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Towards sustainability: Does energy efficiency reduce unemployment in African societies?

Mawunyo Agradi [a,*], Philip K. Adom [b], Andrea Vezzulli [c]

[a] Department of Economics, University of Insubria, Via Monte Generoso 71, Varese-Milan 21100, Italy
[b] Department of Development Policy, School of Public Service and Governance, Ghana Institute of Management and Public Administration (GIMPA), Accra, Ghana
[c] Department of Economics, University of Insubria, Via Monte Generoso 71, Varese-Milan 21100, Italy

A R T I C L E I N F O

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A B S T R A C T

The Sustainable Development Goal 7 seeks universal access to energy, substantial increase in the share of renewable energy and doubling of energy efficiency efforts. The success of these targets most likely depends on maximizing, where they exist, positive synergies or trade-offs with other development outcomes. Studies investigating the relationship between energy efficiency and (un)employment remain inconclusive and mainly focus their analysis on the energy-supply side, neglecting the demand side. Moreover, these empirical studies lack a sound theoretical framework that links unemployment to energy efficiency. Synthesizing the neoclassical endogenous growth model with Okun's Law, this study adopts a demand-side approach to examine the nexus between unemployment and energy efficiency, conditioning for heterogeneities in education. We apply the stochastic frontier approach and the generalized method of moments to an unbalanced panel dataset for 51 African countries, spanning 1991–2017. We conduct several robustness checks to assess the stability of the estimated relationship. The results confirm our theoretical prediction that, directly, energy efficiency reduces unemployment. However, further empirics show that economies with better human capital experience greater reduction in unemployment than those with less-developed human capital. This implies that investing in education is a key complementary factor to enhance the unemployment-reducing effects of energy efficiency.

1. Introduction

This article examines the nexus between improvements in energy efficiency (EE) and unemployment, conditioning for heterogeneities in education. The Sustainable Development Goal 8 (SDG 8) targets to promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all. However, in developing countries especially, the challenges of high unemployment, vulnerable employment, labor underutilization, persistent sex wage gaps and decent work deficits remain key threats to achieving the SDG 8. The performance of African countries with respect to sustained inclusive growth and decent work has been worse (ILO, 2019). The world's highest unemployment rate (28.2%) in 2019 was in Africa, with five[1] out of the 10 worst unemployment rates worldwide also from the African continent (UN, 2019). African youth are three times more vulnerable to unemployment than adults (AfDB, 2020). Unemployment rates among people with intermediate or advanced level of education in Africa are the highest globally (AfDB, 2020), mainly because of a mismatch between skills and jobs (Adeleye and Esposito, 2018). Further, there has been a rising labor-underutilization trend in Africa since 2008 (Gomis, Kapsos and Kuhn, 2020). Africa needs to create 12 million new jobs every year to keep the current unemployment rate constant (AfDB, 2020). The projected growth in the number of people living in cities, especially in developing economies, is expected to increase from 3.5 billion to 5 billion by 2030 (Songsore, 2020). This is likely to worsen the unemployment problem in Africa and its cities because of the mass rural-urban migration to cities to seek better employment opportunities. This, in the long term, could affect the sustainable growth of cities and societies in Africa. This is because high unemployment impacts livelihoods and the environment negatively, and in turn, affects the sustainable growth of cities (Cobbinah, Erdiaw-Kwasie and Amoateng, 2015). Reducing the unemployment rate in Africa will help build sustainable

* Corresponding author.
E-mail address: magradi@uninsubria.it (M. Agradi).

[1] Lesotho (28.2%), South Africa (27.6%), Eswatini (26.5%), Mozambique (24.8%) and Namibia (23.2%) compared to the world and Africa's average of 5.4% and 7.8% respectively (UN, 2019).

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cities and societies by reducing crime, income inequality, psychological problems, potential social and political uprisings and risky illegal international migration across the Sahara Desert and the Mediterranean Sea (Ahmed, 2014; Azeng and Yogo, 2013; Broecke, 2013; Kadi, 2019; UN, 2019). The income effect associated with reducing unemployment could facilitate the transition to sustainable energy consumption and, in turn, promote the sustainable growth of cities.

The International Labor Organization (ILO) observes that Africa needs innovative economic and social transformative processes that lead to socially-inclusive and sustained growth with environmental integrity (ILO, 2019) to address the unemployment challenges and, in turn, improve SDG 8. This partly requires identifying and enhancing, where they exist, positive synergies or trade-offs among the SDGs 7, 8, 11 and 13. As noted by Kruse, Dellink, Chateau and Agrawala (2017), EE improvements can help integrate the SDGs 7, 8, 11 and 13. EE improvements can reduce energy cost burden and then create new direct, indirect, and expenditure-induced jobs (Bell, Nadel and Hayes, 2011; Wei, Patadia and Kammen, 2010). The International Energy Agency (IEA) (2020) sees EE as a powerful tool to cut down operating costs, enhance competitiveness and productivity, improve the economy to generate jobs and reduce environmental pollution (Reinaud and Goldberg, 2012). In its fact sheet, the American Council for Energy-Efficient Economy (2011) noted that each dollar invested in EE generates more jobs than a similar investment in traditional energy supply. Moreover, EE improvements reduce pressure on economic infrastructure including energy, and this helps promote sustainable growth of cities and societies. Sustainable growth of cities and societies would become an economic good that could trigger reduction in unemployment. In this study, we ask the question, does EE improvement trigger reduction in unemployment in Africa?

A review of empirical studies on unemployment-EE nexus remains inconclusive even in developed economies where there have been significant improvements in EE investments (see Costantini, Crespi and Paglialunga, 2018; Kemna, Wierda, and Aarts, 2016; Moscovitch, 1994; Stavropoulos and Burger, 2020; Wei et al., 2010, inter alia). In the context of Africa, there are only a few studies, but these studies are generally based on country-specific data such as those on South Africa (Borel-Saladin and Turok, 2013; Ruzive, Mkhombo, Mhaka, Mavikela and Phiri, 2019), and Tunisia (Lehr, Mönnig, Missaoui, Marrouki and Salem, 2016), and on developing countries (Cantore, Nussbaumer, Wei and Kammen, 2017). We note three important gaps in the literature. First, the existing literature lacks a strong theoretical framework, which makes the empirical models ad hoc and raises questions about the grounds for the interpretation of empirical results. Second, the existing literature builds the argument of the nexus between unemployment and energy efficiency from the supply-side of energy to the neglect of the demand-side. Consequently, these studies mainly examine employment scenarios with input-output methods, which are inappropriate to address identification issues caused by endogeneity. Thirdly, although EE improvements have the potential to create jobs, the take-up of these jobs would depend on, for example, the human capital base within the economy. As economies are likely to be starkly distinguished by the levels of human capital (education), the effect of EE improvements on unemployment rates is likely to be heterogeneous. Failing to account for possible conditioning factors, which might be sources of heterogeneities, might be one of the reasons to explain the ambiguity in the nexus between unemployment and EE improvements identified in the literature.

The current study makes the following important contributions. First, theoretically, we uniquely synthesize the endogenous growth model with Okun's Law to derive a theoretical link between unemployment and EE. This novel approach provides the theoretical foundation to incorporate EE into the empirical unemployment model for improved identification and interpretation of the causal effect. Second, we adopt a demand-side approach in this study and then compare the results with those of the previous studies focusing on the energy-supply side to determine any potential biases on the direction of the causal effect. Third, we condition for the effect of education, arguing that education is a complementary factor that can transform the generated 'desired' employment opportunities from EE into 'effective' employment. Finally, econometrically, we implement a unique technique of using the adjustments of the lags of the variables in the GMM system to test the robustness of the unemployment effects of EE. This provides an assurance that the direction of the effect is not dependent on the number of instruments and/or lags deployed in the GMM system. Unlike in tthe previous studies, applying the GMM technique also addresses the endogeneity issues of EE, among others. In terms of policy relevance, our findings have implications for energy sustainability, as it seeks to attract support for EE policies from policy makers. This has important implications for building sustainable cities and societies in Africa, as EE improvements in cities and societies help cities improve employment levels, improve municipal services, achieve energy security and increase competitiveness. Moreover, as this study seeks to identify the synergies among SDG 7, 8, 11 and 13, the findings offer important inputs into the United Nations' efforts to identify and enhance important synergies and trade-offs among the SDGs. The remainder of this study is structured as follows. A review of the relevant literature is in Section 2, while Section 3 describes the method and data. Section 4 presents and discusses our findings. Section 5 concludes and provides policy implications.

2. Literature review

2.1. Theory: unemployment and energy efficiency link

The neoclassical growth theory considers energy and EE as part of technology that is held constant in their models. However, because technological progress can lead to changes in EE, studies (Howarth, 1997; Saunders, 1992) model energy (or EE) as an endogenous variable in the neoclassical economic growth model. Besides, macroeconomic theory asserts that economic growth has (un)employment response and based on this, Okun (1962) theorizes economic growth to reduce unemployment as the Okun's Law (Sadiku, Ibraimi and Sadiku, 2015). This Law has become a crucial empirical regularity in macroeconomics (Christopoulos, McAdam, and Tzavalis, 2019). The Law asserts that firms adapt production to low demand conditions by reducing the total hours of work or hours per worker, leading to labor underutilization or unemployment (Pizzo, 2020). Thus, as output falls, unemployment increases, and the magnitude of the increase is captured by what is referred to as the Okun's coefficient. Thus, EE can be linked to unemployment through its effect on economic growth (Adom et al., 2021).

Implicitly, the technology that helps produce EE products or solutions could also indirectly link EE to (un)employment. A disruptive innovation meant to produce energy-efficient products, for instance, would push some workers out of their jobs (Urban, 2015). Low-skilled workers are the most adversely affected and, incidentally, dominant in developing countries[2] (Caselli and Coleman, 2006). Besides, there is a huge wage gap between low-skilled and high-skilled workers globally (Acemoglu and Autor, 2011; Nokelainen, Nevalainen and Niemi, 2018), and as tasks get more complex, employees need to acquire new skills. Frictional unemployment theory asserts that it takes time for, especially, low-skilled workers to acquire new skills. Besides, it takes time for firms to explore other production possibilities to employ more or re-engage labor. The optimists see this as a temporary phenomenon because the tasks of some workers only become temporarily obsolete due to the disruptive technology (Autor, 2015; Feldmann, 2013). From the perspective of the pessimists, the disruptive technology would cause an appreciable increase in unemployment (Urban, 2015).

However, economic theory suggests that the market mechanism can provide a variety of ways to offset the increase in unemployment.

[2] Majority of African workers (57%) are engaged for low-skilled jobs compared to those in high-skilled jobs (10%) (AfDB, 2020).

Vivarelli (2014) identified some of these mechanisms as new demand, lower costs, lower prices, new investments, and lower wages. The introduction of new energy-efficient solutions can create new demand and, consequently, more jobs. The technology that produces these solutions could also make it possible to produce at a reduced cost and charge lower prices. In addition, the savings on energy bills due to EE improvements could reduce the cost of production, leading to either lower prices or higher volumes of production and more demand for inputs. Lower prices could induce higher demand, driving more production and demand for labor (Blien and Ludewig, 2017) depending on the elasticity of demand. Blien and Ludewig, 2017 have demonstrated that jobs expand if demand is elastic but shrink for goods with inelastic demand. The higher input demand could boost capital investment, production, and employment, depending on the input intensity of production and the degree of substitutability or complementarity between energy and labor inputs. The foregoing suggests that the net effect of EE on unemployment cannot be determined a priori.

Porter and van der Linde (1995a,b) developed the Porter's hypothesis, which postulates that properly designed environmental-protection measures can trigger innovations that would bring about environmental performance together with business productivity, profitability, and economic growth. The Porter's hypothesis advocates that environmentally friendly policies, like EE, would encourage innovations that would improve commercial competitiveness and business performance. Consequently, environmental policies can lead to a win-win situation in terms of business creation, economic growth and employment. Indeed, in many instances, the gains from such policies outweigh the costs (Ambec, Cohen, Elgie and Lanoie, 2013; Kozluk and Zipperer, 2015). The innovation effect leads to the discovery and introduction of energy-efficient processes and products, which also generate new demand and jobs Wagner (2003). The competitiveness and business performance effect would raise productivity, profitability and living standards with the lowest possible levels of involuntary unemployment (Iraldo, Testa, Melis and Frey, 2011). This should also lead to a reduction in unemployment because profitability enhances the survival and expansion of businesses. However, this result will depend on the type of environmental-regulation instruments adopted – whether market-based or non-market-based – and the response of businesses to these regulatory instruments (Iraldo et al., 2011). Market-based instruments are argued to be more favourable in realizing the Porter's hypothesis (Ambec et al., 2013).

Energy efficiency improvements can lead to lower unemployment in three ways (Wei et al., 2010). First, improvements in EE can create direct jobs through design, manufacturing, construction, distribution, project management, installation, operation, and maintenance of EE solutions. Second, EE creates indirect jobs in the whole EE supply chain. For instance, installers of thermal insulations will purchase materials, tools, etc. from other local suppliers. This would create supply-chain jobs throughout the economy for manufacturers and service providers. Lastly, EE investments can further the creation of new jobs in two ways. The direct and indirect new jobs would enhance the disposable income of households, and this can make them increase their demand or expenditure on other goods and services in the local economy. EE also leads to savings on energy bills, which could boost the levels of expenditure on other goods and services and, hence, increases the demand for labor indirectly. Despite the theories explaining the mechanisms by which EE improvements can lead to lower unemployment, we found no attempt in the literature to model this relationship theoretically. In this study, we provide a theoretical framework to link unemployment to EE changes. This has important implications for modeling the relationship empirically.

2.2. Empirical literature

The empirical evidence on the unemployment effect of EE remains inconclusive, although this tilts towards a positive effect. In developed economies, the findings seem to suggest that EE generates more jobs (Stavropoulos and Burger, 2020). Kemna, Wierda, and Aarts, 2016 projected that the EU's Ecodesign Directives on EE measures would create an estimated 0.8 million additional direct jobs and increase indirect employment by 3–5 times the number of direct jobs by 2020. In the US economy, EE is reported to have generated almost 2.2 million jobs in 2017, with a 7% EE employment growth over the 2015 figures (U.S-DOE, 2017). In addition, Wei Patadia and Kammen, (2010) showed that EE, together with other non-fossil fuel technologies, generates more jobs per unit of energy produced in the US economy than fossil fuel technologies. In the UK, Allan, Hanley, McGregor, Swales, and Turner, 2006 and Rosenow, Platt and Demurtas, (2014), Barker, Ekins and Foxon, (2007) all found positive impacts of EE on employment. Allan, Hanley, McGregor, Swales, and Turner, 2006 found EE improvements to have increased employment by 0.21% in the long run, while Barker et al. (2007) found UK's 2000–2007 EE policy to have achieved 0.27 million additional jobs in 2010. Ryan and Campbell, 2012 estimated that about 90 jobs are generated for every One million euros invested in EE, if public and private finance is leveraged. In contrast, Heindl and Voigt (2012), Henriques, Coelho and Cassidy (2016), and Moscovitch (1994) found negative effects of EE on employment in Portugal, Germany, and the USA, respectively. Besides, Costantini et al. (2018) also found that sectoral EE gains in 15 EU countries displayed a negative effect on employment growth, especially in energy-intensive industries.

In the case of developing economies, especially in Africa, there is paucity of studies on the effect of EE on (un)employment. Lehr et al. (2016) applied the input-output analysis to estimate the impact of renewable energy and EE on job creation for the Tunisian economy. This followed the passage of the Tunisian Solar Plan law to support green energy and EE in electricity consumption. They found that additional investment in green energy (efficiency) created more than ten thousand extra jobs across all sectors of the economy. Cantore et al. (2017) applied the scenario and sensitivity analysis to examine the direct and indirect impacts of renewable energy and EE in Africa. They found that the uptake of renewable energy and EE measures would lead to additional direct, indirect, and induced jobs. However, they cautioned that the higher costs of uptake of renewable energy might adversely offset the positive effect.

In South Africa, Borel-Saladin and Turok (2013) made projections on the employment impact of greening the South African economy. This followed the promulgation of the "Green Economy Accord" in November 2011 to create, at least, 0.3 million jobs by 2020. Out of the estimated total net employment potential of 0.98 million jobs, the green energy generation is projected to add 130, 023 new jobs, with EE measures contributing 67, 977 long-term new jobs. Thus, a positive effect of EE on net job creation is expected. Using electricity intensity as a measure of electricity (energy) efficiency and a quantile regression approach, Ruzive et al. (2019) argued that electricity intensity positively correlated with unemployment rates for the periods before the electricity crisis in South Africa in 2008. Thus, lower EE is associated with higher unemployment. However, during the post-crisis period, electricity intensity and unemployment have a negative relationship for all the quantiles.

The foregoing literature presents gaps that are worth discussing. First, the existing literature lacks a strong theoretical framework for the EE-unemployment nexus. Second, several factors account for the inconclusiveness of this nexus in the empirical literature. Country-specific observed and unobserved heterogeneities (i.e. economic, social and environmental factors) might influence the way EE affects (un) employment. In this respect, this study differs from previous studies by analyzing the role of human capital or education for several African countries. The human capital, job filter (selection), job competition and (frictional) unemployment theories all suggest that education can influence unemployment (Lavrinovicha, Lavrinenko and Teivans-Treinovskis, 2015). According to filter and job competition theories, there is a huge cost involved in finding capable (skilled) workers among low-qualified candidates, hence employers use information about their educational level as a filter and a signal to choose the most educated and experienced candidates for the job. The theory of frictional unemployment asserts that education can also reduce the mismatch between skills and available jobs. The human capital theory postulates that education provides knowledge and skills that enhance the chances of individuals getting employed. Adom (2020a) noted that the decision to invest in EE and energy conservation is contingent on the knowledge level of the consuming agent. Education can help in creating environmental awareness and consciousness to engage in energy-saving practices and protect the environment (Adom, 2020a; Chen, Heerink and van den Berg, 2006; Littledyke, 2008) to support sustainability. Moreover, as the theory of human capital espouses, education generates an income effect that can encourage innovation as well as investment in energy-saving technologies and appliances (Acemoglu, 2002). Obviously, improvement in EE could also generate a rebound effect, as consumers spend their income from energy bill savings to acquire more energy-using appliances, which could potentially hamper the employment-induced effect of EE.

Lastly, many of the studies reviewed mainly focus their analysis on the energy-supply side, neglecting the demand side. This could have influenced the nature of the effects. Besides, whether the analysis is done by applying input-output methods, computational general equilibrium (i.e. impact analysis) methods or econometric techniques could also make a difference, especially for studies on the effect of EE on (un) employment (see Stavropoulos and Burger, 2020). As a departure from previous studies, the current study uses GMM estimators as part of the econometric technique to address potential endogeneity in identifying the effect of EE.

3. Methods and data

3.1. Estimation of energy efficiency

We estimate the energy efficiency (EE) scores using the Stochastic Frontier Analysis (SFA) technique for these reasons. Compared with the non-parametric Data Envelopment Analysis (DEA) technique, the SFA handles the problem of omitted variable bias better (Hu, Li and Zhang, 2019). The SFA better deals with measurement errors, outlier observations in the data and data uncertainty than the DEA where these problems can cause biases in the EE scores (Adom, Agradi and Vezzulli, 2021; Mutz, Bornmann and Daniel, 2017). Besides, the SFA, unlike the DEA, permits a decomposition of the energy efficiency scores into the transient and persistent composition for policy attention.

Measuring energy efficiency (EE) involves reporting the extent to which the actual energy use deviates from the optimal energy use or a normative benchmark (Malghan, 2019). To estimate the EE using the SFA, we follow Filippini and Hunt (2011) to define a single conditional energy demand frontier function as Eq. (1). Then, we specify a Cobb Douglas energy demand function as Eq. (2) and take logarithms to get Eq. (3), where energy demand, e^d_{it}, is a function of the price of energy (p_{it}), income (y_{it}), and other factors (x_{it}); $f(p_{it}, y_{it}, x_{it}; \theta)e^{v_{it}-u_{it}}$ is the benchmark energy demand frontier, with 'e' being the Euler's mathematical constant and θ being the energy-demand elasticities; A is a constant, ε_{it} is the error term comprising a measure of energy inefficiency, u_{it}, (assumed be half-normally distributed) and 'v_{it}' is the idiosyncratic noise term (assumed to be normally distributed) in Eq. (4). The price of energy (p_{it}) and income (y_{it}) are proxied by the per liter price of gasoline (ln*Gasoprz*) in US$ and real per capita gross domestic product (GDP) at market exchange rates, respectively. The subscript i represents individual countries while t is time in years. Considering the extant literature on other factors that can influence energy demand (Adom, 2020a, 2019a; Adom et al., 2021; Adom, Amakye, Abrokwah and Quaidoo, 2018; Filippini and Hunt, 2011; Zhang and Adom, 2018), the following variables are included in the vector 'x': urbanization (*Urbnizn*), foreign direct investment (*FDIn*), human capital (*HCI*), temperature (*Tempz*), share of industry's output in GDP (*indshao*), financial development index (F*indevt*) and population density (*Popdens*). Technical EE (ef_{it}) is computed as the exponential of -u_{it} as in Eq. (5).

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

$$e^d_{it} = f(p_{it}, y_{it}, x_{it}; \theta) = Ap_{it}^{\theta_p}y_{it}^{\theta_y}x_{it}^{\theta_x} \tag{2}$$

$$lne^d_{it} = \alpha + \theta_p lnp_{it} + \theta_y lny_{it} + \theta_x lnx_{it} + \varepsilon_{it} \tag{3}$$

$$lne^d_{it} = \alpha + \theta_p lnp_{it} + \theta_y lny_{it} + \theta_x lnx_{it} + v_{it} - u_{it} \tag{4}$$

$$ef_{it} = \exp(-u_{it}) \ \textbf{where}\boldsymbol{0} \leq \ ef_{it} \ \leq 1 \tag{5}$$

We follow the arguments of Adom, Minlah and Adams (2018), Alberini and Filippini (2018), Filippini and Zhang (2016), Kumbhakar (2014), and Greene (2005) to decompose the energy inefficiency term, u_{it}, into a time-varying (transient) efficiency (τ_{it}) and a time-invariant (persistent) efficiency (u_i) while accounting for unobserved country-specific heterogeneities [ϑ_i] Greene, 2005) in Eqs. (6) and ((7). These studies argued that there is a specification bias when the three components are not included. Besides, this decomposition is a key requisite for policy interventions – whether to adopt short-term or long-term policies – to address the inefficiency.

$$u_{it} = u_i + \vartheta_i + \tau_{it} \tag{6}$$

$$lne^d_{it} = \alpha + \theta_p lnp_{it} + \theta_y lny_{it} + \theta_x lnx_{it} + v_{it} - u_i - \vartheta_i - \tau_{it} \tag{7}$$

The empirical estimation of Eq. (7) requires four steps (Kumbhakar et al., 2014). First is a fixed-effect or random-effect estimation based on the Hausman test as in Table A.1 of Appendix A. Second is to estimate the transient EE ($\exp(-\tau_{it})$). Third is to estimate the persistent EE ($\exp(-u_i)$) factor, using the stochastic frontier residuals. Fourth is to compute the product of the transient EE and the persistent EE ($exp(-\tau_{it} - u_i)$) as the overall EE score.

One empirical issue that must be addressed is the type of stochastic frontier to specify. Schmidt and Sickles (1984) proposed a test of skewness to guide this. Negatively skewed OLS residuals require a production-type stochastic frontier whereas a cost-type stochastic frontier is preferred for positively skewed residuals (see Adom and Adams, 2020b). The results of this test, in Table 1, indicate the former.

3.2. Theoretical underpinning: Energy efficiency-unemployment nexus

This study has a theoretical framework that involves the synthesis of the Howarth (1997) model with the Okun's Law (Sadiku et al., 2015). Howarth (1997) assumes a simple Cobb-Douglas production function as in Eq. (8) and expressed in per capita terms as Eq. (9), where Output (Y), capital (K), energy services (E) and labor (L), $k = K/L$; $e = E/L$, and $y = Y/L$ and α is technology, $\beta, \ \gamma > 0$ are the output elasticities with $\beta + \gamma < 1$.

$$Y = \alpha K^\beta E^\gamma L^{1-\beta-\gamma} \tag{8}$$

$$y = \alpha k^\beta e^\gamma \tag{9}$$

Howarth (1997) eventually arrived at the steady-state output of the economy (y^*) as in Eq. (10) where $c > 0, g > 0$ and $s > 0$ are the unit cost of energy services, the population growth and the constant share of output devoted to capital investment, respectively.

$$y^* = \left[\alpha\left(\frac{\gamma}{c}\right)^\gamma\left(\frac{s}{g}\right)^\beta\right]^{\frac{1}{1-\beta-\gamma}} \tag{10}$$

Now we relate the output function to unemployment using the Okun's Law. We use the differenced version of the Okun's Law Sadiku et al., 2015) taken in a logarithmic form as in Eqs. (11) and ((12). We

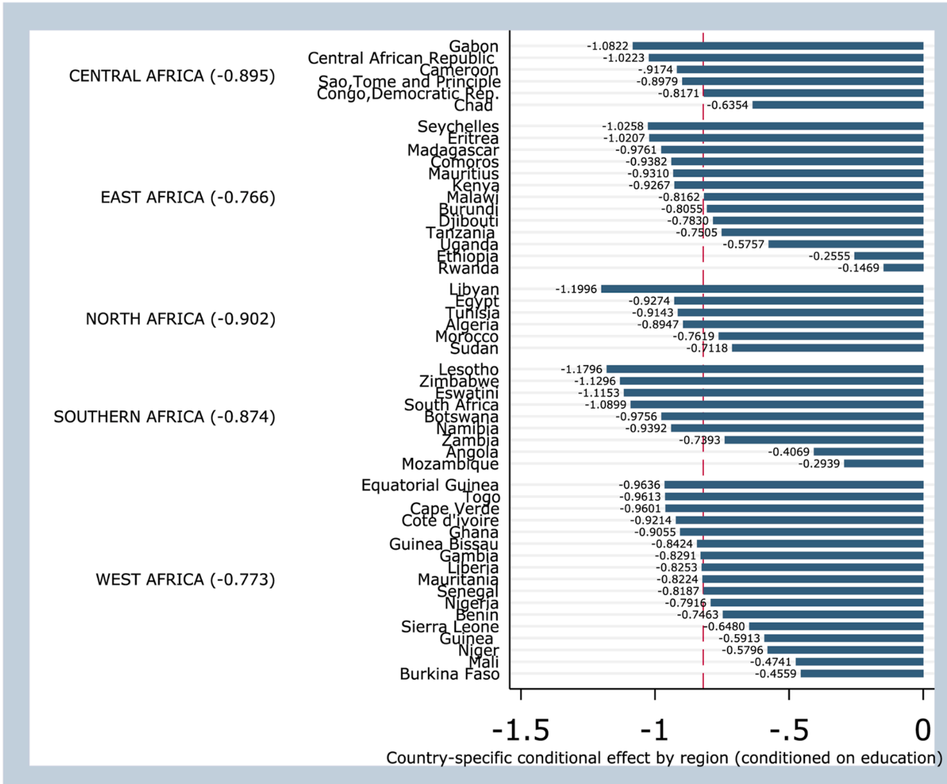

Fig. 1. Country-specific average conditional effect of energy efficiency on the unemployment rate (conditioned on heterogeneities in education. Regional average effects are in brackets).Source: Authors' elaborations.

then derive Eq. (13) by taking antilogs of Eq. (12).

$$\Delta U = \varphi + \sigma \Delta y + \varepsilon \tag{11}$$

$$lnU = \varphi + \sigma lny + \varepsilon \tag{12}$$

$$U = Ay^{\sigma}, \sigma < 0 \tag{13}$$

where U is unemployment, $\sigma < 0$ is the Okun's coefficient and Δ is a difference operator.

Substituting Eq. (10) into Eq. (13) produces Equations (14) and (15):

$$U^* = A\left[\alpha\left(\frac{\gamma}{c}\right)^{\gamma}\left(\frac{s}{g}\right)^{\beta}\right]^{\frac{\sigma}{1-\beta-\gamma}} = f(s,\ v(ef), g) \tag{14}$$

$$U^* = Z_0\left(\frac{\gamma}{c}\right)^{W_1}\left(\frac{s}{g}\right)^{W_2} \tag{15}$$

where $W_0 = A\alpha^{\frac{\sigma}{1-\beta-\gamma}}$, $W_1 = \frac{\gamma\sigma}{1-\beta-\gamma}$ and $W_2 = \frac{\beta\sigma}{1-\beta-\gamma}$; $W_1,\ W_2 < 0$ since $\sigma < 0$.

Energy efficiency (EE) reduces the effective cost of energy services, thereby increasing the long-run use of energy. Thus, all else equal, EE improvements would reduce the cost of energy services and, consequently, improve economic growth, thereby causing a reduction in unemployment. From Eq. (15), the relationship between the cost of energy services and unemployment can be derived by estimating the elasticity of unemployment with respect to the cost of energy services as in Equations (16) and (17). Equation (17) shows that the elasticity of unemployment with respect to the cost of energy services is positive.

$$\frac{\partial U^*}{\partial c} = -W_0W_1\left(\frac{1}{c}\right)\left(\frac{\gamma}{c}\right)^{W_1-1}\left(\frac{s}{g}\right)^{W_2} = -W_0W_1\left(\frac{\gamma^{W_1-1}}{c^{W_1}}\right)\left(\frac{s}{g}\right)^{W_2} > 0\text{since}W_1 < 0 \tag{16}$$

$$\frac{U^*}{c} = W_0\left(\frac{1}{c}\right)\left(\frac{\gamma}{c}\right)^{W_1}\left(\frac{s}{g}\right)^{W_2} = W_0\left(\frac{\gamma^{W_1}}{c^{W_1+1}}\right)\left(\frac{s}{g}\right)^{W_2}$$

$$\frac{\frac{\partial U^*}{\partial c}}{U^*/c} = -W_1\left(\frac{c}{\gamma}\right) > 0\text{since}c, \gamma > 0 \text{ but } W_1 < 0 \tag{17}$$

From Eq. (15), the steady state unemployment level is a function of the cost of energy services per worker (c), capital investment (s) and population growth (g). This can be expressed in the mathematical form as in Eq. (18):

$$U^* = f(s, c, g) \tag{18}$$

Assuming that technical efficiency improvement in energy usage monotonically reduces the cost of energy services, we specify that the cost of energy services is a linear function[3] of EE (Eq. 19), where $\frac{dc}{def} < 0$. The substitution of Eq. (19) into Eq. (18) (see Eq. 20), implies Eq. (21), which theoretically suggests a negative relationship between unemployment and energy efficiency.

$$c = v(ef) \tag{19}$$

$$U^* = f(s, c = v(ef), g) \tag{20}$$

$$\frac{\partial U^*}{\partial ef} = \frac{\partial U^*}{\partial c}\frac{\partial c}{\partial ef} < 0 \tag{21}$$

[3] Of course, a non-linear function is also probable because of a possible rebound effect from EE. The pass-through is the price of energy. However, the energy market in Africa is highly regulated so the pass-through will not work to produce a non-linear relationship.

3.3. Specification of Empirical Unemployment Model

Based on Eq. (20), we specify the reference unemployment model as Eq. (22), where the dependent variable is U (i.e. unemployment); ef, s and g are EE, capital formation and population growth, respectively, with β_1, β_2 and β_3 being the associated coefficients of these regressors, β_0 is the intercept, and ε_{it} is the error term. The subscript i represents individual countries while t is time in years. With reference to Equations (15) and (21), we would expect[4] the coefficients in Eq. (22) to be $\beta_1, \beta_2 < 0$ and $\beta_3 > 0$ since $W_2 < 0$.

$$lnU_{it} = \beta_0 + \beta_1 lnef_{it} + \beta_2 lns_{it} + \beta_3 lng_{it} + \varepsilon_{it} \tag{22}$$

In Eq. (22), EE is endogenous. The level of education can induce energy-saving and environmentally friendly behaviours, and improve human resource capabilities, which would also influence (un)employment levels. This suggests that education could interact with energy efficiency in Eq. (22). The input intensity of production is another key variable to consider when modeling the effect of EE on unemployment. Energy efficiency can lead to productivity growth when it generates energy-bill savings that are invested in acquiring additional inputs. The (un)employment effect can be positive or negative, conditional on the structure of technology – whether labor-intensive or capital-intensive. For a labor-intensive production technology, improvements in EE would reduce unemployment. However, there would not be much improvement in employment if the production technology is capital-intensive. In developing economies, a negative effect of EE on unemployment is expected since production technology is mostly labor-dominated.

Government expenditures in Africa constitute the largest share of expenditures in the economy. This often gives the direction of the economic activities for which jobs are created. Government expenditures, as postulated by the Keynesian macroeconomic theory, create demand for goods and services. Firms often meet the extra demand by employing additional inputs to produce more output. However, unemployment will not reduce if the increase in government expenditures goes into unproductive activities, like corruption and rent-seeking. We therefore included government expenditures (*GOV*) in the model as a control for the fiscal sector of the economy.

$$lnU_{it} = \beta_0 + \beta_1 lnef_{it} + \beta_2 lns_{it} + \beta_3 lng_{it} + \beta_4 lnU_{it-1} + \beta_5 lnef_{it-1} + \beta_6 lnHCI_{it} + \beta_7 lnef_{it}{*}lnHCI_{it} + \beta_8 lnINF_{it} + \beta_9 lnFDI_{it} + \beta_{10} lnGOV_{it} + \beta_{11} lnLABIN_{it} + \beta_{12} lnef_{it}{*}lnLABIN_{it} + \tau_t + \varepsilon_{it} \tag{23}$$

Inflation could also influence both unemployment and EE. The Philips curve theorizes a negative relationship between unemployment and inflation so far as the unemployment level deviates from the natural rate of unemployment. Because EE depends on the cost of energy services, a rise in inflation will make energy services costly. Inflation (*INF*) is included in the model to control for the influence of the monetary sector on unemployment.

Foreign direct investment (FDI) eases access to finance and liquidity for firms to stimulate investment in new plants and factories (Sadorsky, 2010). FDI can, therefore, have significant influence on unemployment by increasing the production capacity of firms, so that they can employ more labor. In the same vein, FDI could also influence EE according to the halo effect hypothesis (HEH) and the pollution haven hypothesis (PHH) (Adom, Opoku and Yan, 2019b). Through FDI inflows, the PHH argues that foreign firms in advanced countries can transfer the production of pollution- and energy-intensive products to developing countries, where there are less stringent and less enforced environmental regulations. Sometimes, energy-intensive intermediate and final products are dumped in developing countries through FDI inflows and trade. This leads to higher cost of energy services and energy inefficiency in developing countries. The halo effect hypothesis (HEH) argues that FDI improves EE. Through FDI, multinational firms can spill over knowledge, superior technologies, and positive environmental practices to domestic firms. These spill-overs help domestic firms to adopt energy-saving strategies and green methods of production, leading to improvements in EE. To address potential endogeneity due to omitted variable bias, we include education (proxied by the human capital index (*HCI*) and its interaction with EE, inflation (*INF*), proxied by the consumer price index (CPI), net FDI inflows (*FDIn*), and labor intensity (*LABIN*) [i.e. input intensity of production], proxied by the inverse of the GDP per person employed, and its interaction with EE as controls in the model. In addition, we include year dummies and report the effect of the Great Recession in 2008–2009 on unemployment.

Reverse causality from unemployment to EE could also be a source of potential endogeneity in Eq. (22). Other things being equal, reducing unemployment with more jobs could increase the disposable income of households, and this might stimulate investments into energy-using appliances. Some of these appliances could be energy-saving, thereby improving EE. Others may be energy-intensive and, therefore, energy-inefficient. As argued by Cantore, Cali and Velde (2016), we include the first lag of the EE variable in the model to address a possible simultaneity problem.

Furthermore, we specify a dynamic panel model by including the autoregressive term, (U_{it-1}), because the current rate of unemployment can easily be influenced by the previous level of unemployment, given that the unemployed people in the previous period are still part of the labor force in the current period. The resultant empirical model adopted for this study is the one specified in Eq. (23), where U_{it} and U_{it-1} are the outcome and autoregressive variables, respectively. The other variables, s, g, ef, ef_{t-1}, HCI, INF, FDI, GOV and $LABIN$, are the regressors, respectively, with β_j, $j = 1, 2, \ldots, 12$ being the associated parameters to be estimated, ε_{it} is the idiosyncratic error term and 'τ_t' is the time-varying specific-country effects, respectively.

3.4. Estimation strategy

Though we included various covariates in Eq. (23) to condition out factors that might correlate with energy efficiency, this may not be exhaustive. Consequently, endogeneity could still be inherent. To deal with further endogeneity, incidental parameter problems and serial correlation, we apply the generalized method of moments (GMM) as indicated by Ozcan and Ozturk (2019) and Wintoki, Linck and Netter, 2012). Again, in the presence of heteroscedasticity and endogeneity problems, the GMM estimator remains asymptotically efficient and consistent unlike the OLS and Instrumental Variable (IV) estimators (Baum, Schaffer and Stillman, 2003). GMM methods applied to estimate dynamic models are mainly of two kinds, namely the difference GMM (Arellano and Bond, 1991) and the system GMM (Blundell and Bond, 1998). GMM estimators use internal lags of the variables as instruments. The choice of lags depends on the type of explanatory variables and the nature of the model transformation (i.e. first-differenced transformation (Arellano and Bond, 1991) or forward-orthogonal deviations

[4] This can be proven, mathematically, by taking partial derivatives in equations (14) or (15) and see equation (21). See Appendix C (Supplementary file)

transformation [FOD] (Arellano and Bover, 1995). GMM estimation based on the difference transformation produces first-order serial correlation in the transformed error term, but when the FOD transformation is used, the transformed errors are still serially uncorrelated if the untransformed errors are serially uncorrelated. Besides, the FOD transformation retains more information than the difference transformation when the panel dataset is unbalanced (Kripfganz, 2019). We use the FOD transformation in our estimations because of these advantages.

This study addresses a number of **pre-estimation** empirical issues. First, following the arguments of Hwang and Sun (2018) and Kripfganz (2019) that a two-step GMM produces a smaller asymptotic variance unlike the one-step GMM, and that a feasible and efficient one-step GMM estimator rarely exists, we based our GMM estimations on the two-step GMM procedure.[5] Second, we test for heteroscedasticity using Koenker, White and Breusch-Pagan (BPGCW) tests (see results in Table 2) as heteroscedasticity in the error term is a necessary condition to use the GMM (Baum et al., 2003). We use the Phillips-Perron unit root test to assess the stationarity of the series (see Table A.2 in Appendix A). The test corrects for heteroscedasticity and autocorrelation of any unknown form, and it is asymptotically robust in determining the stationarity of the series (Zivot, 2003).

Third, we follow the guidelines in Roodman (2009) and classify the autoregressive term and EE as our endogenous explanatory variables and instrument them with 2 to 3 lags in the first-differenced model and 1 to 3 lags in the forward orthogonal deviation (FOD) model. The other variables are classified as exogenous regressors and instrumented with up to a maximum of three lags for both the first-differenced and the forward orthogonal deviation (FOD) models, following the requirements for GMM moment conditions outlined in Kripfganz (2019). We restrict the use of lags to a maximum of three in our GMM system because the use of more lags could result in overfitting and instrument proliferation problems, and cause biased coefficients, standard errors, and weak specification tests. Instrument proliferation is checked by ensuring the number of countries in the panel exceeds the number of GMM instruments used (Roodman, 2009). Overfitting problems are checked by ensuring the validity of the Sargan and Hansen overidentifying restrictions tests. Both tests assume the overidentifying restrictions are valid. Roodman (2009) cautions that accepting the validity of the overidentifying restrictions with a (Hansen) p-value higher than 25% is an indication that instrument proliferation has possibly weakened the results of the test. In addition, we carry out robustness checks on the coefficient estimates, with respect to the choice of lags,[6] to show the extent to which these lags influenced the direction of the estimated causal effect. This involves holding some lags constant while adjusting the others. The aim of this is to report whether the choice of the number of lags has any consistent pattern of changes on the estimates. We check the strength of the internal GMM instruments using the Cragg-Donald robust (to heteroscedasticity) continuously updating estimator (CUE)--based weak identification test (Sanderson and Windmeijer, 2016; Stock, Wright and Yogo, 2002).

For the **actual estimation**, we determine which estimator - a difference GMM or a system GMM - would fit our data following Bond, Hoeffler, and Temple, 2001. The more appropriate estimator is the one for which the estimated coefficient of the lagged dependent variable falls within those estimated with the OLS and the fixed effect (FE) panel regressions. For the OLS regression, this coefficient is upward biased, because it positively correlates with the error term. On the contrary, it is downward biased for the FE regression because the coefficient of the lagged dependent term negatively correlates with the error term. A system (*or difference*) GMM fits the data if the coefficient of the autoregressive term falls outside (*or within*) the range.

Moreover, we implement the arguments of Ahn and Schmidt (1995) that augmenting the linear GMM instruments with nonlinear ones can yield efficiency gains for better identification of the model parameters (Gorgens, Han and Xue, 2019). We also apply the iterated GMM estimator to Eq. (23) following the suggestions of Hansen and Lee (2018) that this removes the arbitrariness in choosing the initial weighting matrix, and, thus, increases the robustness of the estimates and the overidentification tests.

Finally, we apply the Andrews-Lu Moment Selection Criteria (MMSC) to identify the best model among the competing GMM specifications and conduct further robustness checks on the best model. Using the MMSC, the model estimator that best fits the data is that which produces the lowest values from the Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC), and the Hann-Quin Information Criterion (HQIC) (Andrews and Lu, 2001; Kripfganz, 2019).

We also examine a number of **post-estimation issues**. First, the justification for the use of GMM instruments assumes that there is no serial autocorrelation in the idiosyncratic error term of the dynamic panel model. We use the Arellano-Bond test to check for a possible autocorrelation of first-differenced residuals. The null hypothesis of this test assumes no autocorrelation of order 1 or 2. A negative first-order autocorrelation, AR(1), with no second-order autocorrelation, AR(2), of the first-differenced residuals would satisfy this requirement (Roodman, 2009).

Second, we perform the Pesaran's weak and strict cross-sectional dependence [CD] tests on the estimations because CD could make the estimates inconsistent Pesaran (2004, 2015). Pesaran (2015) test relies on the null hypothesis of weak CD and that of the Pesaran (2004) test is strict cross-sectional independence. We find the presence of CD and, because the GMM estimation procedure has no option to control for CD directly, we use (an alternative estimator) the Driscoll-Kraay Fixed Effect (DKFE) estimator (Driscoll and Kraay, 1998) to check whether CD has affected the direction of the estimated causal effect. The standard errors of the DKFE estimator are robust to general forms of CD, thereby improving the identifiability of the parameters.

For the conditional effects of energy efficiency on the unemployment rate, we use the minimum, maximum, mean, and median values of the human capital index. We account for possible heterogeneities in educational attainment by computing the specific conditional marginal effects. Further, we determine the differential validity of the moderation effect (Andersson, Cuervo-Cazurra and Nielsen, 2014; Baron and Kenny, 1986) of education by splitting the sample between countries with higher versus lower than average and median human capital index values and testing for the difference in means of the estimated total unemployment effect of EE. We also test for the significance of the difference in means of the human capital index values between countries that have higher versus lower than estimated average total unemployment effect of EE.

Finally, further robustness checks on the direction of the unemployment effect of EE also involve a number of sensitivity analyses. We follow (Adom et al., 2019b) to form a sub-sample of SSA countries by excluding Egypt, Libya, Algeria, Tunisia, and Morocco. This is meant to reduce the potential outlier effects as these countries are classified as upper middle-income economies by the World Bank (World Bank, 2018). Besides, these countries also have relatively better education systems (Adom et al., 2020a). Moreover, we use the respective female and male unemployment rates as dependent variables, respectively and estimate the same models to check the direction of the estimated unemployment effect of EE for sex-sensitive measures of unemployment.[7] Sex considerations have become crucial in our world currently and, therefore, the latter robustness checks serve to satisfy this perspective.

[5] We analyzed the data using the community-contributed Stata program for GMM estimation "xtdpdgmm" written by Kripfganz.

[6] Roodman (2009, pg. 156) strongly indicate that results should be aggressively tested with respect to the number of instruments or lags used.

[7] The ILO reports only male and female unemployment rates in the data and so we rely on only these dimensions.

3.6. Data description and sources

Data for this study covers 51 countries[8] from Africa and spans from 1991 – 2017. For the estimation of the energy demand frontier in Eq. (7), we follow Ahmad and Zhang (2020), Bayomi and Fernandez (2018), and Inglesi-Lotz and Morales (2017) to use total primary energy consumption (*Pengwh*) in GWh from the database of the USA Energy Information Administration (EIA) as a proxy for aggregate energy demand (e^d_{it}). For the total primary energy consumption of each country, the EIA includes the consumption of petroleum, dry natural gas, coal, net nuclear, hydro-electric and non-hydroelectric renewable electricity as well as net coke and net electricity imports. Primary energy consumption denotes the overall use of energy (Ahmad and Zhang, 2020) or the aggregate energy demand. Due to unavailability of consistent energy price index data on these countries, we use the per liter price of gasoline (G*asoprz*), in US$, from various sources,[9] as a proxy for the price of energy (p_{it}). Although the price of gasoline may be a weak indicator of energy price, oil constitutes a major share of all energy sources, about 42% of total energy consumption (UNEP, 2017). Moreover, it might share important correlations with other energy products such as electricity and gas. For example, thermal sources of electricity, largely powered by fuel and gas, are major sources of electricity in Africa. In Nigeria and North African countries, electricity is largely powered by petroleum-fired generation plants. Currently, in Ghana, thermal generation provides the highest share of electricity generated. That notwithstanding, readers are cautioned to interpret the coefficient of price as gasoline price elasticity. Further, there are studies on Africa that indicate important association between electricity price and oil price. For example, Adom et al. (2018) in their study on electricity price drivers in Ghana found that the positive pass-through effect of oil price on electricity price materialises in the long-term. Similarly, Jantuah and Adom (2020) found that oil and electricity markets are integrated, with evidence of asymmetric relationship between electricity price and oil price. Also, Adom, Insaidoo, Minlak and Abdul-Mumuni (2017), in their study on predicting the variance in electricity price, found that oil price increases exert significant positive effect on the uncertainty in electricity price in the short and long runs.

The set of additional variables included in the vector x_{it}, (Eq. (3)) is defined as follows. The mean annual temperature obtained from the Climate Change Knowledge Portal of the World bank represents temperature (*Tempz*) in centigrade. As a proxy for education, we obtain data on human capital index (*HCI*), based on average years in school and returns to education, from the Penn World Tables (version 9). To proxy the level of financial development, a composite index, *Findevt*, is computed from principal component analysis based on five indicators of financial depth namely, assets and liquid liability, financial system deposits, bank credit to the private sector (all from the International Monetary Fund (IMF) database) and domestic credit to the private sector (sourced from the World Development Indicators (WDI) database). Energy efficiency scores (ef_{it}) are estimated from the residuals in Eq. (7).

We also obtain data on the variables below from the WDI database. Unemployment (*U*) rate is defined as the share of the total labor force that is unemployed but seeking and available for jobs. We use three measures of the unemployment rate (from the ILO/WDI database): total unemployment rate (*U*), male unemployment rate (*mU*), and female unemployment rate (*fU*). Output (*Y*) in Eq. (8) is the real per capita gross domestic product (GDP) (in US$) at market exchange rates. Labor intensity (*LABIN*) is proxied by the inverse of GDP per person employed (*GDPPPE*). A country's population per square kilometer of land is a proxy for population density (*Popdens*). The logarithm of gross capital formation, in US$, is a proxy for capital investment (*s*). Population growth (*g*) is proxied by the logarithm of a country's total population, in millions. Consumer Price Index (CPI) inflation is our measure for inflation (*INF*), while government expenditures (*GOV*) include government expenses on goods and services as well as for the salary of government employees. Urbanization (*Urbnizn*) is proxied by the share of the population resident in urban areas. The share of industrial output in GDP represents industry share of output (*indshao*). Net foreign direct investment inflows from the UNCTAD database is a proxy for foreign direct investment (*FDIn*). The descriptive statistics of the variables are provided in Table 3.

4. Results and discussion

4.1. Analysis of the stochastic energy demand frontier and EE scores

Table 4 presents the determinants of the estimated energy demand frontier for Eq. (7). It shows that the price of gasoline (ln*Gasoprz*) and human capital index (*HCI)* have a significant negative effect on primary energy demand. Both temperature and net FDI exert insignificant negative effect on primary energy demand. Population density, urbanization, the share of industry's output in GDP, per capita GDP and financial development exert significant positive effects on primary energy demand. These findings confirm the evidence on the drivers of energy demand in the empirical literature (Zhang and Adom (2018); Adom and Adams, 2020b and 2020c; Adom et al., 2018; Filippini and Zang, 2016).

Table 5 shows a decomposition of the estimated EE scores into the two components, the persistent and the transient EE. The average transient EE (0.8792) exceeds the persistent EE (0.0852). This implies the overall average EE score is 0.0750. This indicates that improving overall EE will make Africa save about 93% of their total primary energy (i.e. 1 minus 0.075). The low overall EE score corroborates Stern (2012). The above results suggest that inefficiency in energy consumption is a structural problem. Adom et al. (2018) found a similar result for Africa. To improve EE, policy interventions should focus on the long-term policies and behaviours instead of short-term[10] ones.

4.2. Energy efficiency-unemployment nexus

This subsection presents and discusses the effect of the estimated energy efficiency (EE) scores on unemployment in Africa, applying the two-step GMM on Eq. (23). The dependent variable for the regressions, reported in Table 6A and Table 6B, is the logarithm of the total unemployment rate. The coefficient of the autoregressive term of the OLS

[8] All countries in Africa except Somalia, South Sudan, and Congo Republic. The countries exempt do not have enough data on the variables.

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

[10] One empirical issue, we note, is that energy demand and income (in Eq. 7) may pose reverse causality concerns leading to endogeneity in the SFA energy demand frontier. This could potentially bias the efficiency estimate. However, within the current literature, there is no approved way to address endogeneity concerns especially when one decomposes the inefficiency term into transient and persistent components. As a robustness check, we adopt a mechanical approach (as employed in Filippini and Zhang (2016) and Zhang and Adom (2018) that relies on standard IV estimator (TSLS). In addition, we apply the Karakaplan and Kutlu's (2017) approach which addresses endogeneity within the SFA but neither accounts for latent country heterogeneity nor decomposes the efficiency term into persistent and transient components. In this study, we used life expectancy and latitude of the countries as instruments for real GDP per capita in the frontier model for both approaches. We then correlate the efficiency estimates obtained from these models with our original estimate. The results show that our original estimate of energy efficiency highly correlates with those obtained using either the IV or the Karakaplan and Kutlu approach (see Tables A.3 and A.4 in Appendix A). This definitely plays down the potential of endogeneity in driving our estimated energy efficiency score. The statistical insignificance of the eta endogeneity test in Table A.3 also supports this conclusion (see Section 2.1 of (ibid).

(Model 1) and FE (Model 2) estimators are statistically significant. Although the coefficient of the autoregressive term in the two-step difference GMM is less than unity (Model 3), it falls outside the range bounded by the OLS and FE estimates. This suggests that the two-step difference GMM is unreliable, so the two-step system GMM estimator is preferable (Bond, Hoeffler, and Temple, 2001). We, then, consider the estimates of the 2-step system GMM based on the forward-orthogonal deviations (FOD) transformation (Arellano and Bover, 1995) as an alternative (i.e. Model 4). The coefficient of the autoregressive term is 0.2900, which is less than unity and falls within the acceptable threshold judged from the estimates of the OLS and FE estimators. Besides, the coefficients (i.e. 0.2875 and 0.2526, respectively) of Model 5 (Ahn and Schmidt, 1995) and Model 6 (iterated GMM) fall within the acceptable range.

In addition, the results of the Andrews-Lu Model and Moment Selection Criteria (MMSC) in Table 6A show that Model 5 has the least values from the AIC, BIC, and HQIC. Among the other competing GMM models, we adopt Model 5 as the (benchmark) model that best fits the data more aptly. A check for instrument proliferation overfit on Model 5 in Table 6A meets the requirement. That is, the number of instruments, 38, has not exceeded the number of countries (i.e. 41)[11]. As required, there is no evidence of higher-order serial correlation (AR(2)) in the residuals of Model 5. In addition, the Hansen test shows that the overidentifying restrictions are valid with a p-value of 0.1487, which is below the 25% limit, indicating instrument proliferation has not suspiciously invalidated the test. The Cragg-Donald robust CUE-based test rejects weak identification (Sanderson and Windmeijer, 2016; Stock et al., 2002). However, there is a cross-sectional dependence (CD) issue with Model 5 in Table 6A, as the Pesaran CD test rejects the null hypothesis of strict cross-sectional independence, although the claim of weak CD is rejected.

The coefficients of the regressors, as estimated for Eq. (23) in Table 6B, can be interpreted as short-run elasticities. The benchmark Model 5 estimates a significant (at 5% level) negative effect of EE on the unemployment rate, assuming that education and labor intensity are at their maximum theoretical value of 1.[12] This is the immediate effect (Wooldridge, 2019, pg.37) of EE on unemployment: a 1% increase (or improvement) in EE leads to a 1.2331% reduction in the growth of the unemployment rate. Besides, the cumulative effect (Wooldridge, 2019, pg.37) of the current and one-year lagged EE translates to a 0.1707% reduction in the unemployment rate.[13] This also translates into a long-run effect[14] of 0.2396% reduction in the growth of the unemployment rate. These results imply that, promoting EE can lead to a reduction in unemployment in Africa, which corroborates the findings of Cantore et al. (2017), Lehr et al. (2016) and Wei et al. (2010), Ruzive et al. (2019). Hence, EE can lead to the creation of direct, indirect, and induced jobs to reduce unemployment. Thus, improving energy efficiency can draw positive synergies with the socio-economic development goal of reducing unemployment. There are two implications of this for sustainable energy consumption or sustainability. First, this would arouse the interest of policy makers to implement EE policies (SDG7 – SE4All) knowing they would also be addressing the high unemployment problem (SDG8) in Africa indirectly. Second, a reduction in unemployment due to EE would create an income effect that could enhance the demand for energy-efficient solutions to ensure sustainable energy consumption. Thus, this would support the transition to low carbon future. The income effect would also support the resilience and sustainability of African cities so that the urban population can afford environmentally sustainable livelihoods like paying for improved sanitation services among others. As unemployment is most prevalent in African cities, EE improvements would help reduce this phenomenon to make the cities more resilient and socially sustainable. The direction of the unemployment effect remains the same (in Model 5A) when the interaction terms are excluded from Model 5. Relating Model 5A to Model 5, the latter shows that, on average, the interaction terms increase the negative immediate effect of EE on unemployment. The other GMM estimators in Table 6B also show a significant negative effect of EE on unemployment.[15] This implies that the same direction of effect exists whether we focus the analysis on the energy-demand or energy-supply side as in the previous studies.

The human capital index, as a proxy for education, has a significant negative direct unemployment effect (at 5% significance level). On average, a 1% increase in the human capital index leads to about 1.40% reduction in the growth of the unemployment rate (when EE is at its maximum theoretical value of 1). This confirms the propositions of the human capital and frictional unemployment theory. That is, education enhances human resource capabilities, reduces skill gap or mismatch, and increases the chances of getting employed. We postpone the explanation of the moderating role of education to subSection 4.3.

Capital formation or investment has a statistically significant negative unemployment effect at 5% level. The results show that, on average, a 1% increase in capital formation leads to around 0.05% of reduction in the growth of unemployment rate. Besides, government expenditures have a statistically significant positive effect (at 5% level) on the unemployment rate. This works against our expectation. This could be the consequence of the crowding-out effects of government expenditures. The public sector is rigid in employing new labor relative to the private sector. Increasing government expenditures could crowd out private sector investment, leading to higher unemployment levels. The direction of the effect of EE (i.e. $\beta_1 < 0$), capital formation (i.e. $\beta_2 < 0$) and population growth (i.e. $\beta_3 > 0$) confirm[16] the expectations of our theoretical underpinning in Eq. (22).

4.3. Education and conditional effects of EE on unemployment

The coefficient of the interaction term of energy efficiency (EE) and education (human capital index) is statistically significant at 5% level in Table 6B. Following Andersson et al. (2014) and Baron and Kenny (1986), this satisfies the moderation hypothesis and, hence, education can be a moderating variable. Thus, education can influence the strength of the unemployment effect of EE. The total effect of EE (conditioned on education) is computed based on the immediate (short run) effect[17] (Wooldridge, 2019, pg. 37), using the minimum, maximum, mean, and median human capital index (HCI) values, as shown in Table 7 A. The estimated conditional effects look similar for the mean and the median,

[11] In analyzing the data, the GMM procedure of lagging and differencing of variables makes the analytical software exclude 10 out of the 51 countries for insufficient observations. Hence, the results apply to 41 countries.

[12] Interpreting the coefficient of the EE term, in Model 5, as a direct effect assumes that the interaction terms with the moderating variables are zero. This implies the log of education, and the log of labour intensity are zero, hence the two measures, HCI and LABIN, are at their maximum theoretical value of 1. Thus, $lnef_{it}*lnHCI_{it} = 0 \Rightarrow lnHCI_{it} = 0 \Rightarrow HCI_{it} = 1$ and $lnef_{it}*lnLABI_{it} = 0 \Rightarrow lnLABI_{it} = 0 \Rightarrow LABI_{it} = 1$.

[13] Sum of −1.2331 and 1.0624 is −0.1707

[14] The long-run effect involves the ratio of the one lag cumulative effect divided by one minus the coefficient of the autoregressive term. Thus, $(-1.2331 + 1.0624)/(1 - 0.2875)$. See Ditzen (2021). pg. 5.

[15] To check for a possible non-linearity of the unemployment-EE nexus, we re-estimate the benchmark Model 5 after including the square of the EE as a variable and this variable is not statistically significant implying non-linearity is not an issue in this current study.

[16] These can be proven mathematically (see Appendix C in the supplementary file).

[17] Taking the partial derivative of Eq. (23) with respect to the log of EE will exclude the coefficient of the first lag of EE. We also exclude the statistically insignificant coefficients of LABIN and its interaction term with EE. Hence, the conditional effect is computed based on the immediate effect and not the cumulative effect. Thus, $\frac{\partial lnU_{it}}{\partial lnef_{it}} = \beta_1 + \beta_7 * lnHCI_{it}$

assuming no significant influence of outliers in the data. Using the minimum and the maximum HCI values, the estimates indicate that economies with better education attainment have a higher negative unemployment effect than those with a relatively less-developed level of human capital.

The results of the differential validity tests, displayed in Table 7B, shows that the total negative unemployment effect of EE is statistically significantly higher (at 1% level) for countries with better education systems or attainment (i.e. HCI above the average or the median) than their counterparts with less-developed human capital. This indicates that, in Africa, education complements the (un)employment-induced effect of energy efficiency. Thus, investment in education can be one effective mechanism by which green policies can trigger higher employment or reduce unemployment.

In addition, Fig. 1 shows the results of country-specific conditional marginal effects (conditioned on HCI values), where the mean total effect (red line) points to −0.8201. Overall, the conditional marginal effect of EE on unemployment is negative for all countries. However, in absolute terms, twenty-nine countries have their estimated total unemployment effect of EE higher than the mean of −0.8201. Not much differences exist in the regional pattern of the average country-specific conditional effect of energy efficiency on the unemployment rate in North (−0.902), Central (−0.895), and Southern Africa (−0.874) on one side, and East (−0.766) and West Africa (−0.773) on the other side, as presented in Fig. 1. However, the estimated regional average effects for the North, Southern and Central Africa are higher than the mean total effect of −0.8201. Similarly, the estimated conditional effects for most countries in the Central, East, Southern, and West Africa exceeded their regional average effects. These differences in the regional average effects may be driven by colonial origins of school systems, wealth inequality, and education investments (Lewin and Sabates, 2011), and low growth elasticity of employment (UNECA, 2021, pg.7/12).

Besides, a test of difference in means (two-sample *t*-test) indicates that the average human capital index (HCI) for countries with the average estimated total unemployment effect above (in absolute terms) the mean of −0.8201 [i.e. 0.5406] is significantly higher (at 1% level) than those with the average total unemployment effect below (in absolute terms) the mean of −0.8201 [i.e. 0.4004] (see Table 7C).

4.4. Robustness checks of the causal effect of energy efficiency on unemployment

First, we present the GMM instrument or lag[18],[19],[20] sensitivity of the estimates in the benchmark model, Model 5. Table B.1 in Appendix B shows the results of the lag sensitivity of the FOD equations. The results point to a stable negative effect of EE on unemployment, although their statistical significance slightly differs. Further, there is no consistent pattern of increase or decrease in the effect of EE on unemployment, following the successive adjustments of the lags of the endogenous and exogenous variables while holding other lags constant. We draw the same conclusion when we adjust the lags of the endogenous and exogenous variables for the level equations of the system GMM as shown in Table B.2 (see Appendix B).

Second, Table B.3 in Appendix B presents the sample sensitivity of the results, using all the countries from the Sub-Saharan African (SSA) region. The results of the two-step GMM estimators show the same direction of the estimated causal effect as for the full sample, although their statistical significance slightly differs. Among the competing GMM estimators, the system GMM and the system GMM augmented with non-linear moment conditions are the most suitable models, as the coefficient of the autoregressive term is dynamically stable and fall within the acceptable OLS-FE range, although the overidentifying restrictions appear invalid because the Hansen p-values are below 10%. The two models estimate a slightly higher (in absolute values) immediate (short-run) effect of −1.4170 and −1.3926, respectively, and a one-lag cumulative effect of −0.2486 and −0.236, respectively, for the SSA group, compared to −1.2331 and a one-lag cumulative effect of −0.1707 for the full sample in Table 6B.

Third, the sensitivity of the results to potential business-cycle issues, using two-year average data series, also shows the same direction of the estimated effect as the one estimated in Table 6B. (see Table B.4 in Appendix B). However, because of the exclusion of some of the years, the first- and second- order autocorrelation p-values were not computed by the analytical software. Generally, the results show that business cycle has not driven our estimates.

Fourth, we present the results, using sex-specific measures of unemployment. Tables B.5 and B.6 in Appendix B presents the results when female and male unemployment rates are used as the dependent variable, respectively. The former still shows the negative unemployment effect of EE, although the magnitude of the effect is lower. Generally, women engage in less-energy intensive activities, which supposes that they are likely to benefit less from EE investments than males. Table B.6 also shows the negative effect of EE on male unemployment, except for the iterated system GMM. In general, other key variables have the same direction of effect as those estimated in Table 6B.

Finally, Table B.7 in Appendix B presents the estimates of the cross-sectional dependence (CD) robust Driscoll-Kraay FE regression for Eq. (23) to check if strict (strong) CD has affected the direction of the effect. Overall, except for Model M1, the unemployment effect of EE remains negative. Model M12 shows the immediate (short-run) effect of EE on unemployment to be −0.4459 with the one-lag cumulative effect of −0.073. Consistent with the main estimates in Table 6B, other variables like education and its interaction with EE also show a significant negative effect on unemployment. Energy efficiency (ef_{it}), capital formation (s_{it}), and population growth (g_{it}) still confirm the expectations of our theoretical underpinning (i.e. $\beta_1 < 0$, $\beta_2 < 0$ and $\beta_3 < 0$) for Eq. (22).

5. Conclusion and policy recommendations

The SDG7 aims at doubling the current global rate of energy efficiency (EE) efforts and renewable energy to enable universal access to sustainable, modern, and clean energy by 2030. Sustainable energy policies would most likely succeed if they, equally, contribute towards the achievement of other economic development objectives like high productivity, economic growth, employment, and poverty reduction. By using an unbalanced panel dataset on 51 African countries from 1991 to 2017, this study examines the effect of EE on unemployment (and by implication on employment) while conditioning for heterogeneities in education, proxied by the human capital index. We apply the stochastic frontier approach and the two-step GMM estimation methods to estimate EE and examine the effect of EE on the unemployment rate in Africa. Further, we conduct several robustness checks on the results, including sample and lag sensitivity analyses.

We find that the estimated average EE in Africa is low, mainly due to structural energy inefficiencies (i.e. lack of consistent and permanent investments in energy, and poor maintenance of energy infrastructures). In addition, we find a direct statistically significant negative effect of EE on unemployment. Moreover, education, via the human capital index, complements the effect of EE on unemployment. On average, the total conditional effect is negative but much higher for countries with better-developed human capital or education, compared to those with less-

[18] Roodman (2009, pg. 156) strongly indicate that results should be aggressively tested to the number of instruments or lags used.

[19] The critical values at % of worst-case bias, tau=5%, tau=10%, tau=20% and tau=30% for TSLS are 11.684, 7.939, 5.787 and 4.974, respectively (see Montiel-Olea & Pflueger (2013). Therefore, the null hypothesis of weak instruments is rejected.

[20] The non-significance of this test shows that endogeneity is not a serious issue in the SFA (see section 2.1 of Karakaplan and Kutlu (2017).

developed human capital. By implication, improving the human capital base of a country can be one effective mechanism by which EE improvements could reduce unemployment or cause an increase in the number of direct, indirect, and induced jobs.

The above findings call for governments of African countries to implement policies that would change long-term behaviours towards accepting and investing in EE. Such policies and regulations include encouraging (or *discouraging*) the use of energy-efficient (*or energy-inefficient*) appliances (e.g. incentivising the use of energy-efficient stickers on devices, supporting innovations for introducing energy-efficient products and solutions, and supporting financing schemes for acquiring energy-efficient appliances. These policies have the potential to create the twin effect of lowering unemployment and promoting sustainable growth of cities in Africa. However, to connect these EE investments to meaningful job creation, governments should take steps to invest in improving their education systems and integrate EE education into the curricular of schools. Beyond the education mechanism, institutional factors, like governance and standards regulatory quality, could be equally decisive in moderating the effect of EE on unemployment. Analyzing the possible complementary role of institutional factors could be an interesting research agenda for future research. Moreover, as this study provides a more macro perspective on the subject, providing a micro perspective on the subject could be another interesting area for future research.

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Data statement

The data that is used for study is publicly available from the Penn World Tables, the World Bank, Climate Change Knowledge Portal of the World Bank, USA EIA, UNCTAD, ILO and IMF databases. Data on the retail price of gasoline was obtained from an IMF staff on condition of not widely circulating the data. The processed data and the codes implemented are available from the corresponding author upon reasonable request.

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.

Table A.1
Hausman Test (on Eq. (7)).

Variable	FE Coefficients	RE Coefficients	Difference (FE – RE)	Standard error
ln*Gasoprz*	−0.0527	−0.0733	0.0206	0.0058
ln*Y*	0.9482	0.8198	0.1284	0.0330
ln*Popdens*	1.4741	0.6506	0.8235	0.1308
ln*FDIn*	−0.0216	−0.0133	−0.0083	0.0024
indshao	0.0075	0.0096	−0.0021	0.0003
HCI	−1.7011	−0.7313	−0.9699	0.1363
Urbnizn	0.0071	0.0098	−0.0027	0.0019
ln*Findevt*	0.2158	0.1476	0.0682	0.0144
ln*Tempz*	−0.1654	−0.7164	0.5510	0.3119
trend	−0.0085	0.0087	−0.0172	0.0029
$trend^2$	0.0003	0.0002	0.0000	0.0000

Dependent variable = logarithm of primary energy consumption. FE = Fixed Effect; RE = Random Effect.
Null Hypothesis: No systematic difference in the coefficients; Test statistic: Chi2(10) =89.67. *p*-value = 0.0000.

Table A.2
Philip-perron unit root test.

Variable	Test Type	Test statistic	p-value	Variable	Test Type	Test statistic	p-value
lnU_t	P	74.2252*	0.9750	$dlnU_t$	P	480.0075	0.0000
	Z	1.3635*	0.9136		Z	−15.2554	0.0000
	L*	1.13327*	0.9081		L*	−18.3641	0.0000
	Pm	−1.8226*	0.9658		Pm	26.8706	0.0000
lnU_{t-1}	P	451.4674	0.0000	$lnef_t$	P	157.1281	0.0000
	Z	−14.2818	0.0000		Z	−1.8572	0.0316
	L*	−17.0956	0.0000		L*	−3.2906	0.0006
	Pm	24.8525	0.0000		Pm	5.642	0.0000
$lnHCI_t$	P	82.1595*	0.9256	$dlnHCI_t$	P	919.8966	0.0000
	Z	3.8940*	1.0000		Z	−22.5892	0.0000
	L*	4.0643*	1.0000		L*	−34.9779	0.0000
	Pm	−1.3891*	0.9176		Pm	57.2642	0.0000
lns	P	162.1878	0.0001	*InFDIn*	P	278.9407	0.0000
	Z	−1.686	0.0459		Z	−7.1944	0.0000
	L*	−2.1736*	0.0153		L*	−8.4352	0.0000
	Pm	4.3973	0.0000		Pm	12.3883	0.0000
lnINF	P	396.8730	0.0000	*lnGOV*	P	165.1302	0.0000
	Z	−11.5873	0.0000		Z	−1.5193	0.0643
	L*	−14.3787	0.0000		L*	−2.4480	0.0075
	Pm	21.3481	0.0000		Pm	4.6054	0.0000
lnLABIN	P	149.9800	0.0009	*lng*	P	435.9942	0.0000
	Z	−1.1414	0.1269		Z	−5.119	0.0000
	L*	−1.3970	0.0818		L*	−11.22	0.0000
	Pm	3.5341	0.0002		Pm	23.3843	0.0000

* indicates a unit root at levels; Pm is modified Inverse chi-squared; L is Inverse logit; Z is Inverse normal; P is Inverse chi-squared.

Table A.3
Alternative Energy demand frontier estimations.

	Pseudo-IV Estimator	Karakaplan and Kutlu (2017) Estimator	
Variables	TSLS SFA	Exogeneity SFA	Endogeneity SFA
ln*Gasoprz*	−0.9217***	−0.0491**	−0.0605***
	(0.1355)	(0.0200)	(0.0220)
ln*Y*	−0.5887**	−0.1922**	−0.1125
	(0.2434)	(0.0914)	(0.1117)
ln*Popdens*	0.0083	0.2657***	0.2535**
	(0.0497)	(0.1008)	(0.1050)
ln*FDIn*	1.8776**	−0.0006	0.0050
	(0.8452)	(0.0312)	(0.0315)
Indshao	0.0267***	0.0047***	0.0028
	(0.0072)	(0.0011)	(0.0019)
HCI	1.7461	−0.1947*	−0.3612**
	(1.7089)	(0.0994)	(0.1595)
Urbnizn	0.0134***	0.0080***	0.0074***
	(0.0051)	(0.0028)	(0.0028)
ln*Findevt*	0.0958	0.0466	−0.0276
	(0.2449)	(0.0505)	(0.0751)
ln*Tempz*	−0.6757*	−0.3556	−0.4474
	(0.3985)	(0.3863)	(0.3839)
t	0.0486**	0.0276***	0.0307***
	(0.0241)	(0.0036)	(0.0043)
t2	−0.0003	−0.0001	−0.0002
	(0.0008)	(0.0001)	(0.0001)
Constant	−27.7300	8.7600***	8.4473***
	(19.0196)	(1.8357)	(1.8108)
Observations	749	749	749
Mean transient EE	0.9968	–	–
Mean persistent EE	0.0491	–	–
Mean overall EE	0.0490	0.0780	0.0778
Kleibergen-Paap UT (Chi2)	100.892***	–	–
o-Donald WIT (F-statistic)	137.255***	–	187.43***
Kleibergen-Paap WIT (F-statistic)	115.482***	–	–
Montiel-Pflueger WIT (F-statistic)	121.811**		–
Hansen J-statistic	28.828***	–	–
eta (η) Endogeneity tests	–	–	TS==1.81, p-value=0.178

Standard errors in parentheses. UT is under-identification test; WIT is weak identification test; EE is energy efficiency; TS is test statistic; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4
Correlation of energy efficiency (EE) scores from alternative estimators.

	Kumbhakar et al. (2014)	Pseudo-IV SFA	Karakaplan and Kutlu (2017)	
EE scores	FE SFA	TSLS SFA	Endo SFA	Exo SFA
FE_SFA	1			
TSLS SFA	0.5731***	1		
Endo SFA	0.7192***	0.4341***	1	
Exo SFA	0.7296***	0.4340***	0.9998***	1

TSLS is two-stage least squares; FE is Fixed effect; IV is Instrumental variable; Endo is Endogenous, and Exo is Exogenous;.
SFA is Stochastic frontier. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.1
Sensitivity of the lags of the endogenous and exogenous variables in the FOD equations.

	Lags of endogenous variables					Lags of exogenous variables				
Variables	Lags (1 1)	Lags (1 2)	**Lags (1 3)**	Lags (1 4)	Lags (1 5)	Lags (0 0)	Lags (0 1)	**Lags (0 2)**	Lags (0 3)	Lags (0 4)
lnU_{it-1}	0.2988***	0.2938***	0.2875***	0.2875***	0.2878***	0.1023	0.1836*	0.2875***	0.3243***	0.3080***
	(0.0871)	(0.0725)	(0.0640)	(0.0913)	(0.0871)	(0.2349)	(0.1023)	(0.0640)	(0.0907)	(0.0924)
$lnef_{it}$	**−1.2995***	**−1.1669****	**−1.2331****	**−0.9369****	**−0.9038***	**−1.1790**	**−1.0364**	**−1.2331****	**−1.3094***	**−1.1623**
	(0.6704)	(0.5813)	(0.5357)	(0.4039)	(0.5086)	(1.5432)	(0.9201)	(0.5357)	(0.7464)	(0.7208)
$lnef_{it-1}$	1.0763*	1.0278**	1.0624***	0.8132***	0.7780**	0.7028	0.9124	1.0624***	1.1935*	1.0268
	(0.5910)	(0.4394)	(0.4117)	(0.2810)	(0.3339)	(1.5066)	(0.9012)	(0.4117)	(0.6140)	(0.6473)
$lnHCI_{it}$	**−1.1084**	**−1.2627***	**−1.3945****	**−1.4811****	**−1.3738**	**−1.4297**	**−1.0687**	**−1.3945****	**−1.7701**	**−1.6724**
	(0.7965)	(0.7065)	(0.6755)	(0.7347)	(1.9101)	(1.4102)	(0.9117)	(0.6755)	(2.1706)	(1.4965)
$lnef_{it}$* $lnHCI_{it}$	**−0.2866***	**−0.3118****	**−0.3376****	**−0.3375****	**−0.3193**	**−0.5596****	**−0.3037**	**−0.3376****	**−0.4075**	**−0.3864**
	(0.1593)	(0.1428)	(0.1393)	(0.1430)	(0.3974)	(0.2466)	(0.1942)	(0.1393)	(0.3997)	(0.2788)
lns_{it}	−0.0551*	−0.0499*	−0.0536**	−0.0378	−0.0446	−0.1269*	−0.0496	−0.0536**	−0.0374	−0.0422
	(0.0311)	(0.0274)	(0.0242)	(0.0280)	(0.0355)	(0.0771)	(0.0302)	(0.0242)	(0.0639)	(0.0734)
lng_{it}	0.0209	0.0217	0.0172	0.0171	0.0242	0.0622	0.0216	0.0172	0.0119	0.0225
	(0.0357)	(0.0252)	(0.0279)	(0.0323)	(0.0432)	(0.0818)	(0.0339)	(0.0279)	(0.0468)	(0.0611)
$lnINF_{it}$	0.0105	0.0112	0.0101	0.0130	0.0083	0.0255	0.0278	0.0101	0.0010	−0.0002
	(0.0118)	(0.0116)	(0.0130)	(0.0156)	(0.0143)	(0.0264)	(0.0243)	(0.0130)	(0.0149)	(0.0141)
$lnFDI_{it}$	−0.0224	−0.0165	−0.0148	−0.0135	−0.0118	0.0422	−0.0304	−0.0148	0.0027	0.0079
	(0.0471)	(0.0323)	(0.0297)	(0.0293)	(0.0296)	(0.0648)	(0.0633)	(0.0297)	(0.0310)	(0.0269)
$lnLABIN_{it}$	−0.1121	−0.0646	−0.0765	−0.0586	−0.0655	−0.2226	−0.0561	−0.0765	−0.0522	−0.0598
	(0.1052)	(0.1015)	(0.1006)	(0.1088)	(0.1665)	(0.1534)	(0.0825)	(0.1006)	(0.1339)	(0.1239)
$lnef_{it}$* $lnLABIN_{it}$	−0.0226	−0.0139	−0.0175	−0.0124	−0.0130	−0.0470*	−0.0122	−0.0175	−0.0121	−0.0137
	(0.0171)	(0.0263)	(0.0251)	(0.0257)	(0.0418)	(0.0270)	(0.0179)	(0.0251)	(0.0270)	(0.0275)
$lnGOV_{it}$	0.0509	0.0452	0.0511**	0.0331	0.0429	0.0942	0.0490	0.0511**	0.0377	0.0366
	(0.0326)	(0.0322)	(0.0257)	(0.0290)	(0.0341)	(0.0654)	(0.0323)	(0.0257)	(0.0558)	(0.0699)
Year 2007	−0.0369	−0.0315	−0.0309	−0.0499	−0.0529	−0.2115	−0.0483	−0.0309	−0.0382	−0.0862
	(0.0310)	(0.0331)	(0.0335)	(0.0373)	(0.0477)	(0.1566)	(0.0398)	(0.0335)	(0.0347)	(0.0551)
Year 2008	−0.1122**	−0.1135**	−0.1063**	−0.1192*	−0.0916*	−0.2085	−0.1948	−0.1063**	−0.0987	−0.0888
	(0.0525)	(0.0472)	(0.0517)	(0.0624)	(0.0532)	(0.1914)	(0.1306)	(0.0517)	(0.0753)	(0.0605)
Year 2009	0.0873*	0.0812*	0.0726	0.0951**	0.0908*	−0.0608	0.0806	0.0726	0.0482	0.0618
	(0.0482)	(0.0474)	(0.0456)	(0.0425)	(0.0498)	(0.2285)	(0.0720)	(0.0456)	(0.0689)	(0.0572)
Year 2010	0.0262	0.0329	0.0316	0.0390	0.0233	0.3356	0.1545	0.0316	0.0013	0.0102
	(0.0545)	(0.0406)	(0.0473)	(0.0504)	(0.0585)	(0.3656)	(0.1358)	(0.0473)	(0.0715)	(0.0686)
Constant	−0.8393	−0.5216	−0.6367	−0.4586	−0.7150	−3.5102	−0.2428	−0.6367	−0.7633	−1.0058
	(1.6641)	(1.0975)	(0.9038)	(0.9725)	(1.1544)	(2.4012)	(1.5366)	(0.9038)	(1.0828)	(1.7641)
Observations	465	465	465	465	465	465	465	465	465	465
Number of Countries	41	41	41	41	41	41	41	41	41	41
Instrument Count	34	36	38	40	42	23	31	38	46	54
AR(1) *p-value*	0.0053	0.0007	0.0005	0.0076	0.0055	0.4460	0.0519	0.0005	0.0023	0.0014
AR(2) *p-value*	0.3863	0.4664	0.4851	0.4123	0.4622	0.7910	0.2074	0.4851	0.5428	0.5378
Sargan *p-value*	0.9043	0.9573	0.9742	0.9497	0.7951	0.9880	0.8195	0.9742	0.6300	0.9538
Hansen *p-value*	0.7238	0.0757	0.1487	0.0150	0.0230	0.9731	0.2238	0.1487	0.0689	0.2994
Mean ρ in Panels	0.04	0.05	0.04	0.06	0.04	0.23	0.14	0.04	0.04	0.05
Pesaran (2004) CD Test	6.863***	7.104***	6.274***	8.625***	5.844***	37.138***	21.156***	6.274***	6.64***	7.336***
Pesaran (2015) CD Test	5.173***	5.444***	4.765***	6.641***	4.397***	29.158***	15.916***	4.765***	4.810***	5.285***

Dependent variable = logarithm of total unemployment rate. The panel OLS, fixed effect (FE) and GMM estimates apply to Eq. (23). ρ is correlation between panel units; CD is cross-sectional dependence; Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.2
Sensitivity of the lags of the endogenous and exogenous variables in 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)	Lags (0 2)	Lags (0 3)
lnU_{it-1}	0.2875***	0.3297***	0.3616***	0.3602***	0.2875***	0.3189***	0.3369***	0.3111***
	(0.0640)	(0.0637)	(0.0855)	(0.0707)	(0.0640)	(0.0577)	(0.0765)	(0.0655)
$lnef_{it}$	**−1.2331****	**−1.0123***	**−0.8600**	**−1.0233****	**−1.2331****	**−0.9403***	**−0.7897**	**−0.8893**
	(0.5357)	(0.6065)	(0.6724)	(0.4641)	(0.5357)	(0.5582)	(0.6517)	(0.6705)
$lnef_{it-1}$	1.0624***	0.9523**	0.8848	1.0672***	1.0624***	0.9459**	0.7786	0.8211
	(0.4117)	(0.4351)	(0.5529)	(0.3314)	(0.4117)	(0.4770)	(0.5293)	(0.5662)
$lnHCI_{it}$	−1.3945**	−1.7415**	−2.4302*	−1.7218	−1.3945**	−1.5844***	0.1356	−0.0546
	(0.6755)	(0.7101)	(1.3757)	(2.1551)	(0.6755)	(0.5753)	(1.7912)	(1.7103)
$lnef_{it}$* $lnHCI_{it}$	**−0.3376****	**−0.3742*****	**−0.4553***	**−0.3379**	**−0.3376****	**−0.3499*****	**0.0125**	**−0.0652**
	(0.1393)	(0.1435)	(0.2671)	(0.4173)	(0.1393)	(0.1354)	(0.3050)	(0.2990)
lns_{it}	−0.0536**	−0.0272	−0.0048	−0.0077	−0.0536**	−0.0350	−0.0316	−0.0500
	(0.0242)	(0.0168)	(0.0342)	(0.0314)	(0.0242)	(0.0224)	(0.0365)	(0.0472)
lng_{it}	0.0172	0.0095	−0.0050	−0.0007	0.0172	0.0139	0.0105	0.0261
	(0.0279)	(0.0312)	(0.0215)	(0.0171)	(0.0279)	(0.0189)	(0.0249)	(0.0291)
$lnINF_{it}$	0.0101	0.0089	0.0048	0.0038	0.0101	0.0066	0.0069	0.0036
	(0.0130)	(0.0136)	(0.0187)	(0.0134)	(0.0130)	(0.0124)	(0.0150)	(0.0144)
$lnFDI_{it}$	−0.0148	−0.0144	0.0062	0.0030	−0.0148	−0.0126	0.0001	−0.0034
	(0.0297)	(0.0220)	(0.0236)	(0.0201)	(0.0297)	(0.0243)	(0.0276)	(0.0248)
$lnLABIN_{it}$	−0.0765	−0.0184	0.0311	0.0335	−0.0765	0.0037	0.0028	−0.0333
	(0.1006)	(0.0785)	(0.0945)	(0.0964)	(0.1006)	(0.0663)	(0.0661)	(0.0751)
$lnef_{it}$* $lnLABIN_{it}$	−0.0175	−0.0058	0.0032	0.0052	−0.0175	0.0013	0.0001	−0.0056
	(0.0251)	(0.0238)	(0.0216)	(0.0223)	(0.0251)	(0.0164)	(0.0161)	(0.0190)
$lnGOV_{it}$	0.0511**	0.0272	0.0081	0.0090	0.0511**	0.0375*	0.0389	0.0471
	(0.0257)	(0.0228)	(0.0290)	(0.0276)	(0.0257)	(0.0211)	(0.0345)	(0.0417)
Year 2007	−0.0309	−0.0291	−0.0334	−0.0395	−0.0309	−0.0386	−0.0490*	−0.0627**
	(0.0335)	(0.0375)	(0.0415)	(0.0353)	(0.0335)	(0.0320)	(0.0284)	(0.0307)
Year 2008	−0.1063**	−0.0994*	−0.0977	−0.0974*	−0.1063**	−0.0888	−0.0976	−0.0885*
	(0.0517)	(0.0529)	(0.0738)	(0.0590)	(0.0517)	(0.0612)	(0.0773)	(0.0505)
Year 2009	0.0726	0.0692*	0.1219***	0.0986**	0.0726	0.0535	0.1059*	0.0956*
	(0.0456)	(0.0410)	(0.0442)	(0.0501)	(0.0456)	(0.0440)	(0.0643)	(0.0524)
Year 2010	0.0316	0.0147	−0.0171	−0.0261	0.0316	0.0184	−0.0056	−0.0027
	(0.0473)	(0.0460)	(0.0633)	(0.0448)	(0.0473)	(0.0457)	(0.0646)	(0.0610)
Constant	−0.6367	−0.0291	0.1278	0.2052	−0.6367	0.0148	−0.3599	−0.6492
	(0.9038)	(0.6571)	(0.7682)	(0.9262)	(0.9038)	(0.5856)	(0.7214)	(1.1021)
Observations	465	465	465	465	465	465	465	465
Number of Countries	41	41	41	41	41	41	41	41
Instrument Count	38	40	42	44	38	43	48	53
AR(1) *p-value*	0.0187	0.0091	0.0067	0.0013	0.0187	0.0077	0.0071	0.0002
AR(2) *p-value*	0.3197	0.4242	0.4080	0.5118	0.3197	0.4996	0.4626	0.47755
Sargan *p-value*	0.9742	0.9521	0.5834	0.7211	0.9742	0.8874	9598	0.9927
Hansen *p-value*	0.1487	0.0298	0.0230	0.0412	0.1487	0.0310	0.1080	0.2605
Mean ρ in Panels	0.04	0.04	0.06	0.05	0.04	0.04	0.05	0.04
Pesaran (2004) CD-test	6.274***	6.47***	8.418***	7.496***	6.274***	5.928***	7.297***	6.726***
Pesaran (2015) CD-test	4.765***	4.791***	6.163***	5.487***	4.765***	4.327***	5.415***	4.917***

Dependent variable = logarithm of total unemployment rate. The panel OLS, fixed effect (FE) and GMM estimates apply to Eq. (23). ρ is correlation between panel units; Robust standard errors in parentheses; CD is cross-sectional dependence; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.3
Estimates for the sub-saharan Africa (SSA) countries.

Variables	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step System GMM	Two-step System GMM with Nonlinear	Two-step System GMM (No Interaction Terms)	Iterated System GMM with Nonlinear
lnU_{it-1}	0.3370*	0.2474***	0.4374**	0.3184***	0.3096***	0.3463***	0.3760
	(0.1866)	(0.0545)	(0.2081)	(0.0626)	(0.0775)	(0.1086)	(8.7271)
$lnef_{it}$	**−0.1502**	**−0.4152***	**−1.8801**	**−1.4170***	**−1.3926***	**−0.9021**	**−1.1925**
	(0.1551)	(0.2075)	(1.6276)	(0.5026)	(0.5086)	(0.5711)	(0.0000)
$lnef_{it-1}$	0.1543	0.3445*	1.1258	1.1684**	1.1576**	0.8486	1.0133
	(0.1463)	(0.1937)	(0.8355)	(0.4813)	(0.4650)	(0.6167)	(0.0000)
$lnHCI_{it}$	−1.8708*	−1.8789**	−1.1154	−1.2204	−0.7817	−0.0644	−1.4020
	(0.9867)	(0.7660)	(0.9387)	(0.8239)	(0.7010)	(0.3035)	(184.3635)
$lnef_{it}$* $lnHCI_{it}$	**−0.3094***	**−0.3587***	**−0.1141**	**−0.3127***	**−0.2324***		**−0.3332**
	(0.1679)	(0.1280)	(0.2143)	(0.1723)	(0.1410)		(24.0328)
lns_{it}	−0.0176	−0.0954***	−0.0411	−0.0469	−0.0535**	−0.0249	−0.0352
	(0.0130)	(0.0342)	(0.0563)	(0.0331)	(0.0249)	(0.0336)	(0.0000)
lng_{it}	0.0102	0.0929	0.2950	−0.0010	0.0057	0.0340	0.0076
	(0.0130)	(0.1263)	(0.4054)	(0.0455)	(0.0413)	(0.0787)	(0.0000)
$lnINF_{it}$	0.0027	0.0092**	−0.0229	0.0069	0.0060	0.0131	0.0100
	(0.0069)	(0.0045)	(0.0261)	(0.0124)	(0.0109)	(0.0124)	(0.6720)
$lnFDI_{it}$	0.0048	−0.0121	0.0176	0.0367	0.0391	0.0314	0.0415
	(0.0170)	(0.0088)	(0.0123)	(0.0233)	(0.0286)	(0.0255)	(0.5206)
$lnLABIN_{it}$	−0.0111	−0.2884*	0.0486	−0.1313*	−0.1288	0.0508	−0.0915
	(0.0241)	(0.1545)	(0.6238)	(0.0791)	(0.1045)	(0.1179)	(0.0000)
$lnef_{it}$* $lnLABIN_{it}$	0.0002	−0.0376**	−0.0291	−0.0260**	−0.0243		−0.0187
	(0.0021)	(0.0180)	(0.1243)	(0.0122)	(0.0158)		(0.2576)
$lnGOV_{it}$	0.0082	0.0653***	−0.0061	0.0419	0.0459*	0.0237	0.0232
	(0.0161)	(0.0227)	(0.0508)	(0.0287)	(0.0265)	(0.0358)	(0.0000)
Year 2007	−0.0359*	−0.0274	−0.0112	−0.0516*	−0.0494*	−0.0481**	−0.0532
	(0.0188)	(0.0178)	(0.1244)	(0.0284)	(0.0296)	(0.0230)	(10.1894)
Year 2008	−0.0023	−0.0015	0.0011	−0.0825	−0.0796	−0.0821	−0.0626
	(0.0249)	(0.0229)	(0.1123)	(0.0605)	(0.0641)	(0.0664)	(3.7239)
Year 2009	0.1154***	0.1204***	−0.0206	0.0734	0.0704	0.0690	0.0425
	(0.0219)	(0.0251)	(0.1943)	(0.0535)	(0.0548)	(0.0607)	(4.3952)
Year 2010	0.0012	0.0255	−0.0592	0.0128	0.0256	0.0192	0.0124
	(0.0274)	(0.0293)	(0.2322)	(0.0554)	(0.0489)	(0.0639)	(5.4616)
Constant	−0.1659	−1.9962	−5.8139	−1.9472**	−2.0359*	−1.0390	−1.6790
	(0.3366)	(1.7073)	(5.0035)	(0.9447)	(1.1921)	(1.3571)	(0.0000)
No of Observations	408	408	408	408	408	408	408
R-squared	0.1763	0.169	–	–	–	–	–
Number of Countries	37	37	37	37	37	37	37
Instrument Count	–	–	29	37	38	34	38
AR(1) *p-value*	–	–	0.0189	0.0184	0.0275	0.0000	0.9526
AR(2) *p-value*	–	–	0.4812	0.5035	0.4576	0.4860	0.9448
Sargan *p-value*	–	–	0.4464	0.9067	0.9334	0.8684	0.1275
Hansen *p-value*	–	–	0.2346	0.0117	0.0168	0.0214	0.1188
Mean ρ in Panels	0.01	0.00	0.07	0.02	0.02	0.03	0.03
Pesaran (2004) CD test	1.734*	−0.414	9.773***	3.027***	2.591**	4.003***	4.072***
Pesaran (2015) CD test	0.356	−0.570	6.718***	2.048**	1.806*	2.794***	2.668***

Dependent variable = logarithm of total unemployment rate. The panel OLS, fixed effect (FE) and GMM estimates apply to Eq. (23). ρ is correlation between panel units; Robust standard errors in parentheses; CD is cross-sectional dependence; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.4
Time sensitivity using two-year average data series.

Variables	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step System GMM	Two-step System GMM with Nonlinear	Two-step System GMM (No Interaction Terms)	Iterated System GMM with Nonlinear
lnU_{it-1}	0.5330***	0.4734***	0.3549***	0.3549***	0.3549***	0.3509***	0.3527***
	(0.0770)	(0.0562)	(0.0764)	(0.0764)	(0.0764)	(0.0982)	(0.0823)
$lnef_{it}$	**−0.5561*** **	**−0.7477*** **	**−1.8963** **	**−1.8963** **	**−1.8963** **	**−1.8244**	**−1.8463** **
	(0.1902)	(0.1961)	(0.8463)	(0.8463)	(0.8463)	(1.1241)	(0.8797)
$lnef_{it-1}$	0.5563***	0.6622***	1.4659*	1.4659*	1.4659*	1.4503	1.4409**
	(0.1875)	(0.1924)	(0.7763)	(0.7763)	(0.7763)	(1.0910)	(0.7224)
$lnHCI_{it}$	**−0.6593**	**−0.6996***	**−0.2896**	**−0.2896**	**−0.2896**	**−0.7593**	**−0.2625**
	(0.5586)	(0.3812)	(0.9275)	(0.9275)	(0.9275)	(0.6047)	(0.8919)
$lnef_{it}$* $lnHCI_{it}$	**−0.0639**	**−0.0385**	**0.0916**	**0.0916**	**0.0916**		**0.1049**
	(0.0673)	(0.0581)	(0.1851)	(0.1851)	(0.1851)		(0.1637)
lns_{it}	−0.0092	−0.0187	−0.0490	−0.0490	−0.0490	−0.0703	−0.0463
	(0.0081)	(0.0140)	(0.0405)	(0.0405)	(0.0405)	(0.0650)	(0.0414)
lng_{it}	0.0030	−0.0948**	−0.0497	−0.0497	−0.0497	−0.0250	−0.0447
	(0.0071)	(0.0409)	(0.1235)	(0.1235)	(0.1235)	(0.1737)	(0.1103)
$lnINF_{it}$	0.0046	0.0159***	0.0188*	0.0188*	0.0188*	0.0206*	0.0187**
	(0.0041)	(0.0053)	(0.0098)	(0.0098)	(0.0098)	(0.0118)	(0.0091)
$lnFDI_{it}$	−0.0077	−0.0247	−0.0180	−0.0180	−0.0180	−0.0513*	−0.0272**
	(0.0110)	(0.0152)	(0.0447)	(0.0447)	(0.0447)	(0.0302)	(0.0128)
$lnLABIN_{it}$	−0.0048	−0.0175	−0.0504	−0.0504	−0.0504	0.2162	−0.0590
	(0.0113)	(0.0462)	(0.1963)	(0.1963)	(0.1963)	(0.1502)	(0.1795)
$lnef_{it}$* $lnLABIN_{it}$	−0.0000	−0.0071	−0.0320	−0.0320	−0.0320		−0.0344
	(0.0014)	(0.0059)	(0.0322)	(0.0322)	(0.0322)		(0.0324)
$lnGOV_{it}$	0.0053	0.0447***	0.0711*	0.0711*	0.0711*	0.1122**	0.0678*
	(0.0077)	(0.0127)	(0.0392)	(0.0392)	(0.0392)	(0.0550)	(0.0395)
Year 2007	0.1661	1.2815	−0.3496	−0.3496	−0.3496	1.0091	−0.0972
	(0.2467)	(0.8818)	(2.3939)	(2.3939)	(2.3939)	(3.0538)	(2.0785)
Observations	361	361	361	361	361	362	361
R-squared	0.3927	0.384					
Number of Countries	42	42	42	42	42	42	42
Instrument Count			19	19	19	17	19
AR(1) *p-value*	–	–	–	–	–	–	–
AR(2) *p-value*	–	–	–	–	–	–	–
Sargan *p-value*	–	–	0.5722	0.5722	0.5722	0.4382	0.5984
Hansen *p-value*	–	–	0.4295	0.4295	0.4295	0.4878	0.5984
Mean ρ in Panels	0.12	0.09	0.06	0.06	0.06	0.05	0.06
Pesaran (2004) CD test	14.692***	10.814***	6.885***	6.885***	6.885***	5.614***	7.096***
Pesaran (2015) CD test	–	–	–	–	–	–	–

Dependent variable = logarithm of total unemployment rate. The panel OLS, fixed effect (FE) and GMM estimates apply to Eq. (23). ρ is correlation between panel units; Robust standard errors in parentheses; CD is cross-sectional dependence; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.5
Effect of energy efficiency on female unemployment Rate.

Variables	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step System GMM	Two-step System GMM with Nonlinear	Two-step System GMM (No Interaction Terms)	Iterated System GMM with Nonlinear
$lnfU_{it-1}$	0.3431*	0.2409***	0.4401***	0.3181***	0.3407***	0.3352***	0.2874**
	(0.1757)	(0.0462)	(0.1424)	(0.0743)	(0.0787)	(0.0855)	(0.1323)
$lnef_{it}$	**−0.1624**	**−0.4767****	**−1.9096**	**−1.1513*****	**−0.9577****	**−0.8588***	**−0.8746***
	(0.1544)	(0.1971)	(1.1967)	(0.4431)	(0.4341)	(0.4428)	(0.5309)
$lnef_{it-1}$	0.1630	0.3803**	1.9839**	1.0938***	0.9100**	0.8276*	0.8612*
	(0.1468)	(0.1837)	(0.8576)	(0.4009)	(0.3638)	(0.4512)	(0.4506)
$lnHCI_{it}$	**−1.9188***	**−1.9055*****	**−0.7189**	**−0.9077**	**−0.7094**	**−0.0480**	**−0.4048**
	(1.0260)	(0.6535)	(0.9549)	(0.6893)	(0.6591)	(0.3550)	(0.5212)
$lnef_{it}$* $lnHCI_{it}$	**−0.3238***	**−0.3552*****	**−0.0627**	**−0.2074**	**−0.1545**		**−0.0880**
	(0.1832)	(0.1099)	(0.2369)	(0.1440)	(0.1478)		(0.1109)
lns_{it}	−0.0129	−0.0958***	−0.0216	0.0010	−0.0132	−0.0161	−0.0157
	(0.0124)	(0.0329)	(0.0482)	(0.0454)	(0.0444)	(0.0330)	(0.0529)
lng_{it}	0.0129	0.0823	0.0220	−0.0131	−0.0001	0.0189	0.0189
	(0.0115)	(0.1086)	(0.3673)	(0.0335)	(0.0321)	(0.0324)	(0.0346)
$lnINF_{it}$	−0.0004	0.0065	−0.0148	0.0118	0.0085	0.0118	0.0111
	(0.0064)	(0.0043)	(0.0156)	(0.0133)	(0.0133)	(0.0129)	(0.0214)
$lnFDI_{it}$	−0.0129	−0.0289	−0.0004	0.0163	0.0093	0.0110	0.0031
	(0.0154)	(0.0185)	(0.0272)	(0.0142)	(0.0141)	(0.0203)	(0.0356)
$lnLABIN_{it}$	−0.0148	−0.3526***	−0.2630	0.0048	−0.0062	0.0179	−0.0004
	(0.0212)	(0.1219)	(0.5092)	(0.0894)	(0.0986)	(0.0439)	(0.0782)
$lnef_{it}$* $lnLABIN_{it}$	−0.0001	−0.0453***	−0.0692	−0.0045	−0.0038		0.0006
	(0.0021)	(0.0135)	(0.0909)	(0.0152)	(0.0203)		(0.0167)
$lnGOV_{it}$	0.0016	0.0605***	0.0302	0.0101	0.0161	0.0132	0.0118
	(0.0143)	(0.0201)	(0.0559)	(0.0387)	(0.0415)	(0.0352)	(0.0543)
Year 2007	−0.0306	−0.0210	−0.0521	−0.0299	−0.0210	−0.0235	−0.0229
	(0.0220)	(0.0211)	(0.1019)	(0.0326)	(0.0314)	(0.0320)	(0.0372)
Year 2008	0.0058	0.0094	−0.0969	−0.1440*	−0.1166	−0.1289	−0.1173
	(0.0233)	(0.0209)	(0.0983)	(0.0847)	(0.0853)	(0.0843)	(0.1360)
Year 2009	0.1259***	0.1333***	0.0243	0.0629	0.0736	0.0683	0.0613
	(0.0210)	(0.0215)	(0.1515)	(0.0462)	(0.0501)	(0.0544)	(0.0536)
Year 2010	0.0059	0.0341	−0.0202	0.0190	0.0232	0.0303	0.0629
	(0.0257)	(0.0240)	(0.1460)	(0.0532)	(0.0549)	(0.0607)	(0.0930)
Constant	0.2002	−1.8322	0.0115	−0.4391	−0.3906	−0.4794	−0.3869
	(0.3158)	(1.5670)	(5.0126)	(0.9453)	(1.0338)	(0.8103)	(1.3704)
Observations	465	465	465	465	465	465	465
R-squared	0.1802	0.171	–	–	–	–	–
Number of Countries	41	41	41	41	41	41	41
Instrument Count	–	–	29	37	38	34	38
AR(1) *p-value*	–	–	0.0409	0.0006	0.0071	0.0061	0.0089
AR(2) *p-value*	–	–	0.6456	0.4469	0.3850	0.3460	0.3773
Sargan *p-value*	–	–	0.8391	0.9353	0.8949	0.8541	0.8674
Hansen *p-value*	–	–	0.4588	0.0583	0.0150	0.6181	0.8674
Mean ρ in Panels	0.01	−0.01	0.06	0.08	0.06	0.07	0.07
Pesaran (2004)-CD-test	1.311	−0.876	8.996***	11.046***	8.94***	10.149***	10.09***
Pesaran (2015)-CD-test	0.454	0.333	6.6126***	7.947***	6.599***	7.682***	7.640***

Dependent variable = logarithm of female unemployment rate. The panel OLS, fixed effect (FE) and GMM estimates apply to Eq. (23). ρ is correlation between panel units; CD is cross-sectional dependence; Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.6
Effect of energy efficiency on male unemployment rate.

Variables	OLS: Upper bound	FE: Lower bound	Two-step Difference GMM	Two-step System GMM	Two-step System GMM with Nonlinear	Two-step System GMM (No Interaction Terms)	Iterated System GMM with Nonlinear
$lnmU_{it-1}$	0.2687**	0.1892***	0.4183***	0.2817***	0.2802***	0.2651**	0.3030
	(0.1353)	(0.0542)	(0.1105)	(0.0789)	(0.0762)	(0.1109)	(5.9240)
$lnef_{it}$	**−0.2058**	**−0.4383****	**−2.8356***	**−0.7521**	**−0.7496**	**−0.7472***	**0.4392**
	(0.1602)	(0.1892)	(1.7113)	(0.6815)	(0.6691)	(0.4472)	(50.8276)
$lnef_{it-1}$	0.2258	0.3375*	2.1061**	0.7560	0.7531*	0.6947	−0.1071
	(0.1538)	(0.1852)	(1.0126)	(0.4715)	(0.4550)	(0.4582)	(43.4047)
$lnHCI_{it}$	**−2.5506****	**−2.5513*****	**−1.8621****	**−2.4639*****	**−2.4738*****	**−0.3914**	**−2.5267**
	(0.9965)	(0.8683)	(0.9151)	(0.9114)	(0.8784)	(0.3761)	(33.1250)
$lnef_{it}$* $lnHCI_{it}$	**−0.4260****	**−0.4654*****	**−0.2675**	**−0.5382*****	**−0.5423*****		**−0.3988**
	(0.1706)	(0.1491)	(0.1902)	(0.1958)	(0.1807)		(1.1024)
lns_{it}	−0.0239*	−0.0849**	−0.0543	−0.0419	−0.0436	−0.0364	−0.0245
	(0.0140)	(0.0319)	(0.0494)	(0.0386)	(0.0344)	(0.0274)	(2.4234)
lng_{it}	0.0052	0.0319	0.0605	0.0254	0.0264	0.0370	0.1015
	(0.0126)	(0.1390)	(0.2579)	(0.0400)	(0.0352)	(0.0299)	(2.6461)
$lnINF_{it}$	0.0057	0.0098*	−0.0361*	0.0087	0.0089	0.0173	0.0460
	(0.0063)	(0.0051)	(0.0195)	(0.0142)	(0.0124)	(0.0147)	(5.1956)
$lnFDI_{it}$	−0.0075	−0.0387	0.0009	−0.0170	−0.0173	0.0180	−0.5434
	(0.0190)	(0.0401)	(0.0299)	(0.0410)	(0.0405)	(0.0410)	(63.5385)
$lnLABIN_{it}$	0.0046	−0.2176	−0.1200	−0.0060	−0.0068	0.0197	0.1395
	(0.0214)	(0.1462)	(0.3924)	(0.1278)	(0.1309)	(0.0593)	(5.9053)
$lnef_{it}$* $lnLABIN_{it}$	0.0018	−0.0301*	−0.0688	0.0010	0.0009		0.0389
	(0.0021)	(0.0174)	(0.0870)	(0.0335)	(0.0338)		(0.8726)
$lnGOV_{it}$	0.0225	0.0797***	0.0377	0.0383	0.0396	0.0299	0.0438
	(0.0165)	(0.0268)	(0.0441)	(0.0350)	(0.0348)	(0.0325)	(5.2363)
Year 2007	−0.0247	−0.0163	−0.0486	−0.0619	−0.0626	−0.0533	−0.0468
	(0.0181)	(0.0185)	(0.0744)	(0.0450)	(0.0420)	(0.0332)	(4.5931)
Year 2008	−0.0144	−0.0089	−0.0248	−0.0930	−0.0934	−0.0947	−0.0903
	(0.0231)	(0.0259)	(0.0737)	(0.0614)	(0.0605)	(0.0640)	(8.8611)
Year 2009	0.0886***	0.0937***	−0.0507	0.0655	0.0661	0.0909	0.1370
	(0.0246)	(0.0303)	(0.1090)	(0.0534)	(0.0521)	(0.0575)	(5.3244)
Year 2010	−0.0008	0.0171	−0.1148	0.0031	0.0061	0.0478	0.0948
	(0.0227)	(0.0273)	(0.1156)	(0.0639)	(0.0522)	(0.0673)	(15.3882)
Constant	0.1695	−0.7970	−2.1698	−0.0176	−0.0255	−0.9217	11.4937
	(0.3505)	(1.9559)	(6.1678)	(1.2380)	(1.2703)	(0.9654)	(1288.5171)
No. of Observations	465	465	465	465	465	465	465
R-squared	0.1320	0.125	–	–	–	–	–
Number of Countries	41	41	41	41	41	41	41
Instrument Count	–	–	29	37	38	34	38
AR(1) *p-value*	–	–	0.0015	0.0026	0.0079	0.0067	0.9821
AR(2) *p-value*	–	–	0.8181	0.5527	0.2703	0.5052	0.9879
Sargan *p-value*	–	–	0.6631	0.7632	0.8104	0.8458	0.4754
Hansen *p-value*	–	–	0.0473	0.1916	0.0144	0.0565	0.0246
Mean ρ in Panels	0.00	0.00	0.07	0.04	0.05	0.05	0.07
Pesaran (2004)-CD-test	0.891	−0.303	10.72***	6.826***	6.892***	7.119***	10.897***
Pesaran (2015)-CD-test	0.181	0.573	7.684***	4.783***	4.834***	5.111***	7.959***

Dependent variable = logarithm of male unemployment rate. The panel OLS, fixed effect (FE) and GMM estimates apply to Eq. (23). ρ is correlation between panel units; Robust standard errors in parentheses; CD is cross-sectional dependence; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.7
Effect of energy efficiency on unemployment (Driscoll-kraay CD-robust standard errors' FE Estimator).

Variables	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
lnU_{it-1}	0.3040**	0.2732**	0.2718**	0.2712**	0.2615**	0.2595**	0.2450**	0.2432**	0.2391**	0.2362**	0.2272**	0.2246*
	(0.1093)	(0.1060)	(0.1050)	(0.1055)	(0.1039)	(0.1044)	(0.1096)	(0.1099)	(0.1094)	(0.1097)	(0.1059)	(0.1097)
$lnef_{it}$	**0.0138**	**−0.2327***	**−0.2489***	**−0.2649***	**−0.2843***	**−0.2753***	**−0.1837**	**−0.1818**	**−0.1675**	**−0.3609***	**−0.4264****	**−0.4459****
	(0.0445)	(0.1328)	(0.1310)	(0.1396)	(0.1427)	(0.1474)	(0.1435)	(0.1446)	(0.1371)	(0.1859)	(0.1752)	(0.1850)
$lnef_{it-1}$		0.3085**	0.3039**	0.3047**	0.3172**	0.2970**	0.3901**	0.3800**	0.3695**	0.3921**	0.3902*	0.3732*
		(0.1368)	(0.1365)	(0.1316)	(0.1305)	(0.1359)	(0.1757)	(0.1703)	(0.1667)	(0.1743)	(0.1886)	(0.2036)
$lnHCI_{it}$			**−0.3051***	**−1.0708****	**−1.2311****	**−1.1737****	**−2.2347*****	**−2.2017*****	**−2.2671*****	**−2.3223*****	**−2.2624*****	**−2.1067*****
			(0.1674)	(0.5084)	(0.4796)	(0.4655)	(0.4902)	(0.4623)	(0.4643)	(0.4242)	(0.4480)	(0.3232)
$lnef_{it}$* $lnHCI_{it}$				**−0.2059***	**−0.2424****	**−0.2563****	**−0.4225*****	**−0.4147*****	**−0.4233*****	**−0.4276*****	**−0.4372*****	**−0.3887*****
				(0.1148)	(0.1166)	(0.1160)	(0.1234)	(0.1175)	(0.1215)	(0.1146)	(0.1097)	(0.0705)
lns_{it}					−0.0145*	−0.0309*	−0.0319	−0.0296	−0.0358*	−0.0387*	−0.0736***	−0.0888***
					(0.0078)	(0.0178)	(0.0205)	(0.0208)	(0.0208)	(0.0211)	(0.0260)	(0.0232)
lng_{it}						0.0963	0.1586	0.1566	0.1422	0.1247	0.0082	0.0590
						(0.0852)	(0.0999)	(0.1013)	(0.1061)	(0.1050)	(0.1018)	(0.0997)
$lnINF_{it}$							0.0055	0.0059	0.0064	0.0056	0.0082	0.0083
							(0.0063)	(0.0063)	(0.0062)	(0.0061)	(0.0063)	(0.0061)
$lnFDI_{it}$								−0.0273**	−0.0285**	−0.0292***	−0.0273**	−0.0327**
								(0.0105)	(0.0106)	(0.0103)	(0.0115)	(0.0149)
$lnLABIN_{it}$									−0.0661	−0.2240**	−0.2343**	−0.2757**
									(0.0642)	(0.1026)	(0.0996)	(0.1072)
$lnef_{it}$* $lnLABIN_{it}$										−0.0266**	−0.0329***	−0.0370***
										(0.0103)	(0.0111)	(0.0117)
$lnGOV_{it}$											0.0714***	0.0697***
											(0.0208)	(0.0215)
Year 2007												−0.0186***
												(0.0063)
Year 2008												−0.0022
												(0.0049)
Year 2009												0.1088***
												(0.0040)
Year 2010												0.0253**
												(0.0115)
Constant	0.0497	0.2997	0.2197	0.1577	0.4468	−0.8154	−1.0594	−0.4892	−0.6746	−1.4591	−0.5099	−1.2334
	(0.1814)	(0.3552)	(0.3753)	(0.3858)	(0.4870)	(0.8565)	(1.1047)	(1.1872)	(1.1742)	(1.0819)	(1.0770)	(1.0703)
Observations	692	541	541	541	525	525	473	473	472	472	465	465
Number of groups	45	43	43	43	42	42	41	41	41	41	41	41

Dependent variable = logarithm of total unemployment rate. FE is Fixed Effects; Robust standard errors in parentheses; CD is cross-sectional dependence; ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1
Test of Skewness of the energy demand function (Eq. (7)).

Skewness	Kurtosis	Pr(Skewness)	Pr(Kurtosis)	Joint Chi-square test
−0.6610	2.7677	0.0000	0.1754	48.47***

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

Table 2
Test for heteroscedasticity (Residuals of Eq. (23)).

Test type	Assumption	Null Hypothesis	df	Chi-sq. test
Koenker	No Normality of residuals	Homoscedastic Disturbance	16	56.93***
White	No Normality of residuals	Homoscedastic	139	190.50**
BPGCW	Normality of residuals	Constant variance	17	773.37***

BPGCW is Breusch-Pagan/Godfrey/Cook-Weisberg; df is degrees of freedom; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3
Descriptive statistics.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
ln*Pengwh*	9.4174	1.8923	5.5494	14.3267	1371
ln*Y*	7.0540	1.0571	5.0865	9.9200	1343
ln*Popdens*	3.6994	1.2875	0.5768	6.4345	1370
ln*Findevt*	1.5779	0.2827	−1.1871	3.2748	1198
HCI	0.4787	0.1258	0.199	0.797	1237
Urbnizn	39.6912	17.4505	5.491	88.976	1371
ln*Gasoprz*	−0.2282	0.5637	−3.9120	1.2030	927
Indshao	24.5578	12.4966	2.0732	87.7969	1255
ln*Tempz*	3.1894	0.1452	2.5360	3.4170	1377
Eff	0.0740	0.1231	0.0001	0.9251	749
U	9.1477	7.5686	0.9800	32.9400	1350
fU	10.8110	9.4837	0.9900	37.0300	1350
mU	8.2521	6.5750	1.3400	32.1700	1350
ln*S*	21.0840	1.7855	14.4887	25.3021	1202
lng	15.7149	1.6147	11.1625	19.0671	1371
GDPPPE	14,119.9	19,558.81	815.751	120,793.3	1296
LABIN	0.0002	0.0002	0.0000	0.0012	1296
INF	28.7910	222.3003	−11.6861	4145.106	1198
ln*FDIn*	22.7815	0.2338	16.3575	23.6671	1361
ln*GOV*	20.7067	1.5993	16.605	25.1386	1196

Source: Authors' elaborations.

Table 4
Determinants of the energy demand frontier (Eq. (7)).

Variables	Coefficient	p-value	Standard Errors
ln*Gasoprz*	−0.0527*	0.0810	(0.0302)
ln*Y*	0.9482***	0.0000	(0.0816)
ln*Popdens*	1.4741***	0.0000	(0.1569
ln*FDIn*	−0.0216	0.6390	(0.0460)
Indshao	0.0075***	0.0000	(0.0017)
HCI	−1.7011***	0.0000	(0.4521)
ln*Findevt*	0.2158***	0.0050	(0.0761)
Urbnizn	0.0071*	0.079	(0.0041)
ln*Tempz*	−0.1654	0.778	(0.5852)
Trend	−0.0085	0.1620	(0.0059)
trend^2	0.0003*	0.092	(0.0001)
Constant	−1.3390	0.564	(2.3335)
R-squared	0.741		
Number of Countries	45		
No. of Observations	749		

The logarithm of total primary energy demand (ln*Pengwh*) is the dependent variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5
Energy efficiency estimates for Africa (Eq. (7)).

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

NB: Multiplying the persistent and the transient energy efficiencies yields the overall energy efficiency. (see Section 3.1).

Table 6
Effect of Energy Efficiency on Total Unemployment Rate (Equation (23).

Variables	Model 1 OLS: Upper Bound	Model 2 FE: Lower Bound	Model 3 Two-step Difference GMM	Model 4 Two-step System GMM	Model 5 Two-step System GMM with Nonlinear	Model 6 Iterated System GMM with Nonlinear	Model 5A Two-step System GMM (No Interaction Terms)
1st Lag of Unemployment (lnU_{it-1})	0.3159*	0.2246***	0.4398***	0.2901***	0.2875***	0.2526***	0.2971***
	(0.1701)	(0.0490)	(0.1307)	(0.0617)	(0.0640)	(0.0639)	(0.0946)
Energy Efficiency ($lnef_{it}$)	-0.1863	-0.4459**	-2.5431*	-1.2750**	-1.2331**	-1.1424***	-0.9154*
	(0.1547)	(0.1904)	(1.3808)	(0.6408)	(0.5357)	(0.3814)	(0.5280)
1st Lag of Energy Efficiency ($lnef_{it-1}$)	0.1988	0.3732*	2.2645**	1.1189**	1.0624***	0.9495***	0.8775
	(0.1473)	(0.1847)	(0.9376)	(0.5155)	(0.4117)	(0.3666)	(0.5481)
Education ($lnHCI_{it}$)	-2.1350**	-2.1067***	-1.3439*	-1.4641**	-1.3945**	-1.4372**	-0.1373
	(0.9662)	(0.6963)	(0.7713)	(0.6681)	(0.6755)	(0.6789)	(0.2946)
Energy Efficiency*Education ($lnef_{it}$* $lnHCI_{it}$)	-0.3591**	-0.3887***	-0.1758	-0.3462**	-0.3376**	-0.3153**	
	(0.1673)	(0.1182)	(0.1804)	(0.1350)	(0.1393)	(0.1322)	
Capital Formation (lns_{it})	-0.0186	-0.0888***	-0.0305	-0.0424	-0.0536**	-0.0437**	-0.0304
	(0.0128)	(0.0306)	(0.0477)	(0.0358)	(0.0242)	(0.0210)	(0.0266)
Population (lng_{it})	0.0080	0.0590	0.0437	0.0090	0.0172	0.0138	0.0292
	(0.0110)	(0.1174)	(0.2930)	(0.0326)	(0.0279)	(0.0182)	(0.0330)
Inflation ($lnINF_{it}$)	0.0029	0.0083*	-0.0313*	0.0106	0.0101	0.0135	0.0150
	(0.0062)	(0.0044)	(0.0178)	(0.0123)	(0.0130)	(0.0085)	(0.0134)
FDI ($lnFDI_{it}$)	-0.0079	-0.0327	-0.0037	-0.0084	-0.0148	-0.0663	0.0121
	(0.0150)	(0.0274)	(0.0283)	(0.0323)	(0.0297)	(0.0682)	(0.0328)
Labour Intensity ($lnLABI_{it}$)	-0.0027	-0.2757**	-0.1100	-0.0617	-0.0765	-0.0909*	0.0115
	(0.0204)	(0.1294)	(0.3810)	(0.1107)	(0.1006)	(0.0527)	(0.0440)
Energy Efficiency*Labour Intensity ($lnef_{it}$* $lnLABI_{it}$)	0.0011	-0.0370**	-0.0625	-0.0158	-0.0175	-0.0199***	
	(0.0020)	(0.0154)	(0.0779)	(0.0263)	(0.0251)	(0.0077)	
Government Expenditures ($lnGOV_{it}$)	0.0133	0.0697***	0.0282	0.0433	0.0511**	0.0416	0.0273
	(0.0152)	(0.0228)	(0.0446)	(0.0322)	(0.0257)	(0.0265)	(0.0315)
Year 2007	-0.0274	-0.0186	-0.0480	-0.0348	-0.0309	-0.0288	-0.0314
	(0.0200)	(0.0190)	(0.0810)	(0.0305)	(0.0335)	(0.0370)	(0.0315)
Year 2008	-0.0067	-0.0022	-0.0565	-0.1139**	-0.1063**	-0.1030**	-0.1114
	(0.0229)	(0.0219)	(0.0702)	(0.0500)	(0.0517)	(0.0426)	(0.0681)
Year 2009	0.1030***	0.1088***	-0.0365	0.0672	0.0726	0.0764*	0.0739
	(0.0205)	(0.0235)	(0.1245)	(0.0446)	(0.0456)	(0.0444)	(0.0555)
Year 2010	0.0032	0.0253	-0.0771	0.0248	0.0316	0.0479	0.0372
	(0.0234)	(0.0252)	(0.1326)	(0.0441)	(0.0473)	(0.0462)	(0.0607)
Constant	0.1472	-1.2334	-0.3798	-0.5914	-0.6367	0.4528	-0.7491
	(0.2852)	(1.6630)	(5.5336)	(0.9207)	(0.9038)	(1.4545)	(0.9884)
Observations	465	465	465	465	465	465	465
R-squared	0.1596	0.153	-	-	-	-	-
Number of Countries	41	41	41	41	41	41	41
Instrument Count	-	-	29	37	38	38	34
Cragg-Donald (CUE-based) WIT (F statistic)	-	-	16.99	31.26	37.90**	37.83*	38.38**
AR(1) *p-value*	-	-	0.0510	0.094	0.0005	-	0.0000
AR(2) *p-value*	-	-	0.6172	0.3852	0.4851	0.3878	0.4353
Sargan *p-value*	-	-	0.8115	0.9705	0.9742	0.9656	0.9128
Hansen *p-value*	-	-	0.8386	0.2279	0.1487	0.9656	0.4468
Mean ρ between Panel Units	0.01	0.00	0.07	0.05	0.04	0.05	0.04
Pesaran (2004) CD-test	1.81*	0.01	10.487***	6.894***	6.274***	7.013***	6.643***
Pesaran (2015) CD-test	0.996	0.644	7.398***	5.198***	4.765***	5.232***	5.125***
Andrews-Lu Model and Moment Selection Criteria (MMSC)							
MMSC-AIC	-	-	-16.3458	-30.1329	**-31.6630**	-31.1498	-26.6846
MMSC-BIC	-	-	-36.9087	-64.4044	**-67.6480**	-67.1348	-59.2425
MMSC-HQIC	-	-	-24.1486	-43.1375	**-45.3178**	-44.8046	-39.0389

Dependent variable: logarithm of total unemployment rate. The panel OLS, fixed effect (FE) and GMM estimates apply to Eq. (23). WIT is weak instrument test. CUE is continuously updating estimator; ρ is correlation between panel units; Robust standard errors in parentheses; CD is cross-sectional dependence. *** p<0.01, ** p<0.05, * p<0.1

Table 7A
Conditional Unemployment Effect at Different Human Capital Index (HCI) Values

Unemployment effect evaluated	Total UE	Std. Error	[95% Confidence Interval]	
At the minimum HCI	-0.2454***	0.0895	-0.4208	-0.0699
At the maximum HCI	-0.9827***	0.1089	-1.1961	-0.7693
At the median HCI	-0.8805***	0.2365	-1.3440	-0.4170
At the mean HCI	-0.8201***	0.1247	-1.0645	-0.5757

UE is Unemployment Effect; *** p<0.01, ** p<0.05, * p<0.1

Table 7B
Difference-in-Means Test for Total Unemployment Effect of Energy Efficiency

Education (Human Capital Index-HCI)	Total UE	Std. Error	Std. Dev.	[95% Confidence Interval]	
Above the average (A)	-0.9366	0.0064	0.1607	-0.9493	-0.9240
Below the average (B)	-0.7213	0.0084	0.2318	-0.7379	-0.7048
Difference in means (A-B)	-0.2153***	0.0110	-	-0.2369	-0.1938
Above the median (0.5) threshold (C)	-0.9712	0.0047	0.1006	-0.9804	-0.9620
Below the median (0.5) threshold (D)	-0.7420	0.0078	0.2374	-0.7574	-0.7266
Difference in means (C-D)	-0.2292***	0.0116	-	-0.2519	-0.2065

This table shows a two-sample t-test of the difference in means of the total unemployment effect of energy efficiency for higher vs. lower human capital index values, using the estimates of Model 5 in Table 6B; UE. is Unemployment Effect; *** p<0.01, ** p<0.05, * p<0.1

Table 7C
Difference-in-Means Test for Human Capital Index

Total Unemployment Effect	Mean HCI	Std. Error	Std. Dev.	[95% Confidence Interval]	
Above the average (A)	0.5406	0.0044	6.0291	0.5319	0.5493
Below the average (B)	0.4004	0.0038	7.2246	0.3930	0.4078
Difference in means (A-B)	0.1402***	0.0060	-	0.1284	0.1520

This table displays a two-sample t-test of the difference in means of the human capital index for countries with a higher vs lower than the estimated average total unemployment effect of energy efficiency, using the estimates of Model 5 in Table 6B; *** p<0.01, ** p<0.05, * p<0.1

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2022.103683.

Appendix A. None

Appendix para

Appendix B. Tables of results on robustness checks

Appendix para

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