaxes the common technology assumption.

We apply the AMG estimator to Equation (9). Since the common dynamic process may depend on the time dummies, we show the sensitivity of the estimates to the inclusion of the time dummies by estimating four variants of Equation (9). The first excludes the time dummies for the years 2008 and 2009, while the second excludes the time dummy for the year 2009 only. The third excludes the time dummy for 2008 only, and the fourth excludes the two time dummies.

2.5. Data sources and description

This study covers an unbalanced panel of 51 African countries[13] for the period 1991–2017. Aggregate energy consumption is proxied as the total primary energy[14] consumption (*Pegwh*) in GWh from the US Energy Information Administration (EIA). Primary energy is the total domestic energy demand. The price of gasoline (*Gasopr*) in US$ per litre obtained from various sources was used as the price variable for energy.[15] Temperature (*Temp*) is the mean annual temperature in centigrade sourced from the World Bank Climate Change Knowledge Portal. A composite index (*Findev*), using principal component analysis, was computed to represent financial development. This index is based on five indicators of financial development: domestic credit to private sector (obtained from the World Development Indicator (WDI) database), bank credit to private sector, financial system deposits, bank assets and liquid liability (all obtained from the IMF database). Globalization is proxied by trade openness (*TOP*), and this is computed as the sum of exports and imports expressed as a percentage of GDP. Data on exports and imports is obtained from the WDI database. Income inequality (*IE*) is proxied by the Gini coefficients based on household disposable income obtained from the Slot's Standard World Income Inequality Database (SWIID), version 8.2 (Slot, 2019). Human capital index (*Hcdi*) is obtained from Penn World Tables, version 9.

Data on the next set of variables were all directly obtained from the WDI database. Real output is measured as real GDP per capita (*Y*) in US$ at market exchange rates and population density (*Popden*) is the total population per square kilometre of land. Foreign direct investment (*FDI*) is measured as net FDIs inflows. Urbanization (*Urbnzn*) is the percentage of the population living in urban areas. Industry share of total output (*indsha*) is measured as the industry output as a percentage of GDP. The share of output devoted to capital investment (*s*) is measured as the gross capital formation in US$. Growth in population (*g*) is proxied by the logarithm of population in millions of people. Inflation (*INF*) is proxied by CPI inflation, while the labour force participation rate (*LAB*) is the proportion of the population that is economically active, supplying labour to produce goods and services. These people are in the age bracket of fifteen years and above (usually 65 or 70 years). EE scores (*eff*) were estimated by the authors with the stochastic frontier approach using Equation (3). Except for the human capital index (*Hcdi*), industry share in total output (*indsha*), urbanization (*Urbnzn*) and inflation (*INF*), all the other variables are measured in logarithms. Table 3 provides the descriptive statistics of these variables. Fig. 1 shows the mean time series plot of some of the key variables.

Table 3
Descriptive statistics.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
ln*Pegwh*	9.4174	1.8923	5.5494	14.3267	1371
ln*Y*	7.0540	1.0571	5.0865	9.9200	1343
ln*Popden*	3.6994	1.2875	0.5768	6.4345	1370
ln*Findev*	1.5779	0.2827	1.1871	3.2748	1198
Hcdi	0.4787	0.1258	0.199	0.797	1237
ln*FDI*	22.7815	0.2338	16.3575	23.6671	1361
ln*Gasopr*	−0.2282	0.5637	−3.9120	1.2030	927
Indsha	24.5578	12.4966	2.0732	87.7969	1255
ln*S*	21.0840	1.7855	14.4887	25.3021	1202
ln*Temp*	3.1894	0.1452	2.5360	3.4170	1377
ln*Pop*	15.7149	1.6147	11.1625	19.0671	1371
ln*Top*	4.1606	0.4893	2.4397	6.2762	1294
Urbnzn	39.6912	17.4505	5.491	88.976	1371
Eff	0.0740	0.1231	0.0001	0.9251	749
IE	45.1724	6.8696	32	66.5	749
INF	28.7910	222.3003	−11.6861	4145.106	1198
LAB	65.7623	12.9926	41.37	90.16	1350

Source: Authors' own elaborations.

[13] All 54 African countries except Congo Republic, South Sudan and Somalia.

[14] But for cost and unavailability of data, final energy would have been a better measure.

[15] WDI database, Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), International Energy Agency (IEA) and Kpodar and Abdallah's (2017).

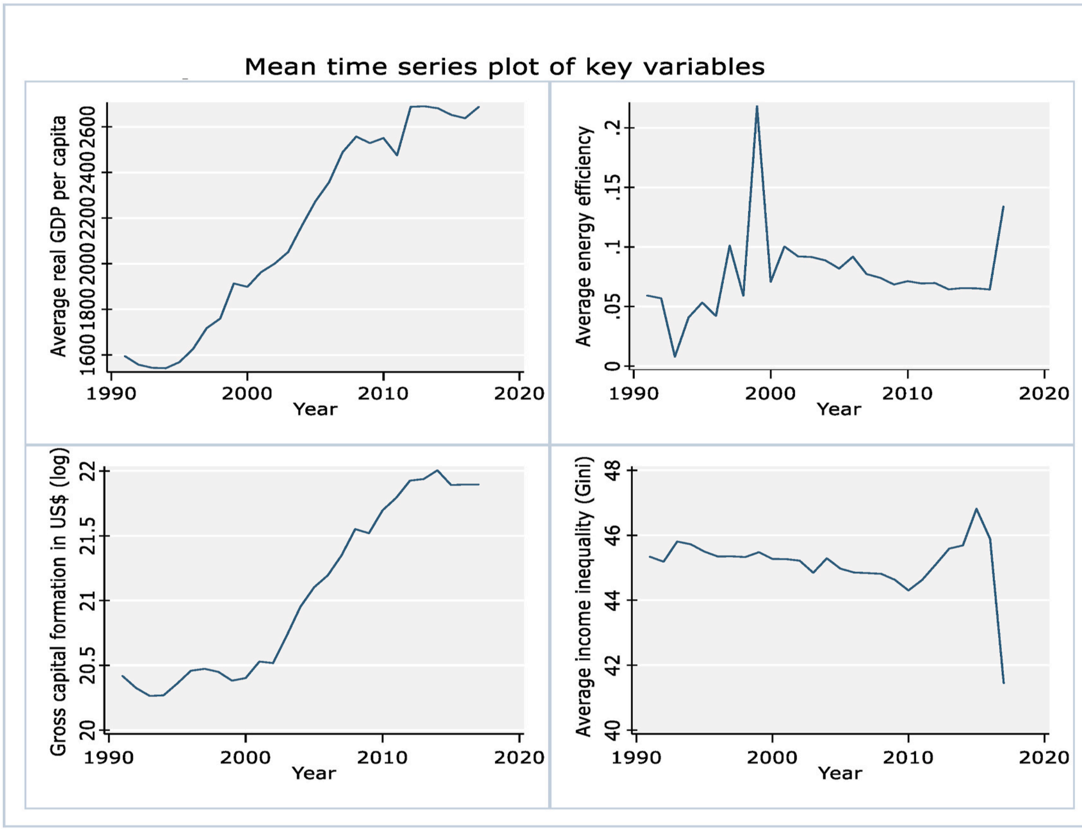

Fig. 1. Time series plot of key variables. This figure contains mean time series plot for real per capita GDP, energy efficiency, gross capital formation and income inequality (Gini index).

3. Results and discussion

This section presents the main findings and a discussion of them. First, we discuss the drivers of energy demand and the subsequent estimation of EE. Second, we discuss the effect of EE improvements (conditioned on income inequality) on economic growth, which we further support by performing some robustness checks.

3.1. *Demand frontier determinants and estimated energy efficiency*

Table 4 shows the drivers of energy demand frontier. Per capita GDP, population density, financial development, share of industry's output in GDP and urbanization have significant positive effects on energy demand. On the other hand, the price of energy (or gasoline) and human capital development exert a significant negative effect on energy demand. These results corroborate established empirical evidence in the energy demand literature (Adom and Adams, 2020b; Adom et al., 2018, 2019b; Zang and Adom, 2018; Filippini and Zang, 2016).

Table 4
Drivers of energy demand frontier (Equation (2)).

VARIABLES	Coefficient	Standard Errors
ln*Y*	0.9482***	(0.0816)
ln*Popden*	1.4741***	(0.1569
ln*Findev*	0.2158***	(0.0761)
Hcdi	−1.7011***	(0.4521)
ln*FDI*	−0.0216	(0.0460)
ln*Gasopr*	−0.0527*	(0.0302)
indsha	0.0075***	(0.0017)
ln*Temp*	−0.1654	(0.5852)
Urbnzn	0.0071*	(0.0041)
t	−0.0085	(0.0059)
t^2	0.0003*	(0.0001)
Constant	−1.3390	(2.3335)
Observations	749	749
Number of Countries	45	45
R-squared	0.741	0.741

The dependent variable is the log of total primary energy consumption. Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5 contains the estimated energy efficiency(EE), decomposed into transient and persistent EE. The mean persistent EE is lower than the average transient EE. On average, the transient EE in Africa is 0.8792, while the persistent EE is 0.0852. This translates into an overall mean EE value of 0.0750. The implication is that by improving overall EE, African can save approximately 93 (i.e. one minus 0.075) percent of the total primary energy. The high-energy inefficiency is primarily due to the high long-term or persistent energy inefficiency, which corroborates the results of Adom et al. (2018) that the energy inefficiency problem in Africa is structural in nature. Stern (2012) similarly estimated EE in Africa to be very low. The low overall mean EE result of 0.075 contradicts the average EE of 0.56 found by Ohene-Asare et al. (2020) using DEA. This might be the consequence of the fact that DEA does not account for the effect of measurement errors, data uncertainty,

Table 5
Estimates of energy efficiency (Equation (6)).

Energy efficiency	Mean	Stand. Dev.	Min.	Max.	Obs.
Transient ($\exp(-\tau_{it})$)	0.8792	0.0490	0.5400	0.9719	749
Persistent ($\exp(-u_i)$)	0.0852	0.1340	0.0001	1.0000	749
Overall ($exp(-\tau_{it}-u_i)$)	0.0750	0.1236	0.0001	0.9256	749

NB: The overall energy efficiency is a product of transient and persistent efficiencies (see Section 2.1). The estimates are based on the application of the stochastic frontier technique to equation (6).

etc in estimating EE scores. Africa's EE compares somewhat with the 0.23 average EE for Belt and Road Initiative (BRI) developing countries (Liu et al., 2020). The high persistent energy inefficiency could be attributed to poor maintenance culture and lack of adequate investments to upgrade technologies and equipment, and build capacity over the years (Adom et al., 2018). Thus, in order to significantly improve EE in Africa, EE policies of governments should target changing long-term behaviours. Policies that provide incentives for individuals to invest in energy-efficient technologies should be encouraged.

3.2. Energy efficiency-economic growth nexus and income inequality

This subsection presents and discusses the effect of EE on economic growth by applying two-step GMM estimators to Equation (9). The dependent variable for all the regressions is the logarithm of real GDP per capita. The coefficient of the autoregressive term estimated by the pooled OLS estimator is 0.9839 (see Table 6). This is statistically significant and represents the upward bias estimate of the first lag of the dependent variable. The coefficient of the lagged dependent variable representing a downward bias coefficient, as fitted by the FE estimator, is 0.8943. This means that the valid GMM model, which would explain the variations in the per capita GDP, should estimate the coefficient of the autoregressive regressor to be less than unity (for dynamic stability). This coefficient should also lie between 0.9839 and 0.8943. The estimated coefficient of the lagged dependent variable by the two-step difference GMM, following Bond et al. (2001), is 0.8917, which is close to the FE estimate and just below it. This means that the estimated coefficients of the two-step difference GMM are not reliable. In line with Ahn and Schmidt (1995), the estimated coefficient of the autoregressive regressor (0.8816) still falls outside the acceptable range after augmenting the two-step difference GMM linear moment conditions with nonlinear moment conditions.

Following Bond et al. (2001), the estimated coefficient of the autoregressive regressor for a two-step system GMM (an alternative to

Table 6
Estimation Results: Effect of energy efficiency on Economic Growth (Equation (9)).

Variables	Model 1 OLS: Upper Bound	Model 2 FE: Lower Bound	Model 3 Two-step Difference GMM	Model 4 Two-step GMM with Nonlinear	Model 5 Two-step System GMM	Model 6 Iterated Difference GMM
1st lag of GDP (lnY_{t-1})	0.9839***	0.8943***	0.8917***	0.8816***	0.9058***	0.9077***
	(0.0040)	(0.0264)	(0.0481)	(0.0382)	(0.0346)	(0.0473)
Energy Efficiency ($lnef_t$)	−0.0562	−0.0029	0.6413**	0.6286**	0.6825*	0.6578**
	(0.0568)	(0.2071)	(0.2865)	(0.2763)	(0.3808)	(0.3206)
1st lag of Energy Efficiency ($lnef_{t-1}$)	0.0550	0.0867**	0.0375	0.0405	0.0093	0.0693**
	(0.0551)	(0.0374)	(0.0604)	(0.0608)	(0.0876)	(0.0333)
Income Inequality ($dlnIE_t$)	0.5586	0.7221	1.0138	0.9847	1.0802	1.5092*
	(0.4674)	(0.6370)	(0.7788)	(0.7461)	(1.1503)	(0.9153)
Energy Efficiency*Income Inequality ($lnef$* $dlnIE$)	−0.0003	−0.0117	−0.1626**	−0.1584**	−0.1853**	−0.1623*
	(0.0027)	(0.0448)	(0.0751)	(0.0734)	(0.0935)	(0.0838)
Capital Formation (lns)	0.0176***	0.0220***	0.0495***	0.0494***	0.0355**	0.0367***
	(0.0035)	(0.0070)	(0.0162)	(0.0164)	(0.0171)	(0.0125)
Population (lng)	−0.0137***	0.0190	−0.1816*	−0.1667**	−0.0485	−0.1436
	(0.0042)	(0.0385)	(0.0999)	(0.0794)	(0.0371)	(0.1109)
Trade Openness ($lnTOP$)	0.0045	0.0025	0.0398**	0.0410**	0.0072	0.0524**
	(0.0057)	(0.0153)	(0.0182)	(0.0199)	(0.0248)	(0.0208)
Inflation (INF)	0.0001	−0.0004	−0.0001	−0.0002	−0.0002	−0.0015***
	(0.0002)	(0.0003)	(0.0019)	(0.0019)	(0.0013)	(0.0005)
Labour Force Participation Rate ($dlnLAB$)	−0.0248	0.1280*	−0.0368	−0.0423	−0.0161	0.0259
	(0.1405)	(0.0695)	(0.1043)	(0.1111)	(0.1334)	(0.1595)
Oil Producing Country ($i.OPC$)	0.0032	–	0.0359	0.0090	0.0834	−0.1133
	(0.0040)	–	(0.2253)	(0.2348)	(0.0743)	(0.1635)
Year 2008	0.0028	0.0040	−0.0294	−0.0297	0.0032	−0.0197
	(0.0042)	(0.0043)	(0.0193)	(0.0206)	(0.0211)	(0.0206)
Year 2009	−0.0275***	−0.0253***	−0.0285	−0.0279	−0.0209	−0.0088
	(0.0056)	(0.0055)	(0.0265)	(0.0280)	(0.0212)	(0.0111)
Constant	−0.0518	0.1439	2.7904**	2.6546***	0.6205	2.5854*
	(0.0546)	(0.6181)	(1.1128)	(0.9344)	(0.4688)	(1.3755)
R-squared	0.9993	0.965	–	–	–	–
Observations	408	408	408	408	408	408
Number of Countries	40	40	40	40	40	40
Instrument Count	–	–	30	31	39	30
No. of Parameters	14	13	14	14	14	14
AR(1) *p-value*	–	–	0.0100	0.0004	0.0056	0.0024
AR(2) *p-value*	–	–	0.4915	0.6121	0.7074	0.2428
Sargan *p-value*	–	–	0.8019	0.8364	0.7904	0.869
Hansen *p-value*	–	–	0.217	0.0586	0.1582	0.869
Mean ρ between Panel Units	0.02	0.01	0.05	0.05	0.00	0.06
Pesaran CD-test	3.436***	1.259	7.65***	7.80***	0.883	8.502***
Andrews-Lu model and Moment Selection Criteria (MMSC)						
MMSC-AIC	–	–	−20.8773	−22.6241	**−30.8617**	−22.0463
MMSC-BIC	–	–	−47.8994	−51.3351	**−73.0837**	−49.0683
MMSC-HQIC	–	–	−31.0654	−33.4489	**−46.7805**	−32.2343

The dependent variable is the log of real GDP per capita. The estimates are based on applying pooled OLS, panel fixed effects and GMM estimators to equation (9). Robust standard errors in parentheses; CD is cross-sectional dependence with the null hypothesis being cross-sectional independence; ρ is correlation between panel units; ***p < 0.01, **p < 0.05, *p < 0.1.

the two-step difference GMM estimator) is 0.9058. This is dynamically stable and lies within the acceptable range. As a further robustness check of model specification, the instrument count of Model 5 in Table 6, being 39, is below the number of countries (i.e. 40) as required.[16] The errors of Model 5 are serially uncorrelated as there is no first-order autocorrelation of the first-differenced residuals, but as required, there is first-differenced residuals' autocorrelation of order two. Again, the Hansen test confirms the validity of overidentifying restrictions in Model 5. The p-value of the Hansen test (i.e. 0.1582 as shown in Table 6) is also below the cautionary 0.25 limit, above which the model would be suspected to have instrument proliferation problems. Moreover, Model 5 has no cross-sectional dependence (CD) problem as the Pesaran CD test has not rejected the null hypothesis of cross-sectional independence. The implementation of the Andrews-Lu model and moment selection criteria (MMSC) that estimates the AIC, BIC and HQIC also produced the least values for Model 5. This further indicates that Model 5 best fits the data among the other competing GMM models. Therefore, Model 5 is adopted as the benchmark model to explain the effect of EE on economic growth.

The coefficients of the regressors in Equation (9) are short-run elasticities. Model 5 shows that EE has a significant positive effect (at the 10% level) on economic growth,[17] which represents the direct effect of EE on economic growth, assuming an egalitarian or equitable state. The egalitarian state is associated with the interpretation of the direct effect because the interaction effect must be zero, which requires that the logarithm of the income inequality variable should be zero, and hence the level of income inequality is 1% (minimal income inequality[18]) since the Gini index values are reported in percentages. A one percent increase in EE would lead to a 0.68 percent increase in economic growth. Generally, this implies that it would be possible to achieve the twin goals of economic growth and environmental sustainability. Thus, EE (SDG 7 target) draws positive synergies with economic growth (a relevant aspect of SDG 8).

Two possible explanations can be argued for this effect. First, EE improvements generate energy savings that can free up additional resources to purchase additional factors of production to boost output, and hence economic growth. However, this assumes that the other factors of production are normal goods, and the production function is not in the stage where there are negative returns. Even if there are diminishing returns to labour, savings from EE improvements could still be invested in the present or future acquisition of capital; hence, economic growth would still increase. However, if the above assumptions totally break down, then savings from EE improvements would still be relevant for achieving environmental quality. Second, if the improvements in EE induce more energy use, economic growth would still increase but at a higher environmental cost due to more pollution. This is the so-called take-back or rebound effect of EE.

The direct positive effect of EE on economic growth is consistent with the findings of a number of studies. This includes similar studies on EE-economic growth in economies like USA (Razzaq et al., 2021) and Canada (Bataille and Melton, 2017); multi-country studies (Rajbhandari and Zhang, 2018), European countries (Marques et al., 2019), China (Hu et al., 2019), UK (Heun and Brockway, 2019) and the BRICS group of countries (Akram et al., 2021). It is also consistent with studies on developing economies like Malaysia (Go et al., 2019), emerging economies (Bayar and Gavriletea, 2019) and others (Ohene-Asare et al., 2020; Cantore et al., 2016). However, it contrasts the findings of no meaningful effect on European countries (Pan et al., 2019), Pakistan (Mahmood and Kanwal, 2017) and India (Sinha, 2015) in the literature. This could be the consequence of the use of total factor energy production efficiency, energy intensity and reduction in fossil-fuel energy waste as proxies for EE respectively, and endogeneity issues. We defer the explanation of the conditional and moderated effect of EE to the next section.

Capital formation has a positive effect on economic growth. The results show that a one percent increase in gross capital formation would, on average, lead to a 0.04 percent increase in economic growth. This confirms the empirical results of Sharma (2010) and the Harod-Domar model of economic growth. There is evidence of convergence in economic growth, which is consistent with the catch-up theory of economic growth (Lakhera, 2016) as the coefficient of the lagged dependent variable (i.e. speed of adjustment) is statistically significant and close to unity (i.e. 0.9058).

The direction of the estimated relationships in the iterated GMM (Model 6) is very consistent with those of the two-step system GMM except that the statistical significance of the coefficients improves slightly. Of particular importance to this study, the direct effect of EE improvements on economic growth is still positive and statistically significant, which confirms the claim that EE contributes to 'green' economic growth. The effects of trade and capital formation are positive and statistically significant, but inflation exerts a significant negative effect on economic growth. However, the Hansen p-value of 0.869 indicates that instrument proliferation can harm the validity of the test for overidentifying restrictions in Model 6.

Finally, the two-step system GMM (Model 5) shows zero mean correlation across panel groups and there is no cross-sectional dependence problem as Pesaran (2004, 2015) residual cross-sectional independence hypothesis is not rejected. However, the other GMM models have a mean correlation between 0.05 and 0.06, as presented in Table 6. These models also exhibit statistically significant cross-sectional dependence at the 1% significance level. We address this problem with an alternative estimator as part of our robustness check in Section 3.4.

3.3. *Conditional effects of energy efficiency on growth*

All the estimated GMM models show that the effect of the interaction of EE and income inequality is negative and statistically significant. This satisfies the moderation hypothesis (Baron and Kenny, 1986; Andersson et al., 2014) for the use of income inequality as a moderating variable. This implies that higher income inequality constrains the growth – induced effect of EE. The total effect of EE, computed at the mean and median income inequality values in Table 7a, shows that the estimated effects are qualitatively similar, ruling out the possibility of significant outliers in the data. The estimates based on the minimum and maximum values of income inequality show that the total positive effect of EE on economic growth is higher (0.8924 vs. 0.3370) for economies with minimal income inequality than those with high income inequality.

Table 7b shows the results of the tests for the differential validity of the moderating effect of income inequality. The estimates show that the total positive effect of EE on economic growth is higher for economies with lower income inequality than for those with widespread income

Table 7a
Estimates of Conditional effect at various Gini index (income inequality) values.

Conditional effect estimated	Total Effect	Standard Error	[95% Confidence Interval]	
At the median Gini	0.6825***	0.0381	0.6078	0.7572
At the mean Gini	0.6857***	0.0382	0.6108	0.7606
At the minimum Gini	0.8924***	0.0485	0.7973	0.9875
At the maximum Gini	0.3370***	0.0215	0.2949	0.3791

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

[16] In doing the analysis, the analytical software dropped 11 out of the 51 countries for insufficient observations for some of the countries due to differencing and lagging of variables as required for GMM. Thus, the results reported here are based on 40 countries.

[17] We checked for a possible non-linearity in the EE-economic growth relationship by estimating Model 5 again after including the square of the EE variable and the coefficient of the square term is not statistically significant.

[18] Thus, $lnef_{it}*lnIE_{it} = 0 \Rightarrow lnIE_{it} = 0 \Rightarrow IE_{it} = 1\% = 0.01$ as the Gini value which is a fairly egalitarian state.

Table 7b
Test for differences in means of total effect of energy efficiency.

Income inequality (Gini values)	Mean Total Effect	Standard Error	Standard Deviation	[95% Conf. Interval]	
Below the average (A)	0.6889	0.0015	0.0416	0.6860	0.6918
Above the average (B)	0.6829	0.0020	0.0463	0.6789	0.6869
Difference in means (A-B)	0.0060**	0.0025	–	0.0012	0.0109
Below the 40% threshold (C)	0.7068	0.0016	0.0230	0.7037	0.7099
Above the 40% threshold (D)	0.6825	0.0014	0.0456	0.6798	0.6852
Difference in means (C-D)	0.0230***	0.0032	–	0.0181	0.0305

This table presents the two-sample *t*-test for difference in means of the estimated total effect of energy efficiency on economic growth for lower vs. higher income inequality countries, based on the estimates of Model 5; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

inequality. These results suggest that, in Africa, widespread income inequality could compromise the growth-induced effect of EE and hence prevent the attainment of 'green' economic growth. Thus, unequal income distribution remains an important barrier to improving EE and hence economic growth.

Fig. 2 shows the country-specific conditional effect of EE on economic growth. The estimated mean total effect (green line) is at 0.6857. Overall, even conditioning for country-specific heterogeneities in income inequality, the mean total effect is positive for all the countries. However, twenty-five countries have a higher than the estimated average total effect of EE after conditioning for income inequality, as shown in Fig. 2. The mean income inequality measure (Gini index) for these countries is lower (average Gini of 43.4) than that of the countries with total effect below the estimated average total effect (average Gini of 46.1). The two-sample *t*-test of difference in means shows that the mean Gini index of countries with higher than the estimated average total effect is significantly lower at the 1% significance level compared to their counterparts with lower than estimated average total effect (see Table 7c). The country-specific marginal effects confirm the results that higher income inequality impedes the growth-induced effect of EE. Thus, while doubling efforts in EE is critical to achieving Sustainable Development Goal 7, in Africa, it can only happen under improved and fairly distributed income situations.

3.4. Robustness of growth effects of energy efficiency

This study applies four empirical procedures to ascertain the robustness of the direction of the effects. These are the sample sensitivity, lag sensitivity of the results, sensitivity of the estimation results with respect to the time period considered and the augmented mean group estimator (AMG). In the case of sample sensitivity, Table B.1 (see Appendix B) contains the results of the estimation for only the sub-Saharan African (SSA) countries. Among the estimators, the two-step difference GMM model is the most suitable model given that the coefficient of the autoregressive regressor is dynamically stable, falling between the upper and lower bounds. Consistently, the direction of effect is similar to the full sample case, albeit statistical significance for the case of the two-step system GMM and the iterated GMM estimators

Table 7c
Test for differences in means of income inequality.

Total Effect	Mean Gini	Std. Error	Std. Deviation	[95% Conf. Interval]	
Below the average (A)	46.1063***	0.2419	6.0291	45.6312	46.5815
Above the average (B)	43.3980***	0.2727	7.2246	42.8627	43.9334
Difference in means (A-B)	2.7083***	0.3686	–	1.9853	3.4313

This table presents the two-sample *t*-test for difference in means of the Gini index between countries that have a lower vs. higher than the average estimated total effect of energy efficiency on economic growth, based on the estimates of Model 5; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

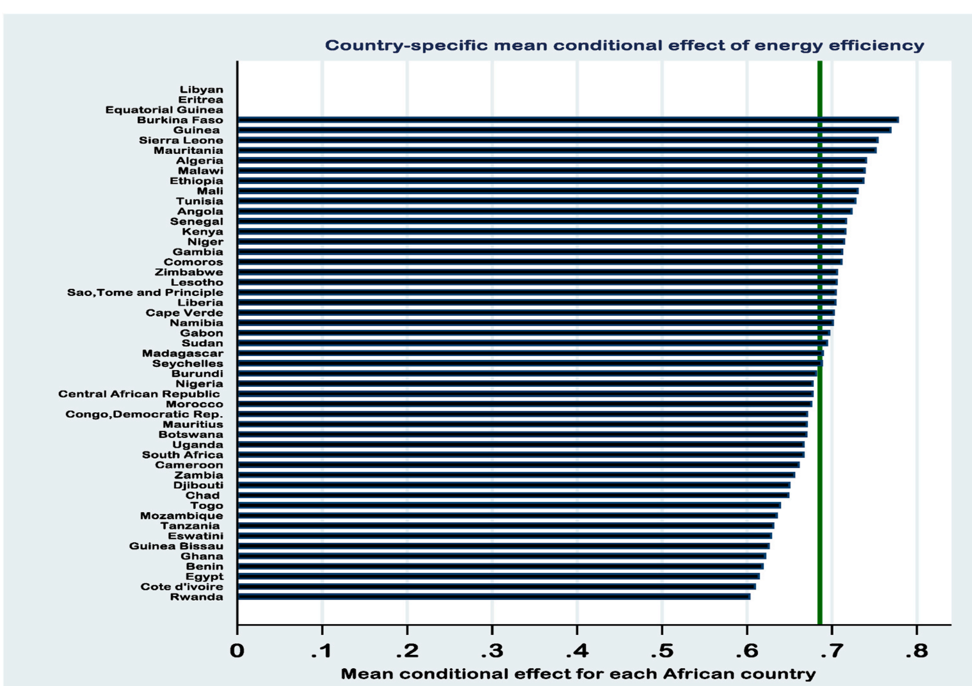

Fig. 2. Country-specific mean conditional effect of energy efficiency (own elaborations). This figure shows the total effect of energy efficiency on economic growth after accounting for heterogeneity in income inequality levels.

differs. Directly, EE triggers economic growth, but income inequality compromises this effect. Thus, reducing income inequality increases the EE elasticity of growth. However, owing to the reduction of the full sample, the instrument count of the two-step system GMM model is higher than the number of countries in the SSA sample. Consequently, the overidentifying restrictions are invalid, as the Hansen p-value is less than 10% (i.e. p-value = 0.0716).

Second, we present the sensitivity of the results to the number of lags used in generating internal instruments[18] in the most correctly specified model, the two-step system GMM (Model 5). The direct effect of EE on economic growth remains positive when the lags of the endogenous variables were adjusted (see Table B.2). The positive direct effect of EE on economic growth is still preserved. In addition, the magnitude of the coefficients associated with EE and with the interaction term are consistent across the estimated models. The estimates are therefore robust with respect to changes in the lags of the endogenous variables. The same conclusion can be drawn when the lags of the exogenous variables were adjusted (see Table B.2). As regards the adjustment of lags used in instrumenting for the level equations, the results follow the same trend (see Table B.3). The signs of the key regressors discussed above are consistent with those of the main results in Table 6.

Further, the sensitivity of the estimation results with respect to time period considered shows the same direction of effect, consistent with the main results in Table 6. Table B.4 and B.5 show consistent positive direct effect of EE on economic growth for the four separate time series subsamples. The interaction between EE and income inequality maintains its robust negative effect on economic growth, confirming the claim that a highly skewed income distribution can hinder the growth-induced effect of EE.

Finally, Table B.6 displays the results of applying the AMG estimator to Equation (9). Overall, the results of the four models show the same direction of the effect of EE on economic growth when compared to the estimates of the GMM models in Table 6. However, the magnitude of the effects is higher in the AMG models than in the GMM models. This is understandable because the AMG estimates pertain to the long run, while the GMM estimates pertain to the short run. The test of cross-sectional dependence shows the non-rejection of the null hypothesis of cross-sectional independence.

4. Conclusion and policy recommendations

This study examines the link between energy efficiency (EE) and economic growth for 51 African countries while conditioning for the moderating effect of income inequality. SDG7 (sustainable energy for all) is closely connected to SDG1 (no poverty), SDG8 (sustainable economic growth or green growth), SDG10 (reduced inequality) and SDG13 (combating climate change impacts). We apply the stochastic frontier technique to estimate EE and the two-step GMM to examine the (conditional) effect of EE on economic growth in Africa. The authors conducted sample and lag sensitivity analyses, among others, as a further robustness check of the results.

The computed average EE score is very low, and the decomposition shows that the problem of energy inefficiency is structural, requiring governments to implement policies targeted at changing long-term behaviours instead of short-term behaviours. Primarily, we find that the direct effect of EE on economic growth is consistently positive and statistically significant. However, the moderating effect via income inequality is consistently negative and statistically significant. The total conditional effect of EE on economic growth is robustly positive, but it is much higher in economies with minimal income inequality. The result revealed that the total effect of EE evaluated at the minimum level of income inequality is approximately 0.5 percentage points higher than when evaluated at the maximum level of income inequality.

On the one hand, the direct effect suggests the possibility of attaining 'green' economic growth via EE. On the other hand, the moderating effect suggests that widespread income inequality can constrain the growth-induced effect of EE. Thus, EE improvements might not lead to a win-win situation, as professed by the Porter hypothesis, in economies with a highly unequal distribution of income.

The above result corroborates the United Nation's stand on the need for countries around the world to double their efforts in EE improvements. In this regard, African governments should favour policies that target changing long-term behaviours, such as the institution and implementation of EE policies and regulations, interventions to discourage the use of inefficient equipment, incentivise the use of energy-efficient equipment and provide flexible financing schemes for such investments. However, the agenda of doubling efforts in EE can only be very effective if significant importance is attached to policies that reduce income inequality or help improve the incomes and living conditions of poor people in Africa. Establishing a guaranteed public financing system that helps people in lower-income brackets could also be critical. To this end, tax holidays on basic energy-efficient appliances mainly used by lower-income people would simultaneously improve EE and reduce income inequality.

The results of this study have revealed that income inequality is an important constraint in advancing the growth-induced effect of EE. However, there are other important socio-economic factors like level of education and institutional environment, which could equally influence the growth-induced effect of EE. Conditioning the effect of EE on these factors could worth future investigation.

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Data availability statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Philip K. Adom: Conceptualization, Methodology, Software, Validation, Visualization, Investigation, Writing – review & editing. **Mawunyo Agradi:** Conceptualization, Methodology, Software, Data curation, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Andrea Vezzulli:** Methodology, Validation, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX A

Table A.1
Hausman test (on Equation (6))

Variable	Coefficients fixed	random	Difference (Fixed-Random)	Standard error
ln*Y*	0.9482	0.8198	0.1285	0.0330
ln*Popden*	1.4741	0.6506	0.8235	0.1308
ln*Findev*	0.2158	0.1476	0.0682	0.0144
Hcdi	−1.7011	−0.7313	−0.9699	0.1364
ln*FDI*	−0.0216	−0.0133	−0.0083	0.0024
ln*Gasopr*	−0.0527	−0.0733	0.0206	0.0057
indsha	0.0075	0.0096	−0.0021	0.0003
ln*Temp*	−0.1654	−0.7164	0.5510	0.3119
Urbnzn	0.0071	0.0098	−0.0027	0.0019
t	−0.0085	0.0087	−0.0172	0.0029
t^2	0.0003	0.0002	0.0000	0.0000

Fixed = consistent under H_o and H_a; obtained from xtreg; Random = inconsistent under H_a, efficient under H_o; obtained from xtreg.
Test: H_0: difference in coefficients not systematic Chi2(10) = 89.67. Prob > chi^2 = 0.0000.

Table A.2
Philip-Perron Unit root tests for the full sample

Variable	test	statistic	p-value	Variable	test	statistic	p-value
lnY_t	P	195.5572	0.0000	*lns*	P	162.1878	0.0001
	Z	−2.3754	0.0088		Z	−1.686	0.0459
	L*	−3.3435	0.0005		**L***	−2.1736*	0.0153
	Pm	6.5503	0.0000		Pm	4.3973	0.0000
lnY_{t-1}	P	195.5639	0.0000	*lng*	P	435.9942	0.0000
	Z	−2.8137	0.0024		Z	−5.119	0.0000
	L*	−3.6872	0.0001		**L***	−11.22	0.0000
	Pm	6.5508	0.0000		Pm	23.3843	0.0000
$lnef_t$	P	157.1281	0.0000	*lnTOP*	P	158.8947	0.0002
	Z	−1.8572	0.0316		Z	−2.6369	0.0042
	L*	−3.2906	0.0006		**L***	−3.016	0.0014
	Pm	5.642	0.0000		Pm	4.1645	0.0000
$lnIE_t$	P	103.2882*	0.2874	*INF*	P	425.3496	0.0000
	Z	1.7777*	0.9623		Z	−12.1703	0.0000
	L*	1.5475*	0.9384		**L***	−15.8807	0.0000
	Pm	0.526*	0.2995		Pm	23.3821	0.0000
$dlnIE_t$	P	637.0047	0.0000	*lnLAB*	P	58.9611*	0.9996
	Z	−17.385	0.0000		Z	4.8733*	1
	L*	−25.116	0.0000		**L***	4.7831*	1
	Pm	39.0437	0.0000		Pm	−2.9019*	0.9981
lnef dlnIE*	P	314.1175	0.0000	*dlnLAB*	P	268.426	0.0000
	Z	−6.356	0.0000		Z	−4.646	0.0000
	L*	−12.301	0.0000		**L***	−6.8449	0.0000
	Pm	18.1253	0.0000		Pm	11.9095	0.0000

Note: P – inverse chi-squared, Z – inverse normal, L – inverse logit, Pm – modified inverse chi-squared; *p > 0.1 is not stationary at levels.

Table A.3
Panel data normality test (Equation (9))

	Skewness Coefficient	Kurtosis Coefficient	Joint test for Normality Chi-square
Error (e)	−0.5616	4.9245***	12.67***
Individual effect (u)	1.3659**	3.2383	9.49***

***p < 0.01, **p < 0.05, *p < 0.1.

APPENDIX B

Table B.1
Estimates for Sub-Saharan African (SSA) Countries

Variables	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step GMM with Nonlinear	Iterated Difference GMM	Two-step System GMM
lnY_{t-1}	0.9821***	0.8934***	0.9283***	0.9430***	0.9541***	0.8853***
	(0.0042)	(0.0289)	(0.0370)	(0.0633)	(0.0524)	(0.0509)
$lnef_t$	**−0.0486**	**0.0206**	**0.4666**	**0.4544**	**0.4554***	**0.8139****
	(0.0588)	(0.2137)	(0.3208)	(0.3274)	(0.2711)	(0.3955)
$lnef_{t-1}$	0.0448	0.0643*	0.0233	−0.0084	0.0652*	0.0425
	(0.0573)	(0.0354)	(0.0714)	(0.0728)	(0.0387)	(0.0739)
$dlnIE_t$	0.7565	1.5200**	2.1964***	2.4818***	1.8501*	2.5239
	(0.5460)	(0.7477)	(0.8458)	(0.9100)	(1.0341)	(2.0329)
lnef dlnIE*	0.0003	−0.0162	−0.1228	−0.1276	−0.1054	−0.2270**
	(0.0027)	(0.0458)	(0.0782)	(0.0845)	(0.0681)	(0.1085)
lns	0.0202***	0.0251***	0.0505***	0.0561***	0.0385***	0.0422**
	(0.0038)	(0.0078)	(0.0158)	(0.0173)	(0.0120)	(0.0175)
lng	−0.0159***	0.0134	−0.2133**	−0.2578*	−0.1895**	−0.0490
	(0.0045)	(0.0427)	(0.0955)	(0.1381)	(0.0909)	(0.0313)
lnTOP	0.0031	−0.0057	0.0440	0.0458*	0.0527***	0.0166
	(0.0061)	(0.0172)	(0.0269)	(0.0260)	(0.0184)	(0.0460)
INF	0.0001	−0.0004	−0.0008	−0.0006	−0.0014***	−0.0003
	(0.0002)	(0.0002)	(0.0017)	(0.0014)	(0.0003)	(0.0018)
dlnLAB	−0.0570	0.1161	−0.0759	−0.1322	−0.0993	−0.0780
	(0.1588)	(0.0806)	(0.1078)	(0.1085)	(0.1813)	(0.1138)
i.OPC	0.0043	–	0.1458	0.3154	−0.0992	0.0525
	(0.0042)	–	(0.3398)	(0.3193)	(0.1769)	(0.0784)
*year*2008	0.0025	0.0036	−0.0276*	−0.0328*	−0.0266*	−0.0092
	(0.0045)	(0.0045)	(0.0161)	(0.0170)	(0.0144)	(0.0239)
*year*2009	−0.0304***	−0.0287***	−0.0261	−0.0356*	−0.0079	−0.0358*
	(0.0063)	(0.0059)	(0.0228)	(0.0210)	(0.0115)	(0.0215)
Constant	−0.0549	0.1433	2.8055**	2.9473*	2.9800***	0.6258
	(0.0604)	(0.6733)	(1.1602)	(1.6080)	(1.1428)	(0.4403)
Observations	357	357	357	357	357	357
R-squared	0.999	0.963	–	–	–	–
Number of ID		36	36	36	36	36
Instrument Count	–	–	30	31	30	39
AR(1) *p-value*	–	–	0.0167	0.0001	0.0077	0.1073
AR(2) *p-value*	–	–	0.5043	–	0.3671	0.6921
Sargan *p-value*			0.7553	0.6948	0.8909	0.8685
Hansen *p-value*	–	–	0.0438	0.2040	0.8909	0.0716
Mean ρ in Panels	0.02	0.00	0.03	0.05	0.08	0.01
P-CD-test	2.152**	0.105	4.607 ***	6.285 ***	10.479 ***	1.004

The dependent variable is the log of real GDP per capita. Robust standard errors in parentheses; CD is cross-sectional dependence; ρ is the correlation between panel units; OLS is Ordinary Least Squares; FE is Fixed Effects; ***p < 0.01, **p < 0.05, *p < 0.1.

Table B.2
Lag sensitivity of endogenous and exogenous variables for the differenced equations

VARIABLES	Lags of the endogenous variables					Lags of exogenous variables				
	Lags (2 2)	Lags (2 3)*	Lags (2 4)	Lags (2 5)	Lags (2 6)	Lags (0 1)	Lags (0 2)	Lags (0 3)*	Lags (0 4)	Lags (0 5)
lnY_{t-1}	0.9095***	0.9058***	0.9035***	0.8999***	0.9080***	0.9162***	0.8844***	0.9058***	0.9091***	0.9111***
	(0.0349)	(0.0346)	(0.0705)	(0.0366)	(0.0279)	(0.0483)	(0.0397)	(0.0346)	(0.0339)	(0.0355)
$lnef_t$	**0.6905***	**0.6825***	**0.6708**	**0.6638**	**0.6021***	**0.5993****	**0.6510***	**0.6825***	**0.5770****	**0.6178***
	(0.4066)	(0.3808)	(1.3894)	(0.4747)	(0.3106)	(0.2932)	(0.3396)	(0.3808)	(0.2879)	(0.3289)
$lnef_{t-1}$	−0.0016	0.0093	0.0235	0.0090	−0.0060	−0.0495	0.0096	0.0093	−0.0052	−0.0192
	(0.0734)	(0.0876)	(0.2297)	(0.0884)	(0.0765)	(0.0727)	(0.0549)	(0.0876)	(0.1057)	(0.0899)
$dlnIE_t$	1.1590	1.0802	0.9821	1.1511	1.0938	1.2537	0.8030	1.0802	0.5626	1.0122
	(1.0884)	(1.1503)	(3.4616)	(1.2972)	(1.2713)	(1.0280)	(1.1509)	(1.1503)	(0.8223)	(2.1488)
lnef dlnIE*	**−0.1839****	**−0.1853****	**−0.1827**	**−0.1784**	**−0.1583****	**−0.1508****	**−0.1777****	**−0.1853****	**−0.1533****	**−0.1615****
	(0.1006)	(0.0935)	(0.3595)	(0.1105)	(0.0738)	(0.0736)	(0.0840)	(0.0935)	(0.0667)	(0.0754)
lns	**0.0359****	**0.0355****	**0.0417**	**0.0437***	**0.0445****	**0.0293****	**0.0353****	**0.0355****	**0.0393****	**0.0420*****
	(0.0176)	(0.0171)	(0.0531)	(0.0241)	(0.0177)	(0.0137)	(0.0139)	(0.0171)	(0.0163)	(0.0154)
lng	−0.0528*	−0.0485	−0.0510	−0.0536	−0.0561*	−0.0582**	−0.0568**	−0.0485	−0.0508	−0.0597*
	(0.0315)	(0.0371)	(0.0905)	(0.0438)	(0.0333)	(0.0288)	(0.0286)	(0.0371)	(0.0332)	(0.0305)
lnTOP	0.0052	0.0072	0.0182	0.0173	0.0149	0.0019	0.0278	0.0072	0.0051	0.0088
	(0.0223)	(0.0248)	(0.0664)	(0.0334)	(0.0324)	(0.0320)	(0.0342)	(0.0248)	(0.0439)	(0.0430)
INF	−0.0001	−0.0002	0.0000	−0.0000	0.0002	−0.0007	−0.0007	−0.0002	0.0000	0.0000
	(0.0015)	(0.0013)	(0.0027)	(0.0019)	(0.0019)	(0.0009)	(0.0017)	(0.0013)	(0.0019)	(0.0016)

(continued on next page)

Table B.2 (*continued*)

VARIABLES	Lags of the endogenous variables					Lags of exogenous variables				
	Lags (2 2)	Lags (2 3)*	Lags (2 4)	Lags (2 5)	Lags (2 6)	Lags (0 1)	Lags (0 2)	Lags (0 3)*	Lags (0 4)	Lags (0 5)
dlnLAB	−0.0168	−0.0161	−0.0428	−0.0328	−0.0426	−0.2881**	−0.1686	−0.0161	−0.0100	−0.0266
	(0.1338)	(0.1334)	(0.4758)	(0.1343)	(0.1312)	(0.1440)	(0.1232)	(0.1334)	(0.1223)	(0.1380)
i.OPC	0.0775	0.0834	0.0667	0.0655	0.0670	0.1095**	0.1256*	0.0834	0.0806	0.0718
	(0.0729)	(0.0743)	(0.3558)	(0.0776)	(0.0746)	(0.0447)	(0.0686)	(0.0743)	(0.0725)	(0.0595)
*year*2008	0.0036	0.0032	−0.0034	−0.0043	−0.0022	0.0312	0.0034	0.0032	0.0068	0.0038
	(0.0213)	(0.0211)	(0.1042)	(0.0326)	(0.0196)	(0.0345)	(0.0177)	(0.0211)	(0.0136)	(0.0149)
*year*2009	−0.0197	−0.0209	−0.0285	−0.0263	−0.0305	−0.0092	−0.0138	−0.0209	−0.0271***	−0.0326**
	(0.0224)	(0.0212)	(0.0744)	(0.0406)	(0.0296)	(0.0354)	(0.0188)	(0.0212)	(0.0103)	(0.0155)
Constant	0.6734*	0.6205	0.5479	0.5600	0.5275	0.8045**	0.7979**	0.6205	0.5587	0.6148
	(0.3969)	(0.4688)	(0.8049)	(0.4661)	(0.3817)	(0.3984)	(0.3659)	(0.4688)	(0.4127)	(0.4769)
Observations	408	408	408	408	408	408	408	408	408	408
Number of Countries	40	40	40	40	40	40	40	40	40	40
Instrument Count	37	39	41	43	45	27	33	39	45	51
AR(1) *p-value*	0.0066	0.0807	0.1025	0.0822	0.1140	0.0149	0.0965	0.0807	0.0970	0.0667
AR(2) *p-value*	0.5454	0.7074	0.3638	0.6556	0.6003	0.9947	–	0.7074	0.5226	0.6388
Sargan *p-value*	0.7301	0.7904	0.5763	0.7440	0.7294	0.7369	0.8070	0.7904	0.8022	0.8646
Hansen *p-value*	0.2075	0.1582	0.0512	0.0839	0.1241	0.2094	0.3022	0.1582	0.1668	0.3384
Mean ρ in Panels	0.01	0.00	0.01	0.01	0.02	0.09	0.01	0.00	0.02	0.02
P-CD-test	1.316	0.883	2.632 ***	2.698***	4.281 ***	12.413 ***	0.985	0.883	3.18 ***	4.068 ***

The dependent variable is the log of real GDP per capita. Robust standard errors in parentheses; CD is cross-sectional dependence; ρ is the correlation between panel units; OLS is Ordinary Least Squares; FE is Fixed Effects; *** p<0.01, ** p<0.05, * p<0.1

Table B.3
Lag sensitivity of endogenous and exogenous variables for the level equations

	Lags of endogenous variables				Lags of exogenous variables	
Variables	Lags (1 1)	Lags (1 2)*	Lags (1 3)	Lags (1 4)	Lags (0 0)*	Lags (0 1)
lnY_{t-1}	0.8663***	0.9058***	0.9196***	0.9149***	0.9058***	0.9458***
	(0.0460)	(0.0346)	(0.0540)	(0.0469)	(0.0346)	(0.0296)
$lnef_t$	**0.7061***	**0.6825***	**0.5727**	**0.5841***	**0.6825***	**0.0900**
	(0.3869)	(0.3808)	(0.3534)	(0.3174)	(0.3808)	(0.2273)
$lnef_{t-1}$	0.0404	0.0093	−0.0004	−0.0030	0.0093	0.0779
	(0.0420)	(0.0876)	(0.0865)	(0.0957)	(0.0876)	(0.0779)
$dlnIE_t$	0.8414	1.0802	1.2624	1.1547	1.0802	0.7884
	(1.3167)	(1.1503)	(1.3474)	(1.2143)	(1.1503)	(1.0602)
lnef dlnIE*	**−0.2029****	**−0.1853****	**−0.1522**	**−0.1542***	**−0.1853****	**−0.0470**
	(0.0972)	(0.0935)	(0.0967)	(0.0814)	(0.0935)	(0.0549)
lns	**0.0435****	**0.0355****	**0.0348**	**0.0365***	**0.0355****	**0.0305*****
	(0.0214)	(0.0171)	(0.0270)	(0.0198)	(0.0171)	(0.0096)
lng	−0.0620	−0.0485	−0.0450	−0.0443*	−0.0485	−0.0347*
	(0.0433)	(0.0371)	(0.0370)	(0.0239)	(0.0371)	(0.0178)
lnTOP	0.0270	0.0072	0.0013	0.0094	0.0072	0.0082
	(0.0168)	(0.0248)	(0.0362)	(0.0302)	(0.0248)	(0.0292)
INF	−0.0011	−0.0002	0.0001	0.0004	−0.0002	−0.0004
	(0.0024)	(0.0013)	(0.0012)	(0.0011)	(0.0013)	(0.0011)
dlnLAB	−0.0293	−0.0161	−0.0383	−0.0755	−0.0161	−0.0137
	(0.1479)	(0.1334)	(0.1692)	(0.1231)	(0.1334)	(0.1112)
i.OPC	0.1552*	0.0834	0.0480	0.0479	0.0834	0.0535
	(0.0795)	(0.0743)	(0.0452)	(0.0352)	(0.0743)	(0.0630)
*year*2008	−0.0002	0.0032	0.0079	0.0047	0.0032	0.0100
	(0.0172)	(0.0211)	(0.0289)	(0.0213)	(0.0211)	(0.0148)
*year*2009	−0.0195	−0.0209	−0.0223	−0.0271	−0.0209	−0.0365**
	(0.0248)	(0.0212)	(0.0234)	(0.0168)	(0.0212)	(0.0146)
Constant	0.7913	0.6205	0.5380	0.4919	0.6205	0.2196
	(0.4979)	(0.4688)	(0.4365)	(0.3128)	(0.4688)	(0.2607)
Observations	408	408	408	408	408	408
Number of Countries	40	40	40	40	40	40
Instrument Count	37	39	41	43	39	44
AR(1) p-value	0.0035	0.0807	0.0086	0.0001	0.0807	0.0073
AR(2) p-value	0.4746	0.7074	0.7441	0.6955	0.7074	0.3663
Sargan p-value	0.5843	0.7904	0.7908	0.7402	0.7904	0.5768
Hansen p-value	0.0408	0.1582	0.0512	0.0839	0.1582	0.1049
Mean ρ in Panels	0.00	0.00	0.02	0.02	0.00	0.07
P-CD-test	0.483	0. .883	3.00***	3.16***	0. .883	8.891***

The dependent variable is the log of real GDP per capita. Robust standard errors in parentheses; CD is cross-sectional dependence; ρ is the correlation between panel units; OLS is Ordinary Least Squares; FE is Fixed Effects; *** p<0.01, ** p<0.05, * p<0.1.

Table B.4
Sensitivity with respect to time I

Variables	Sub-sample 1994–2014 (i.e. Excluding first 3 and last 3 years)						Sub-sample 1991–2017 excluding 2003, 2004 && 2005					
	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step GMM with Nonlinear	Iterated Difference GMM	Two-step System GMM	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step GMM with Nonlinear	Iterated Difference GMM	Two-step System GMM
lnY_{t-1}	0.9869***	0.8772***	0.8606***	0.8539***	0.8408***	0.9182***	0.9788***	0.9058***	0.9314***	0.9306***	0.9673***	0.9160***
	(0.0042)	(0.0285)	(0.0788)	(0.0496)	(0.2024)	(0.0423)	(0.0045)	(0.0254)	(0.1109)	(0.1086)	(0.0853)	(0.0371)
$lnef_t$	−0.0499	0.3208	**0.5537****	**0.5501*****	**0.6495**	**0.5414**	−0.0591	−0.0458	**0.4556****	**0.4565****	**0.5095*****	**0.0930**
	(0.0567)	(0.2331)	(0.2854)	(0.2806)	(0.5198)	(0.4653)	(0.0621)	(0.2279)	(0.2503)	(0.2442)	(0.2458)	(0.2814)
$lnef_{t-1}$	0.0539	0.0588*	0.0449	0.0447	0.0248	0.0408	0.0530	0.0953**	0.0477	0.0481	0.0662	0.0715
	(0.0551)	(0.0312)	(0.0625)	(0.0605)	(0.0631)	(0.0665)	(0.0604)	(0.0397)	(0.0557)	(0.0553)	(0.0670)	(0.0762)
$dlnIE_t$	0.3301	0.7696	1.0083	0.9892	1.2129	1.3607	1.0171*	1.3192	2.4070	2.3889*	2.2918	1.4033
	(0.4463)	(0.7878)	(0.8876)	(0.8567)	(1.0934)	(0.9386)	(0.5946)	(1.0943)	(1.4767)	(1.4358)	(1.6415)	(1.5236)
$lnef^{*}\ dlnIE$	−0.0017	−0.0966*	**−0.1402****	**−0.1387****	**−0.1674**	**−0.1548**	0.0006	−0.0037	**−0.1299****	**−0.1295****	**−0.1357****	**−0.0476**
	(0.0029)	(0.0511)	(0.0743)	(0.0731)	(0.1278)	(0.1193)	(0.0027)	(0.0473)	(0.0708)	(0.0698)	(0.0695)	(0.0760)
lns	0.0150***	0.0279***	**0.0549******	**0.0545******	**0.0584****	**0.0394******	0.0208***	0.0256***	**0.0616******	**0.0620******	**0.0577******	**0.0542******
	(0.0038)	(0.0082)	(0.0143)	(0.0147)	(0.0332)	(0.0101)	(0.0040)	(0.0085)	(0.0121)	(0.0116)	(0.0132)	(0.0183)
lng	−0.0102**	−0.0260	−0.1674*	−0.1560**	−0.1669	−0.0590**	−0.0169***	0.0084	−0.2471*	−0.2477*	−0.2740**	−0.0618**
	(0.0045)	(0.0430)	(0.0986)	(0.0709)	(0.2852)	(0.0241)	(0.0049)	(0.0386)	(0.1388)	(0.1317)	(0.1183)	(0.0245)
$lnTOP$	0.0096	0.0216	0.0290*	0.0287*	0.0358*	−0.0022	0.0047	0.0017	0.0317	0.0314	0.0328	−0.0082
	(0.0058)	(0.0179)	(0.0152)	(0.0151)	(0.0202)	(0.0408)	(0.0067)	(0.0166)	(0.0227)	(0.0222)	(0.0220)	(0.0425)
INF	0.0000	−0.0007**	0.0003	0.0003	0.0008*	0.0020	0.0001	−0.0004	0.0032*	0.0032*	0.0025	0.0014
	(0.0002)	(0.0003)	(0.0016)	(0.0016)	(0.0005)	(0.0016)	(0.0002)	(0.0003)	(0.0018)	(0.0016)	(0.0021)	(0.0030)
$dlnLAB$	0.0328	0.1228*	−0.0682	−0.0667	−0.2718	−0.1465	−0.0190	0.1018	−0.1245	−0.1240	−0.1752	−0.1176
	(0.1390)	(0.0660)	(0.1532)	(0.1526)	(0.7681)	(0.1553)	(0.1949)	(0.0932)	(0.1247)	(0.1233)	(0.1287)	(0.1183)
$i.OPC$	0.0013	–	0.0117	−0.0003	0.1295	0.0640	0.0076	–	0.0798	0.0855	0.0602	0.0708
	(0.0040)	–	(0.1762)	(0.1816)	(0.2081)	(0.0621)	(0.0047)	–	(0.1920)	(0.1786)	(0.2050)	(0.0553)
*year*2008	0.0012	0.0019	−0.0217	−0.0214	−0.0317	−0.0106	0.0065	0.0065	−0.0339***	−0.0338***	−0.0311**	−0.0124
	(0.0042)	(0.0038)	(0.0185)	(0.0194)	(0.0434)	(0.0145)	(0.0042)	(0.0047)	(0.0118)	(0.0114)	(0.0131)	(0.0162)
*year*2009	−0.0287***	−0.0248***	−0.0198	−0.0189	−0.0169	−0.0260	−0.0239***	−0.0235***	−0.0323	−0.0320	−0.0318	−0.0415***
	(0.0056)	(0.0056)	(0.0170)	(0.0169)	(0.0344)	(0.0210)	(0.0055)	(0.0058)	(0.0198)	(0.0196)	(0.0250)	(0.0128)
Constant	−0.0928	0.6923	2.7114**	2.5952**	2.5595	0.6746*	−0.0460	0.1518	3.0859**	3.1020**	3.5756***	0.3784
	(0.0571)	(0.6829)	(1.2392)	(1.0582)	(3.3141)	(0.3585)	(0.0654)	(0.6522)	(1.5159)	(1.5028)	(1.2866)	(0.3126)
Observations	370	370	370	370	370	370	312	312	312	312	312	312
R-squared	0.9993	0.952	–	–	–	–	0.999	0.969	–	–	–	–
Number of ID	40	40	40	40	40	40	40	40	40	40	40	40
Instrument Count	–	–	30	31	30	39	–	–	30	31	30	39
AR(1) p-value	–	–	0.0024	0.0000	0.0015	0.1708	–	–	0.0470	0.0846	0.0868	0.0000
AR(2) p-value	–	–	0.2634	0.3681	0.1098	0.6782	–	–	0.3892	0.4436	0.4756	0.6279
Hansen p-value	–	–	0.1957	0.1023	0.7307	0.0579	–	–	0.0695	0.0957	0.6951	0.0296
Mean ρ in panels	0.02	0.00	0.31	0.31	0.31	0.34	0.04	0.02	0.23	0.23	0.23	0.30
P-CD-test	2.655***	.018	46.566***	46.952***	47.146***	49.366***	4.42***	2.329**	32.265***	32.217***	31.78***	39.945***

The dependent variable is the log of real GDP per capita; Robust standard errors in parentheses; CD is cross-sectional dependence; ρ is the correlation between panel units; OLS is Ordinary Least Squares; FE is Fixed Effects; *** p<0.01, ** p<0.05, * p<0.1

Table B.5
Sensitivity with respect to time II.

Variables	Sub-sample 1994–2012 (i.e. Excluding first 3 and last 5 years)						Sub-sample 1996–2014 (i.e. Excluding first 5 and last 3 years)					
	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step GMM with Nonlinear	Iterated Difference GMM	Two-step System GMM	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step GMM with Nonlinear	Iterated Difference GMM	Two-step System GMM
lnY_{t-1}	0.9853***	0.8733***	0.8786***	0.8794***	0.8775***	0.9392***	0.9868***	0.8601***	0.8551***	0.8479***	0.9530***	0.9351***
	(0.0047)	(0.0318)	(0.0991)	(0.0809)	(0.0447)	(0.0250)	(0.0042)	(0.0301)	(0.0648)	(0.0453)	(0.0437)	(0.0381)
$lnef_t$	−0.0330	0.3410	**0.6499***	**0.6505***	**1.0852****	**0.3822**	−0.0492	0.3388	**0.6146****	**0.6157****	**0.4951**	**0.3503**
	(0.0589)	(0.2712)	(0.3464)	(0.3481)	(0.4671)	(0.3099)	(0.0566)	(0.2448)	(0.2695)	(0.2666)	(0.3749)	(0.3573)
$lnef_{t-1}$	0.0413	0.0786*	0.0511	0.0512	0.0432	0.0297	0.0537	0.0513	0.0425	0.0417	0.0607	0.0907
	(0.0573)	(0.0429)	(0.0673)	(0.0599)	(0.0402)	(0.0732)	(0.0550)	(0.0313)	(0.0425)	(0.0440)	(0.0383)	(0.0735)
$dlnIE_t$	0.1973	0.4585	1.0623	1.0606	1.9134**	0.4596	0.3242	0.7609	1.0139	1.0100	3.5085***	1.1424
	(0.4772)	(0.8665)	(0.8698)	(0.9189)	(0.7834)	(1.2616)	(0.4452)	(0.7543)	(0.7040)	(0.6988)	(1.3374)	(0.9669)
$lnef^{*}\ dlnIE$	−0.0030	−0.1003	**−0.1656***	**−0.1659***	**−0.2979****	**−0.1113**	−0.0018	−0.1060*	**−0.1617****	**−0.1622****	**−0.1201**	**−0.1149**
	(0.0031)	(0.0632)	(0.0959)	(0.0955)	(0.1227)	(0.0746)	(0.0029)	(0.0551)	(0.0717)	(0.0721)	(0.0951)	(0.0885)
lns	0.0179***	0.0327***	**0.0612*****	**0.0612*****	**0.0548*****	**0.0378****	0.0150***	0.0271***	**0.0525*****	**0.0519*****	**0.0400*****	**0.0359*****
	(0.0041)	(0.0088)	(0.0187)	(0.0182)	(0.0147)	(0.0148)	(0.0038)	(0.0092)	(0.0167)	(0.0163)	(0.0125)	(0.0112)
lng	−0.0132***	−0.0464	−0.2247*	−0.2255*	−0.1010	−0.0409*	−0.0102**	−0.0048	−0.1755	−0.1630**	−0.2282**	−0.0516**
	(0.0049)	(0.0488)	(0.1336)	(0.1272)	(0.0945)	(0.0247)	(0.0046)	(0.0484)	(0.1074)	(0.0712)	(0.0895)	(0.0255)
$lnTOP$	0.0037	0.0146	0.0259	0.0262	−0.0045	−0.0276	0.0095	0.0250	0.0432**	0.0433**	0.0546**	−0.0061
	(0.0059)	(0.0223)	(0.0319)	(0.0292)	(0.0216)	(0.0262)	(0.0061)	(0.0195)	(0.0193)	(0.0196)	(0.0214)	(0.0287)
INF	0.0001	−0.0008*	−0.0003	−0.0003	0.0006	0.0010	0.0000	−0.0009*	−0.0007	−0.0007	−0.0022***	0.0013
	(0.0002)	(0.0004)	(0.0015)	(0.0011)	(0.0008)	(0.0014)	(0.0003)	(0.0005)	(0.0013)	(0.0013)	(0.0009)	(0.0013)
$dlnLAB$	−0.0475	0.0495	−0.0398	−0.0451	−0.1975	−0.0149	0.0339	0.1103	−0.0723	−0.0742	0.0252	−0.0696
	(0.1198)	(0.0975)	(0.1606)	(0.1568)	(0.1365)	(0.2293)	(0.1395)	(0.0675)	(0.1413)	(0.1439)	(0.3175)	(0.1354)
$i.OPC$	0.0034		0.0279	0.0267	0.0388	0.0423	0.0013		0.0851	0.0800	−0.0520	0.0355
	(0.0044)		(0.2197)	(0.2143)	(0.1683)	(0.0497)	(0.0040)		(0.1688)	(0.1657)	(0.2474)	(0.0557)
$year2008$	−0.0011	0.0021	−0.0225	−0.0228	−0.0124	−0.0095	0.0012	0.0034	−0.0195	−0.0190	0.0012	−0.0025
	(0.0043)	(0.0039)	(0.0170)	(0.0179)	(0.0105)	(0.0186)	(0.0043)	(0.0045)	(0.0170)	(0.0173)	(0.0094)	(0.0161)
$year2009$	−0.0312***	−0.0254***	−0.0218	−0.0217	−0.0184*	−0.0375	−0.0287***	−0.0241***	−0.0140	−0.0130	−0.0104	−0.0292
	(0.0058)	(0.0056)	(0.0152)	(0.0156)	(0.0101)	(0.0265)	(0.0057)	(0.0055)	(0.0189)	(0.0182)	(0.0126)	(0.0192)
Constant	−0.0726	1.0874	3.4240*	3.4305*	1.4076	0.3615	−0.0923	0.3678	2.7703**	2.6251***	3.5123***	0.5773
	(0.0601)	(0.7730)	(1.8705)	(1.7858)	(1.2145)	(0.3299)	(0.0597)	(0.7652)	(1.3065)	(1.0186)	(1.1980)	(0.3820)
Observations	327	327	327	327	327	327	365	365	365	365	365	365
R-squared	0.9993	0.942	–	–	–	–	0.999	0.948	–	–	–	–
Number of ID		39	39	39	39	39		40	40	40	40	40
Instrument Count	–	–	30	31	30	39	–	–	30	31	30	39
AR(1) p-value	–	–	0.0268	–	0.1007	0.0516	–	–	0.0026	0.000	0.000	0.1145
AR(2) p-value	–	–	0.2265	0.0097	0.5166	0.3088	–	–	0.2199	0.2520	0.6098	0.6311
Hansen p-value	–	–	0.3308	0.0497	0.8720	0.0432	–	–	0.4896	0.1465	0.6848	0.0342
Mean ρ in panels	0.01	0.00	0.28	0.28	0.32	0.31	0.02	0.00	0.30	0.31	0.31	0.35
P-CD-test	2.385**	0.11	42.277***	42.241***	46.645***	45.353***	2.653***	0.05	46.008***	46.777***	45.607***	50.146***

The dependent variable is the log of real GDP per capita. Robust standard errors in parentheses; CD is cross-sectional dependence; ρ is the correlation between panel units; OLS is Ordinary Least Squares; FE is Fixed Effects; *** p<0.01, ** p<0.05, * p<0.1

Table B.6
Effect of energy efficiency on Economic Growth (using AMG Estimator)

Variables	Model 1	Model 2	Model 3	Model 4
1st lag of GDP (lnY_{t-1})	0.3383**	0.3679**	0.3152**	0.3029
	(0.1326)	(0.1469)	(0.1309)	(0.2810)
Energy Efficiency ($lnef_t$)	1.4893	1.5088*	1.6984*	6.5526**
	(0.9092)	(0.8596)	(0.9516)	(3.2478)
1st lag of Energy Efficiency ($lnef_{t-1}$)	−0.1157	−0.1366	−0.1816	−0.6966*
	(0.1368)	(0.1645)	(0.1244)	(0.3884)
Income Inequality ($dlnIE_t$)	0.2122	0.3689	0.9822	3.4289
	(1.0485)	(0.8880)	(1.0584)	(2.8763)
Energy Efficiency*Income Inequality (*lnef*dlnIE*)	−0.3799*	−0.4049*	−0.4406*	−1.7019**
	(0.2258)	(0.2337)	(0.2364)	(0.8437)
Capital Formation (*lns*)	0.0549***	0.0476***	0.0566***	0.1815
	(0.0149)	(0.0140)	(0.0159)	(0.1211)
Population (*lng*)	−0.9890***	−0.8608***	−0.8787***	−1.4582**
	(0.2025)	(0.2413)	(0.1789)	(0.6033)
Trade Openness (*lnTOP*)	0.0070	0.0228	0.0069	0.1114**
	(0.0357)	(0.0355)	(0.0206)	(0.0535)
Inflation (*INF*)	−0.0000	−0.0006	0.0002	0.0016
	(0.0009)	(0.0010)	(0.0008)	(0.0023)
Labour Force Participation Rate (*dlnLAB*)	−10.6432	−13.0791	−10.4003	−18.1527
	(9.3436)	(13.4982)	(9.3455)	(17.4385)
Oil Producing Pountry (*i.OPC*)	0.0000	–	–	–
	(0.0000)	–	–	–
Year 2008		0.0004		0.4438***
		(0.0105)		(0.0350)
Year 2009			0.5155***	0.4726***
			(0.0055)	(0.0141)
Constant	19.1658***	17.1534***	17.1227***	23.3648***
	(2.9949)	(3.5911)	(2.9176)	(8.0829)
Mean ρ in the Panel	0.00	0.00	0.00	0.00
P-CD-test	−1.032	0.17	−0.749	−0.588
Wald Chi2 Test	56.04***	43.78***	36891.56***	33350.12***

The dependent variable is the log of real GDP per capita. Robust standard errors in parentheses; CD is cross-sectional dependence; ρ is the correlation between panel units; AMG is Augmented Mean Group; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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