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Assessing the role of economic globalization on energy efficiency: Evidence from a global perspective

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ABSTRACT

There has been concern that economic globalization will increase energy consumption and reduce energy efficiency. A slew of studies investigating this assertion have used trade, foreign investment, or both as indicators of economic globalization, with mixed findings. A number of concerns challenge the empirical literature including measurement issues, infrequent temporal variations in the data, business cycle effects and heterogeneity bias, which affect the causal ability of economic globalization. This study used global data of 141 countries to assess the effects of economic globalization on energy efficiency. Our identification strategies involved using more refined measures of economic globalization and energy efficiency, addressing infrequent temporal variations as well as business cycle effects and concerns of heterogeneity bias. Largely, economic globalization positively drives energy efficiency, but this effect suffers from upward bias without controls. We note that infrequent temporal variations in the data and business cycle effects and heterogeneity bias drive the result. Concerning the latter, the result has shown that economic globalization improves energy efficiency only in upper-middle and lower-middle income countries and not in high and lower-income countries. Our results raise serious caution about the causal abilities of existing studies. And we discuss the policy implications.

1. Introduction

Energy efficiency improvements are critical to achieving the Paris Agreement goals and the United Nations' Sustainable Development Goals (SDGs) (United Nations, 2015). The International Energy Agency (2019) projected that energy efficiency improvements alone are expected to reduce global greenhouse gas (GHG) emissions up to 40% in the next 20 years. Energy efficiency improvements can also contribute meaningfully to energy security improvements as well as reduce energy infrastructure investment. Other studies have also provided evidence on the growth (Adom, Mawunyo, & Vezzulli, 2021) and employment (Mawunyo, Adom, & Vezzulli, 2022)

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effects of energy efficiency improvement. Therefore, energy efficiency enhancements have taken a central role in national energy and environmental policies, as countries around the world continue to inculcate energy efficiency strategies and targets into their national plans (Sun, Edziah, Sun, & Kporsu, 2019). Part of these strategies have involved promoting technological progress and the diffusion of cost-effective energy-saving technologies (Wurlod & Noailly, 2018). In this regard, globalization has emerged as one of the effective instruments that can expedite the process of technological process and diffusion (Lv & Xu, 2018). Economic globalization makes technological exchanges between and among countries extremely easy (Ahmed, Zhang, & Cary, 2021; You and Lv, 2018).

Economic globalization—a process by which companies, governments, and other institutions from all around the globe increasingly interact—is believed to promote global trade, foreign direct investment (FDI), industrial efficiency, capital circulation, and innovations. Gozgor, Mahalik, Demir, and Padhan (2020) assert that economic globalization promotes energy efficiency by facilitating the transfer of environmentally friendly, innovative, and energy-saving technologies from developed economies to less developed economies. Developing countries might benefit from international trade by gaining access to energy-saving technologies from rich and developed countries, improving efficiency (Verdolini & Galeotti, 2011). For example, a growth in FDI can help transmit industrialized countries' production efficiency to developing ones (Wang & Zhao, 2015). Furthermore, due to globalization, the growing notion of global information and shared knowledge has proven to raise awareness of energy and environmental-related issues across the globe, thereby improving energy efficiency (Ahmed et al., 2021). Motivated by this, the current study aims to examine the effect of economic globalization on technical energy efficiency for a global sample of 141 countries.

The empirical literature presents a number of challenges that may affect the causal influence of economic globalization on energy efficiency. First, one daunting issue prevalent in the current literature relates to measurement issues of economic globalization. Existing studies have used various measures of economic globalization that have been described as either inappropriate or inadequate (Lv & Xu, 2018). Previous studies use either trade openness (Adom, 2016; Adom & Kwakwa, 2014; Ahmed, 2017) or FDI (Jiang, Zhu, & Green, 2015; Keho, 2016; Wang, 2017) or both (Huang, Du, & Tao, 2017; Keho, 2016) to assess the degree of economic globalization on energy outcomes. Indeed, linking trade (or FDI) to energy efficiency is essential from a policy perspective (Sun, Edziah, Song, Kporsu, & Taghizadeh-Hesary, 2020). However, according to Lv and Xu (2018), either trade openness or FDI (or both) are not sufficient enough to take care of the influence of other facets of economic globalization, for example, the degree of capital controls, the diffusion of technological innovation, and restrictions on knowledge across national borders. Thus, ignoring such elements may be problematic and lead to erroneous conclusions about how economic globalization and energy efficiency are linked. Moreover, the measurement problems affect the causal ability of previous studies. The outcome of these measurement problems is an inconclusive result in the empirical literature. For instance, studies such as (Fresner, Morea, Krenn, Aranda Uson, & Tomasi, 2017; He & Huang, 2020; Kohler, 2013; Sun et al., 2019) use trade liberalization and FDI as measures of economic globalization. These studies show that trade liberalization or FDI reduces energy consumption through imported energy-saving technologies. Yao et al. (2021), for 36 countries, find that trade and FDI (being a measure of globalization) significantly improve energy efficiency.

In contrast, other studies report that economic globalization as measured by trade and FDI does not enhance energy efficiency improvements. In Bangladesh, Pan, Uddin, Han, and Pan (2019) observe that trade openness fosters energy intensity. Sadorsky (2011) finds that increasing trade (as in exports and imports) increases short-term and long-term energy intensity in the Middle East. Cole (2006) finds that, in 32 countries, trade liberalization increases their per capita usage of energy. Destek and Okumus (2019) observe that FDI might allow developed countries to transfer their energy-consuming technology into undeveloped and developing countries, increasing their energy intensity.

Other studies have used the multidimensional measure of economic globalization developed by Dreher (2006) (also known as the KOF index). The KOF index covers three dimensions of economic globalization – economic, social and political. Dreher (2006) economic globalization measure takes into account several other facets of movements of goods and services, including trade, FDI, income outflows to other countries, and portfolio investments, as well as restrictive measures like tariff rates, import barriers, foreign trade taxes, and restrictions on capital account. Dreher (2006) reveals that increased economic globalization improves economic performance and transforms the way people use energy. Shahbaz, Mallick, Mahalik, and Sadorsky (2016) examine the effect of KOF index of economic globalization on energy use in India and find that economic globalization increases energy consumption. Shahbaz, Shahzad, Mahalik, and Sadorsky (2017) also examine the effect of KOF index of economic globalization in developed countries and find that economic globalization increases energy consumption. Similarly, Shahbaz, Lahiani, Abosedra, and Hammoudeh (2018) using KOF index of economic globalization observe that economic globalization encourages energy use in top-2 globalized economies. Despite the multidimensional nature of Dreher's measure, the KOF index, does not capture trade rules, international reserves, diversity of trade partners, and foreign debt. For this reason, Gygli, Haelg, Potrafke, and Sturm (2019) have re-examined Dreher (2006) classic economic globalization index and updated it to include additional indicators such as trade partners diversity, foreign debt, investment restrictions, international reserves, and trading rules.

Another empirical issue relates to the measurement of energy efficiency. Largely, studies have used energy consumption or intensity as a benchmark of energy efficiency to appraise the effect of economic globalization on energy efficiency. But, according to the IEA (2009), employing energy consumption or intensity as a measurement of energy efficiency might be misleading because energy intensity may not accurately capture factors that would have been considered in energy efficiency. For example, if the fuel mix or weather differs between countries, energy intensity will not accurately capture the difference in energy efficiency among countries (Ang, 2006). Other studies such as Adom, Amakye, Abrokwa, and Quaidoo (2018) and Filippini and Zhang (2016) have shown that energy intensity is weakly associated with energy efficiency. To solve this problem, studies have relied on more reliable measurable techniques of energy efficiency such as the stochastic frontier analytic and data envelope analytic techniques (Adom et al., 2018; Filippini & Zhang, 2016; Sun et al., 2019; Zhang & Adom, 2018). However, it is largely assumed in these studies that technical energy efficiency exhibits very rapid changes across countries. This might not be the case for at least some countries because of the difficulty to switch from one technology to another and for the reason that different energy users may use different discounting factors. Thus, failing to address the possibility of persistent movement in computed energy efficiency can also influence the causal ability of economic globalization. Lastly, the context dependent nature of the empirical results suggest that the literature may be suffering from heterogeneity bias. For example, while it is expected that there may be little or no 'low-hanging fruit' existing in developed economies as related to energy efficiency improvements, it might not be the case in developing economies. Moreover, the difference in environmental regulations and technology absorptive capacity of countries imply that the impact of economic globalization may be driven by context unobserved heterogeneities.

Based on the identified gaps in the prevailing literature, this study makes a number of significant contributions to the current literature. First, in addition to using KOF index of economic globalization, this study also used the updated version of Dreher's measure of economic globalization developed by Gygli et al. (2019). These addresses omitted factors that may limit the causal ability of KOF index of economic globalization to energy efficiency. Second, we follow the previous literature to estimate technical efficiency in energy consumption based on the stochastic frontier analytic technique. However, in contrast to the previous literature, we relax the assumption that temporal variation in technical energy efficiency is very rapid across countries. To address the issue that temporal variations in technical energy efficiency may not be rapid, we performed regressions at higher time changes. We consider both five- and ten-year average changes in the data of technical energy efficiency to deduce whether such medium to long-term changes in the data are associated with economic globalization. Third, in contrast to the prevailing literature, we use global data that consists of 141 countries – developed and developing. While the global data enhances the external validity of our results, it allows us to address concerns of heterogeneity bias both in terms of technology and the effect of economic globalization. In this study, we consider sub-sample analysis classified by the level of economic development – Higher Income, Upper-Middle Income, Lower-Middle Income, and Lower-Income economies.

The remainder of the research is well-thought-out as follows. Given that the research aims to estimate energy efficiency to draw a link between economic globalization and energy efficiency, section two provides a quick summary of the literature on energy efficiency measurement. The distance function model, its application in the stochastic frontier approach, and the data are all explained in section three. Section four displays and analyzes the empirical outcomes, and section five presents the conclusions, policy recommendations and future research possibilities.

2. Measurement of energy efficiency

According to Erbach (2015), energy efficiency is calculated as the proportion of the output of performance, good or service to the amount of energy used to produce that output or service or good. In other words, energy efficiency is defined as the use of less energy to accomplish the same work – essentially trying to eliminate energy losses. From an economics perspective, there are numerous indicators for calculating energy efficiency (Patterson, 1996). But, Hu and Wang (2006), claim that these measures can be categorized under two broad groups – the partial or single factor energy efficiency (PFEE) measure and the total factor energy efficiency (TFEE) measure. The widely-used measure is PFEE, and it is sometimes referred to as energy intensity. It measures, in particular, the connection between energy input and output, where energy is generally considered the only component in the production process (Jebali, Essid, & Khraief, 2017). As a result, the PFEE index has been challenged in recent years since it only assesses a proportionate relationship between energy as an input and gross domestic production (GDP) as an output, while ignoring the importance of other factors of production like capital and labour in the production process (IEA, 2009). With this in mind, the TFEE index was initially introduced by Hu and Wang (2006). Under the neoclassical production theory, TFEE considers the energy component and other production factors like labour and capital in the production process when estimating energy efficiency (Edziah, Sun, Anyigbah, & Li, 2021; Sun, Edziah, Sun, & Kporsu, 2021).

The following is a summary of the TFEE framework:

(i) It defines the set of production possibilities (given a production technological level).
(ii) It generates a production frontier making use of the input and output data from each country or firm.
(iii) It examines the link between the production frontier and each unit of production, where departure from frontier shows underutilization of resources and potential for Pareto improvement.

A plethora of research has been conducted on the level of energy efficiency of sectors and countries employing various TFEE indices, the most common of which is the non-parametric data envelopment analysis (DEA) and the parametric stochastic frontier analysis (SFA). The former is suggested by Charnes, Cooper, and Rhodes (1978) and the latter by Aigner, Lovell, and Schmidt (1977) and Meeusen and van Den Broeck (1977). The two approaches are frontier procedures based on distance functions (Coelli, Rao, O'Donnell, & Battese, 2005). While the parametric SFA method is oriented around economic optimization, non-parametric DEA methods are oriented around technical optimization. Each method has some advantages and disadvantages, and selecting one necessitates making a trade-off.

For SFA, it enables the residual separation into two separate terms: random noise and inefficiency effect. Therefore, the primary merit of the parametric SFA is its capacity to compute efficiency whilst accounting for statistical noise. However, as a deficiency, a priori definition of the shape and probability distribution of the efficient frontier's efficiency levels is necessary. The chosen style of a function introduces induction bias into the stochastic method. In cases when the shapes do not match the data, it can significantly degrade the results. Alternatively, the DEA avoids such specification problems since it is not predicated on the efficient frontier's shape or the probability distribution. As a result, the DEA ignores random estimation errors, deeming any deviation inefficient. Thus, the DEA does a deterministic frontiers examination, indicating that no statistical underpinnings exist.

Overall, neither approach appears to be superior to the other, nor does choosing one strategy appear to be a challenging undertaking. However, because macroeconomic data may contain sizeable statistical noise, the parametric SFA technique is used in this study, as advocated by Filippini and Hunt (2015). Furthermore, as a statistically oriented parameter estimation technique, SFA supports statistical testing for model settings. Because of these advantages, SFA has been frequently used in assessing energy efficiency performance at both the micro and macro levels. See Table 1 below for examples.

From the Table 1, many studies have either examined sectoral or country-level energy efficiency. Unlike previous, which focused on one or few countries, this research offers evidence from a global viewpoint. To that purpose, by centering on a sample of 141 countries, this study adopts the Shepard energy distance function (SEDF)[1] and Greene (2005a) True Fixed Effects model to estimate energy efficiency, thereby providing policymakers worldwide with invaluable quantitative evidence of energy efficiency performance at the global level.

3. Model specification and variables selection

3.1. Energy distance function

Following the neoclassical production framework, we consider a production process where countries use inputs like capital (K), energy (E) and labour (L) to create gross domestic product (GDP) (Y). In theory, the production technology is as such:

$$\mathrm{T} = \{(\mathrm{K,L,E,Y}) : (\mathrm{K,L,E}) \text{ produces } (\mathrm{Y})\} \tag{1}$$

where, **T** in production economic theory must satisfy the following: basically, this means: first (i) production of GDP requires inputs (ii) but those inputs and outputs are also disposable, as inaction is always an option (3) T is finite (iii) T is bounded and (iv) T is convex. Following the Shepard energy distance function recommended by Zhou et al. (2012), we defined the Shepherd energy distance function as:

$$D_E\,(K,L,E,Y) = sup\left\{\beta : \left(\mathrm{K,L},\frac{E}{\beta},Y\right) \in T\right\} \tag{2}$$

Eq. (2) attempts to calculate the most significant likely reduction in E whilst maintaining the input and output vectors specified within the constraints of the production process. As a result, $D_E(K,L,E,Y)$ signifies a country's hypothetical optimal energy use. According to Hu and Wang (2006), energy efficiency [expressed as an economy-wide energy efficiency measure (EEM)] is calculated by applying the formula:

$$\mathrm{EEM} = \frac{1}{D_E(K,L,E,Y)} \tag{3}$$

EEM measures how far a country's actual energy use deviates from the optimal energy level required for output. The EEM's definition specifies that it is between 0 and 1. A score of one indicates that the country consumes energy at its optimal level; thus, its energy efficiency is on the frontier curve. On the other hand, an EEM score below one indicates energy inefficiency in the production process because production is stationary within the frontier curve.

3.2. Estimation of distance function through SFA

Using the energy distance model specification with a translog functional form,[2] we get an econometric form of the distance function as follows:

$$\begin{aligned} LnD_E^t\left(K_c^t,L_c^t,E_c^t,Y_c^t,\right) = {} & \beta_0 + \beta_k LnK_c^t + \beta_l LnL_c^t + \beta_e LnE_c^t + \beta_y LnY_c^t + \frac{1}{2}\beta_{kk}\left(LnK_c^t\right)^2 + \frac{1}{2}\beta_{ll}\left(LnL_c^t\right)^2 + \frac{1}{2}\beta_{ee}\left(LnE_c^t\right)^2 + \frac{1}{2}\beta_{yy}\left(LnY_c^t\right)^2 \\ & + \beta_{kl}\left(LnK_c^t\right)\left(LnL_c^t\right) + \beta_{ke}\left(LnK_c^t\right)\left(LnE_c^t\right) + \beta_{ky}\left(LnK_c^t\right)\left(LnY_c^t\right) + \beta_{le}\left(LnL_c^t\right)\left(LnE_c^t\right) + \beta_{ly}\left(LnL_c^t\right)\left(LnY_c^t\right) \\ & + \beta_{ye}\left(LnY_c^t\right)\left(LnE_c^t\right) + \beta_t\mathrm{T} + \beta_{tt}T^2 + \beta_{tk}(\mathrm{T})\left(LnK_c^t\right) + \beta_{tl}(\mathrm{T})\left(LnL_c^t\right) + \beta_{te}(\mathrm{T})\left(LnE_c^t\right) + \beta_{ty}(\mathrm{T})\left(LnY_c^t\right) + v_c^t \end{aligned} \tag{4}$$

where the last term in Eq. (4) v_c^t is an error element that accounts for statistical noises and random external shocks that occur outside of the production process and it is believed to be normally distributed. The βs are the yet to be assessed parameters. The subscript T captures technical progress as well as other non-economic elements such as customer behavior and style of living. According to Chitnis and Hunt (2012), non-economic elements are difficult to quantify due to the scarcity of appropriate data, and they might have a non-linear effect. As a result, we include the squared T term (T^2), because we believe the time trend (T) influences energy efficiency non-

[1] From an econometrics point of view, Filippini and Hunt (2015) suggested 3 different specific requirements under SFA frontier functions, namely – (i) energy requirement function (ERF); (ii) shepherd energy distance function (SEDF) and (iii) energy demand function (EDF).

[2] We chose the trans-log due to its flexibility. Furthermore, according to Christensen, Jorgenson, and Lau (1973), trans-log has no prior technological constraints.

Table 1
Literature on energy efficiency employing stochastic frontier analysis (SFA).

Sectoral Analysis	
Boyd (2008)	U.S. Milling industry
Shen and Lin (2017)	Chinese Sub-industries
Xie, Bai, and Wang (2018)	Chinese Transport sector
Oh and Hildreth (2014)	U.S. Car manufacturing industry
Haider and Mishra (2021)	Indian iron and steel industries
Boyd and Lee (2019)	U.S. Manufacturing sector
Haider and Ahmad Bhat (2018)	Indian Paper industry
Lin and Long (2015)	Chinese chemical industry
Lundgren et al. (2016)	Swedish manufacturing
Weyman-Jones, Boucinha, and Inácio (2015)	Portuguese households
Otsuka (2020)	Japanese industrial and commercial sector
Lin and Wang (2014)	Chinese iron and steel industry
Single country analysis	
Filippini and Hunt (2012)	The U.S.
Otsuka (2017)	Japan
Honma and Hu (2014)	Japan
Du, Wang, and Zhang (2018)	China
Zhang and Zhou (2020)	China
Zou et al. (2013)	China
Filippini and Zhang (2016)	China
Hu, Li, and Zhang (2019)	China
Ouyang, Wei, Sun, and Du (2018)	China
Zou, Lu, and Cheng (2019)	China
Zhang, Fan, and Zhou (2020)	China
Ouyang, Chen, & Du (2021)	China
Hu, Chang, and Tsay (2018)	Taiwan, China
Cross-country analysis	
Filippini and Hunt (2011)	29 OECD countries
Zhou, Ang, and Zhou (2012)	21 OECD countries
Filippini, Hunt, and Zorić (2014)	27 EU countries
Marin and Palma (2017)	10 EU countries
Alarenan, Gasim, Hunt, and Muhsen (2019)	Gulf Cooperation Council (GCC) countries
Hu and Honma (2014)	14 OECD countries
Hsiao, Hu, Hsiao, and Chang (2019)	10 countries across the Baltic Sea
Sun et al. (2019)	71 countries across the globe
Adom et al. (2018)	22 African countries
Jin and Kim (2019)	21 emerging countries
Sun, Edziah, Kporsu, Sarkodie, and Taghizadeh-Hesary (2021)	24 innovative countries
Edziah et al. (2021)	10 developing countries

linearly.

According to Lovel, Richardson, Travers, and Wood (1994), Eq. (4) can be expressed as follows since the Shephard distance function is linearly homogeneous with respect to the energy input:

$$LnD_E^t\left(K_c^t, L_c^t, E_c^t, Y_c^t\right) = LnE_c^t + LnD_E\left(K_c^t, L_c^t, 1, Y_c^t\right) \tag{5}$$

With an econometric estimation on Eq. (5), we expand the formula as follows:

$$\begin{aligned} LnD_E^t\left(K_c^t, L_c^t, E_c^t, Y_c^t\right) = {} & LnE_c^t + \beta_0 + \beta_k LnK_c^t + \beta_l LnL_c^t + \beta_y LnY_c^t + \frac{1}{2}\beta_{kk}\left(LnK_c^t\right)^2 + \frac{1}{2}\beta_{ll}\left(LnL_c^t\right)^2 + \frac{1}{2}\beta_{yy}\left(LnY_c^t\right)^2 + \beta_{kl}\left(LnK_c^t\right)\left(LnL_c^t\right) \\ & + \beta_{ky}\left(LnK_c^t\right)\left(LnY_c^t\right) + \beta_{ly}\left(LnL_c^t\right)\left(LnY_c^t\right) + \beta_t \mathrm{T} + \beta_{tt}T^2 + \beta_{tk}(\mathrm{T})\left(LnK_c^t\right) + \beta_{tl}(\mathrm{T})\left(LnL_c^t\right) + \beta_{ty}(\mathrm{T})\left(LnY_c^t\right) \\ & + v_c^t \end{aligned} \tag{6}$$

After simple transformation, Eq. (6) becomes:

$$\begin{aligned} -LnE_c^t = {} & \beta_0 + \beta_k LnK_c^t + \beta_l LnL_c^t + \beta_y LnY_c^t + \frac{1}{2}\beta_{kk}\left(LnK_c^t\right)^2 + \frac{1}{2}\beta_{ll}\left(LnL_c^t\right)^2 + \frac{1}{2}\beta_{yy}\left(LnY_c^t\right)^2 + \beta_{kl}\left(LnK_c^t\right)\left(LnL_c^t\right) + \beta_{ky}\left(LnK_c^t\right)\left(LnY_c^t\right) \\ & + \beta_{ly}\left(LnL_c^t\right)\left(LnY_c^t\right) + \beta_t \mathrm{T} + \beta_{tt}T^2 + \beta_{tk}(\mathrm{T})\left(LnK_c^t\right) + \beta_{tl}(\mathrm{T})\left(LnL_c^t\right) + \beta_{ty}(\mathrm{T})\left(LnY_c^t\right) + D_c + v_c^t - u_c^t \end{aligned} \tag{7}$$

where, the new term introduced in Eq. (7), i.e. D_c are dummies for each country. In research like Sun et al. (2019), D_c controls for variation in geographic, climatic, environmental and socio-economic aspects of the sample countries. The last term u_c^t is a non-negative one-sided error random variable represents the inefficiency of energy use in country c, taking current production technology into account at time t. Eq. (7) may be used to estimate the energy inefficiency component u_c^t of country c. The following formula should calculate the appropriate annual energy efficiency for each country.

$$EE_c^t = exp(-u_c^t) \tag{8}$$

According to Battese and Coelli (1995), a collection of explanatory variables can explain the inefficiency component u_c^t. Therefore, to acquire an understanding of the connection between economic globalization and energy efficiency with some control variables, we specify the inefficiency function u_c^t as:

$$u_c^t = \vartheta_o + \varphi Eco_c^t + \varphi EP_c^t + \varphi Pop_c^t + \varphi Urb_c^t + \varepsilon_c^t \tag{9}$$

where Eco_c^t is the economic globalization index, the other variables are considered factors capable of affecting changes in energy efficiency, and they are thus included as control variables. One of them is the price of energy (EP_c^t). Higher energy prices should, in theory, improve energy efficiency. Also, connected to energy efficiency is population growth (Pop_c^t). Energy efficiency could be influenced positively or negatively by population size. Countries with dense populations will implement more energy-efficient infrastructure to meet the increased energy needs. However, according to Moshiri and Duah (2016), countries may become less energy efficient due to increased facility utilization and transportation congestion if the infrastructure does not keep pace with population expansion. A growing urban population (Urb_c^t) can also impact energy use by increasing demand, raising overall energy use and, therefore, the energy inefficiency in cities. However, urbanization's scale effects, such as population agglomeration and increased public transportation infrastructure, improves energy efficiency and saves energy (Sadorsky, 2013). ε_c^t is an error term and φ denotes the corresponding vector of parameters to be estimated.

Given the inefficiency component u_c^t, an inverse relationship between any of the explanatory variables and the underlying inefficiency suggests decreasing energy inefficiency. For example, if economic globalization (Eco_c^t) increases energy efficiency, we can expect a negative coefficient, indicating that the distance from the frontier is decreasing due to economic globalization. Positive coefficients, on the other hand, increase energy inefficiency and distance from the frontier.

In conventional SFA, the unobservable country effects are either assumed unimportant and therefore ignored or calculated and interpreted as a component of the inefficiency effect (Song & Yu, 2018). For instance, the widely used method developed by Battese and Coelli (1995) does not account for the unobserved country's effects. Schmidt and Sickles (1984) treated it as part of the technical effects of dealing with individual heterogeneity. Greene (2005b) suggested that the efficiency and individual effects should be treated separately in the estimation to avoid distortion of the efficiency measure of interest. The individual effects can bias the coefficients of the explanatory variables when there is a correlation between the two. Farsi, Filippini, and Kuenzle (2005) suggested estimating individual heterogeneity as a function of the mean independent variables to address the correlation problem. This estimation method fails to allow inefficiency to vary over time and does not solve the correlation issue. Greene (2005a) recommended the true fixed-effects model by including chains of individual-specific fixed effects. Therefore, we adopt Greene's true-fixed effect, stochastic model, by including a series of country dummies.[3]

3.3. Variables selection

The dataset comprises an unbalanced panel of a sample of 141 countries from 1980 to 2016. The paper considers four variables as the input-output indicators in estimating the production frontier. Capital stock, labour, and energy use comprise the three inputs, and GDP is an output. The GDP, capital, population and consumer price index (a proxy for energy prices) data are obtained from Penn World Table. Urbanization data is extracted from the World Development Indicators (WDI). Economic globalization data came from Dreher (2006) KOF globalization index (see Table 2 for more information) and the revised economic globalization measure also came from Gygli et al. (2019).[4] The degree of economic globalization is modelled using both indices. Both indices take a value of 0 to 100, with a higher value signifying greater globalization. Table 3 contains information on the definitions and sources of all variables, and Table 4 shows the descriptive statistics of variables.

4. Discussion of empirical results and findings

4.1. Results of the frontier production function

Table 5 shows the estimated maximum likelihood parameters for the translog stochastic frontier production function using Dreher (2006) economic globalization index. Our empirical approach involves a systematic inclusion of the independent variables in the inefficiency equation. The rationale was to ascertain the stability and consistency of the effect of economic globalization on technical inefficiency in energy consumption.

Irrespective of the model set-up, we find a consistent negative and statistically significant effect of economic globalization on

[3] There is a possibility that this process might pose an incidental parameter problem. However, Greene (2005b) argues that employing a large "T" with a half-normal distribution reduces the bias caused by the incidental parameter problem.

[4] For further information on the KOF globalization indices, read Dreher (2006) & Gygli et al. (2019)

Table 2
Dreher (2006) economic globalization components.

Economic Globalization	Variables and Indices	Weights
1 Actual flows		50%
	1. Trade	21%
	2. FDI stocks	28%
	3. Portfolio Investment	24%
	4. Income Payments to Foreign Nationals	27%
2 Restrictions		50%
	1. Hidden Import Barriers	22%
	2. Mean Tariff Rate	28%
	3. Taxes on International Trade (percentage of current revenue)	26%
	4. Capital Account Restrictions	24%

Note: All variables under actual flow are measured as percentage of GDP.
Source: http://globalization.kof.ethz.ch/media/filer_public/2017/04/19/variables_2017.pdf

Table 3
Variable definitions and sources.

Variables	Definition	Unit	Source
GDP	Gross value added in an economy	millions of US$ at 2011	Penn World Tables
Capital Stock	Total capital stock invested	millions of US$ at 2011	Penn World Tables
Labor	Number of persons engaged	millions	Penn World Tables
Energy consumption	Total amount of primary energy consumed	British thermal unit	Energy Information Administration
Economic Globalization	The KOF index of economic globalization	–	KOF globalization index by Dreher (2006) and Gygli et al. (2019).
Energy Price	Consumer Price Index used a proxy for Energy price	–	Penn World Tables
Population	Total population of a country	millions	World Bank (WDI)
Urbanization	Total number of people living in urban areas	millions	World Bank (WDI)

Table 4
Summary statistics of all variables.

Variable	Observations	Mean value	Std. Dev.	Min	Max
lnGDP	5131	10.86268	2.142754	5.479676	16.71649
lnCap	5132	11.67051	2.371733	5.152609	18.37624
lnlab	5123	0.9382867	1.906257	−4.732323	6.675288
lnEne	5122	−4.093939	2.422078	−10.47062	3.411248
lnEco	5137	3.888818	0.359729	2.559085	4.558402
lnEco2	5079	3.888711	0.3611928	2.565046	4.556875
lnEP	5057	−0.8290939	0.5085143	−2.448907	1.382993
lnPop	5135	1.892401	1.876051	−2.864844	7.246725
lnUrb	5210	14.97762	1.893985	10.28541	20.47762

Note: All variables are in their natural log form.

technical inefficiency in energy consumption. We observe, however, that the size of the coefficient is dependent on the model set-up. Failing to account for important variables in the inefficiency equation introduces absolute positive bias in the coefficient of economic globalization, suggesting that, in this case, the price of energy, population and urbanization may be sharing meaningful positive correlation with economic globalization. As shown in the general preferred model (i.e. model 5), the effect of economic globalization reduces in absolute terms from 2.015 to 0.361, indicating a positive bias of 1.654. The preferred model shows that 1% age point movement on the scale of economic globalization is associated with 0.361% reduction in technical energy inefficiency. The positive role of economic globalization in influencing technical energy efficiency corroborates with the portion of the literature that provides findings to support the energy-saving effect of economic globalization (Fresner et al., 2017; He & Huang, 2020; Kohler, 2013; Sun et al., 2019; Yao et al., 2021). Our results underscore the importance of economic globalization in stimulating energy efficiency around the world and by extension achieving SDG target 7.3. Economic globalization, characterized by increased financial, trade, and capital inflows, typically results in a surge in FDI influx into an economy, accompanied by increased technological innovation and more significant economic growth. When foreign investors enter an economy to establish their businesses and investments, they may bring innovative and sophisticated production approaches that require less energy consumption than those employed by the host country (especially in the developing ones). In addition, economic globalization that encourages information sharing about best environmental practices can help the world recognize the importance of energy conservation and climate change, thereby improving energy efficiency (Ahmed et al., 2021). For instance, information exchange on climate mitigation strategies among industries or countries allows people

Table 5
Results for the frontier production function using the economic globalization index by Dreher (2006).

Distance Function	Model (1)	Model (2)	Model (3)	Model (4)
lnLab	0.583***	0.572***	0.990***	0.747***
	(0.162)	(0.165)	(0.145)	(0.122)
lnCap	−0.298***	−0.283***	−0.390***	0.0513
	(0.0985)	(0.0993)	(0.0987)	(0.126)
lnGDP	−2.467***	−2.459***	−2.273***	−2.068***
	(0.161)	(0.167)	(0.161)	(0.175)
$lnLab^2$	0.0596***	0.0527**	0.140***	0.0320**
	(0.0221)	(0.0222)	(0.0195)	(0.0143)
$lnCap^2$	0.00572	0.00649	−0.0483***	0.204***
	(0.0186)	(0.0190)	(0.0169)	(0.0306)
$lnGDP^2$	0.137***	0.136***	0.0654**	0.300***
	(0.0286)	(0.0296)	(0.0298)	(0.0435)
lnLab*lnCap	−0.0535***	−0.0495***	−0.0508***	0.00936
	(0.0109)	(0.0108)	(0.0102)	(0.0132)
lnLab*lnGDP	−0.0538***	−0.0553***	−0.105***	−0.0655***
	(0.0168)	(0.0171)	(0.0165)	(0.0179)
lnGDP*lnCap	0.0226	0.0204	0.0826***	−0.218***
	(0.0208)	(0.0213)	(0.0209)	(0.0335)
Time	−0.0151***	−0.0175***	−0.0350***	−0.0502***
	(0.00533)	(0.00537)	(0.00507)	(0.00788)
$Time^2$	0.000834***	0.00082***	0.000695***	0.00112***
	(4.68e-05)	(4.70e-05)	(3.78e-05)	(9.51e-05)
Time*lnCap	−0.00615***	−0.00582***	−0.00192**	−0.0166***
	(0.000938)	(0.000962)	(0.000897)	(0.00176)
Time*lnLab	0.00126**	0.00137**	−2.43e-05	0.00236***
	(0.000612)	(0.000606)	(0.000563)	(0.000854)
Time*lnGDP	0.00581***	0.00566***	0.00336***	0.0188***
	(0.00104)	(0.00106)	(0.00103)	(0.00202)
Constant	14.98***	15.06***	14.54***	14.42***
	(0.802)	(0.819)	(0.755)	(0.639)
Country Dummies	Yes	Yes	Yes	Yes
lnEco	−2.015***	−1.554***	−1.758***	−0.361***
	(0.179)	(0.166)	(0.108)	(0.114)
lnEP		−0.532***	−0.813***	−1.013***
		(0.108)	(0.0731)	(0.0875)
lnPop			−0.698***	−0.828***
			(0.0240)	(0.114)
lnUrb				0.541***
				(0.110)
Constant	4.569***	2.785***	5.214***	−6.563***
	(0.607)	(0.629)	(0.452)	(1.476)
Sigma_v				
Constant	−2.950***	−3.133***	−4.270***	−1.811***
	(0.0489)	(0.0691)	(0.0690)	(0.0670)
Log-likelihood	−420.90424	−390.41998	122.96413	−4626.8095
Prob>chi2	0.000	0.000	0.000	0.000
Observations	5104	5038	5038	5035

Note: The prefix "ln" preceding the independent variables imply that the variables are in logarithmic form. As for the inefficient factors, when the explanatory variables have a negative sign, this indicates that energy inefficiency reduces, and therefore that there is a positive link between energy efficiency and the inefficient elements. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. The standard errors of the coefficients are represented by the figures in ().

to discover the best environmental practices in other nations or other industries and sectors of the economy. That knowledge helps inspire countries to acclimate and apply the same ecological practices in their home countries to conserve energy and the environment. Similarly, national governments sign various international treaties like the Kyoto agreement to adopt the best environmental and energy conservation practices that reduce climate change and follow global standards to address global warming and carbon dioxide emissions. Hence, economic globalization with positive externalities (such as more research and development, new knowledge, foreign investments, green and new production methods, technology spillover, better managerial skills, and energy-efficient technologies) can positively influence energy efficiency.

Regarding the controls, the effect of energy price is consistently negative and statistically significant. According to the preferred model, increasing the price of energy by 1% reduces technical inefficiency in energy consumption by 1.01%. According to Tajudeen (2021), the threat of an increase in energy prices may force people to make lifestyle adjustments and move businesses to use more efficient and cost-effective technology that will remain in place even after the cost of energy has returned to lower prices. This outcome is coherent with Dong, Sun, Hochman, and Li (2018), who discover that energy prices have a negative effect on China's energy intensity.

Also, the effect of population is negative and statistically significant across all the model set-ups. According to the preferred model, increasing population by one-percent reduces technical inefficiency in energy consumption by 0.828%. Adom et al. (2018) mentioned that changes in demographics, especially changes in population size, have ramifications for energy use patterns and pollutant emissions. For example, growing populations can drive up the usage of non-energy-based means of transportation (like bikes, treks, and horses) as well as other means of transport that are less energy-intensive (like motorbikes). Based on this result, the findings of Jain and Goswami (2021) are confirmed.

In contrast, the effect of urbanization is positive and statistically significant. According to the coefficient, 1% increase in urbanization is associated with 0.541% increase in technical inefficiency in energy consumption. Sadorsky (2013) shows that urbanization can promote economic development and improve living situations, but it can also increase or decrease energy efficiency. The effect can

Table 6
Robustness tests.

Distance Function	(1) Gygli et al. measure	(2) CD_Gygli	(3) CD_Dreher	(4) 5-yr average_ Dreher	(5) 5-yr average_ Gygli	(6) 10-yr average_ Dreher	(7) 10-yr average_Gygli
lnLab	0.737***	0.208***	0.202***	0.643**	0.642**	0.647	0.648
	(0.122)	(0.0121)	(0.0118)	(0.255)	(0.256)	(0.400)	(0.401)
lnCap	0.0751	−0.222***	−0.220***	−0.120	−0.120	−1.135**	−1.130**
	(0.127)	(0.0136)	(0.0136)	(0.284)	(0.285)	(0.478)	(0.478)
lnGDP	−2.089***	−1.035***	−1.034***	−1.792***	−1.794***	−0.608	−0.616
	(0.175)	(0.0179)	(0.0179)	(0.393)	(0.393)	(0.596)	(0.597)
$lnLab^2$	0.0264*			0.0154	0.0151	0.0156	0.0155
	(0.0143)			(0.0309)	(0.0310)	(0.0496)	(0.0496)
$lnCap^2$	0.209***			0.193***	0.195***	0.175	0.176
	(0.0310)			(0.0670)	(0.0676)	(0.117)	(0.117)
$lnGDP^2$	0.311***			0.227**	0.229**	0.0284	0.0303
	(0.0440)			(0.0968)	(0.0974)	(0.155)	(0.156)
lnLab*lnCap	0.0162			−0.0139	−0.0142	−0.0653	−0.0653
	(0.0134)			(0.0296)	(0.0296)	(0.0481)	(0.0481)
lnLab*lnGDP	−0.0698***			−0.0287	−0.0282	0.0300	0.0299
	(0.0180)			(0.0401)	(0.0401)	(0.0609)	(0.0609)
lnGDP*lnCap	−0.226***			−0.182**	−0.184**	−0.0840	−0.0849
	(0.0339)			(0.0741)	(0.0746)	(0.125)	(0.126)
Time	−0.0511***			−0.0591***	−0.0596***	0.226	0.228
	(0.00787)			(0.0191)	(0.0191)	(0.392)	(0.392)
$Time^2$	0.00110***			0.00115***	0.00116***	−0.0107	−0.0111
	(9.51e-05)			(0.000243)	(0.000243)	(0.0632)	(0.0633)
Time*lnCap	−0.0163***			−0.0177***	−0.0178***	−0.144*	−0.144
	(0.00176)			(0.00434)	(0.00434)	(0.0875)	(0.0876)
Time*lnLab	0.00179**			0.00114	0.00113	0.0175	0.0176
	(0.000871)			(0.00203)	(0.00204)	(0.0389)	(0.0389)
Time*lnGDP	0.0187***			0.0208***	0.0208***	0.153	0.153
	(0.00202)			(0.00498)	(0.00498)	(0.101)	(0.101)
constant	14.43***	9.992***	9.972***	13.87***	13.90***	12.80***	12.82***
	(0.636)	(0.103)	(0.102)	(1.281)	(1.283)	(2.103)	(2.109)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inefficiency regression							
lnEco2	−0.403***	−0.507***	−0.479***	−0.154	−0.234	−0.305	−0.300
	(0.114)	(0.160)	(0.159)	(0.277)	(0.277)	(0.490)	(0.512)
lnEP	−1.001***	−2.002***	−2.001***	−1.423***	−1.396***	−1.804***	−1.807***
	(0.0860)	(0.171)	(0.166)	(0.228)	(0.227)	(0.482)	(0.486)
lnPop	−0.818***	−2.138***	−2.155***	−1.076***	−1.087***	−1.240**	−1.242**
	(0.111)	(0.202)	(0.198)	(0.263)	(0.261)	(0.544)	(0.546)
lnUrb	0.530***	1.793***	1.806***	0.755***	0.763***	0.929*	0.931*
	(0.107)	(0.189)	(0.186)	(0.247)	(0.245)	(0.525)	(0.526)
USigmas							
constant	−6.252***	−24.03***	−24.30***	−10.66***	−10.43***	−12.86*	−12.90*
	(1.433)	(2.626)	(2.572)	(3.315)	(3.284)	(7.506)	(7.536)
VSigmas							
Constant	−1.817***	−1.251***	−1.247***	−1.824***	−1.829***	−1.803***	−1.804***
	(0.0653)	(0.0433)	(0.0428)	(0.134)	(0.134)	(0.233)	(0.235)
Log-likelihood	−406.47982	−4780.4956	−4816.7307	−840.39377	−839.65975	−350.41926	−350.44124
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	5012	5012	5035	968	967	422	422

Note: The prefix "ln" preceding the independent variables imply that the variables are in logarithmic form. As for the inefficient factors, when the explanatory variables have a negative sign, this indicates that energy inefficiency reduces, and therefore that there is a positive link between energy efficiency and the inefficient elements. ***, **, and * signify statistical significance at the 1%, 5%, and 10% levels. The standard errors of the coefficients are represented by the figures in ().

take the form of increased economic growth and clean energy substitutes, both of which contribute to energy efficiency. Furthermore, the sharing of urban infrastructure may help either to contribute to a country's overall competitiveness and efficiency or intensity of urban infrastructure, such as public transport (Lv, Yu, & Bian, 2017), and this could negatively impact energy efficiency. In some cases, firms within the same geographic space may benefit from improved transport efficiency and reduced energy use (Sun, Edziah, Kporsu, et al., 2021).

4.2. Sensitivity Analysis of the results

So far, we have used the KOF index of economic globalization by Dreher (2006), which is limited in scope, as it does not capture diversity of trade partners, trade rules, and international reserves. This could influence the result, as those ignored factors may share meaningful correlations with the independent variables in the regression, particularly, the measure of economic globalization. To

Table 7
Regression by level of development.

Distance Function	High-Income	Upper-Middle	Lower-Middle	Low-Income
lnLab	4.173***	4.862***	0.453	−3.772***
	(0.711)	(0.726)	(0.465)	(0.895)
lnCap	2.980***	−0.145	−1.650***	0.935**
	(0.505)	(0.602)	(0.505)	(0.468)
lnGDP	−7.482***	−5.401***	0.451	4.726***
	(0.860)	(0.533)	(0.745)	(0.911)
$lnLab^2$	0.530***	0.453***	−0.0193	−0.404***
	(0.0743)	(0.0773)	(0.0686)	(0.133)
$lnCap^2$	−0.186**	0.103	−0.490***	−0.129
	(0.0762)	(0.0794)	(0.0608)	(0.0824)
$lnGDP^2$	0.683***	0.614***	−0.988***	−0.737***
	(0.103)	(0.0907)	(0.141)	(0.108)
lnLab*lnCap	0.330***	0.185***	−0.286***	−0.162**
	(0.0464)	(0.0640)	(0.0568)	(0.0652)
lnLab*lnGDP	−0.768***	−0.622***	0.291***	0.589***
	(0.0866)	(0.0528)	(0.0927)	(0.152)
lnGDP*lnCap	−0.0698	−0.155**	0.713***	0.0504
	(0.0666)	(0.0780)	(0.0725)	(0.0548)
Time	0.00707	−0.202***	−0.210***	−0.161***
	(0.0257)	(0.0385)	(0.0232)	(0.0417)
$Time^2$	0.000257**	0.000621***	0.000537***	0.000674**
	(0.000111)	(0.000172)	(0.000180)	(0.000263)
Time*lnCap	0.00668**	0.0114***	−0.00767**	−0.00780
	(0.00325)	(0.00418)	(0.00355)	(0.00496)
Time*lnLab	0.00683***	−0.0222***	−0.00841***	−1.25e-05
	(0.00240)	(0.00406)	(0.00251)	(0.00399)
Time*lnGDP	−0.00912***	0.00570	0.0268***	0.0252***
	(0.00349)	(0.00441)	(0.00396)	(0.00560)
constant	23.67***	32.78***	9.972***	−20.63***
	(3.536)	(3.647)	(0.102)	(3.368)
Country Dummies	Yes	Yes	Yes	Yes
Inefficiency regression				
lnEco2	−0.519	−0.446**	−1.200***	2.561***
	(0.355)	(0.202)	(0.208)	(0.421)
lnEP	−1.020***	−1.118***	−1.255***	0.779**
	(0.168)	(0.120)	(0.150)	(0.339)
lnPop	−2.839***	0.273	−1.983***	−1.936***
	(0.295)	(0.197)	(0.165)	(0.320)
lnUrb	2.320***	−0.312	1.532***	2.156***
	(0.298)	(0.196)	(0.154)	(0.341)
USigmas				
constant	−30.60***	4.372*	−15.72***	−36.60***
	(3.843)	(2.546)	(1.783)	(4.649)
VSigmas				
constant	−2.676***	−2.543***	−2.987***	−1.865***
	(0.0927)	(0.195)	(0.198)	(0.0991)
Log-likelihood	−761.54428	−1170.8235	−947.00256	−531.81961
Prob>chi2	0.000	0.000	0.000	0.000
Observations	1756	1461	1115	703

Note: The prefix "ln" preceding the independent variables imply that the variables are in logarithmic form. As for the inefficient factors, when the explanatory variables have a negative sign, this indicates that energy inefficiency reduces, and therefore that there is a positive link between energy efficiency and the inefficient elements. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. The standard errors of the coefficients are represented by the figures in ().

ascertain whether it matters what kind of measure is used, we re-estimated the general model using the revised economic globalization measure developed by Gygli et al. (2019). Model 1 of Table 6 contains the result. In terms of the sign of effect, the result remains very robust. The revised KOF index of economic globalization has a statistically significant and negative effect on technical inefficiency in energy consumption. In terms of size, the coefficient is marginally larger in absolute terms, suggesting KOF index of economic globalization may suffer from downward bias. This raises serious caution about previous studies' causal capabilities. Regarding the controls, the results remain very robust both in sign of direction and magnitude of effect (but with small variations).

Next, so far, we have assumed a translog production technology. While it is favored due to the desirable feature of flexibility, we may have incorrectly identified the technology. This could introduce some bias in the coefficient estimate, if actually, the true underlying technology is of a Cobb-Douglas form. To verify this, we re-estimated the model using both KOF index and revised KOF index measures of economic globalization. This is shown in Models 2 and 3 of Table 6. The effect of economic globalization remains robust as it shows statistically significant and negative effects on technical inefficiency in energy consumption. This suggests that our results are not driven by possible misidentification of the underlying technology. The control variables also remain robust in result.

So far, our estimations have assumed that technical inefficiency in energy consumption exhibits very high temporal variations across countries. This may not be true for at least some countries due to difficulty in switching between technologies and the reason that different energy users may be using different discounting factors. Moreover, business cycle effects may drive the result. To address the fact that technical inefficiency in energy consumption may not exhibit very high and rapid temporal variations, we performed a five-year and ten-year average generation regression, again using both measures of economic globalization. Models 4 to 7 in Table 6 show the results. Consistently, the effect of economic globalization (i.e. revised and unrevised versions) on technical inefficiency in energy consumption remains negative but statistically not significant. This suggests that either business cycle effects or temporal time-invariant movements in technical inefficiency in energy consumption drives the result. The control variables remain very robust.

Finally, we controlled for the level of economic development to address (1) possible heterogeneity in the effect of economic globalization and (2) assumption of homogeneity of production technologies across all countries. Table 7 shows the results for the different income classification economies. The effect of economic globalization on technical inefficiency in energy consumption is negative and statistically significant only for upper-middle and lower-middle income countries. For lower-income countries, the effect of economic globalization is positive and statistically significant. This suggests that the energy-saving effect of economic globalization is more likely in upper-middle and lower-middle income countries than in high and low-income countries. This suggests that failing to account for the level of economic development introduces heterogeneity bias in the coefficient of economic globalization.

4.3. *Energy efficiency analysis*

4.3.1. *Country-level perspective*

While the primary purpose of this research is to study the connection between energy efficiency and economic globalization, we also utilize the general model, that is 4th model in Table 5 to investigate the average economy-wide energy efficiency level of each country across the period. The overall global energy efficiency position from the study is 0.77 with efficiency estimates ranging from 0.18 to 0.95. About half of the countries have their efficiency above the mean. The top-most performing countries include the United States (0.952), Germany (0.940), Japan (0.940), France (0.939), the United Kingdom (0.932), Italy (0.928), and China (0.924). The

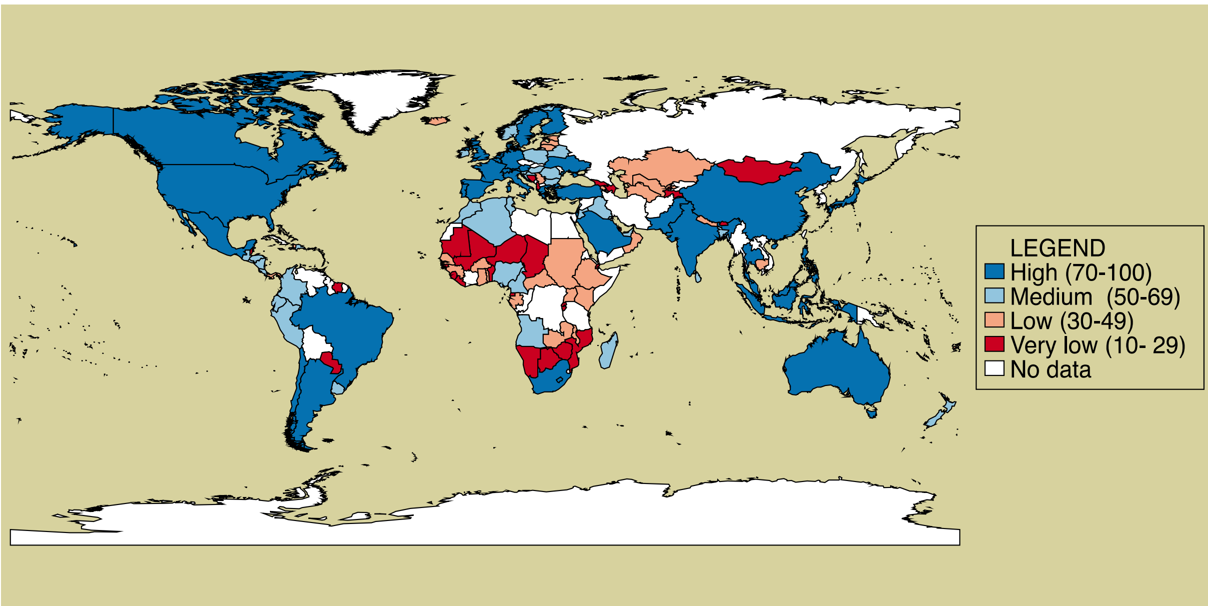

Fig. 1. Spatial distribution of energy efficiency performance.

relatively high level of energy efficiency demonstrates that these countries are making meaningful progress to catch up to benchmark technology in the short run and is coherent with previous aggregate energy efficiency results in Zhou et al. (2012) and Sun et al., 2019. The least performing countries are Equatorial Guinea (0.487), Djibouti (0.464), Paraguay (0.451), Aruba (0.443), Maldives (0.441) and Bhutan (0.185).

We use Fig. 1 to depict the spatial distribution of the energy efficiency performance of the sample countries. Geographically, it is evident that most countries with better energy efficiency are located in North and South America, Europe, and certain regions of Asia. Developed countries such as the United States, Germany, Italy, Australia, the Netherlands, Canada, Belgium, France, and Japan are located in these regions. However, some emerging economies, such as China, Indonesia, Brazil, India, Mexico, and the Philippines with higher energy efficiency are located in these regions. On the other hand, Africa, which is dominated by developing countries, several of which are energy inefficient (e.g., Sierra Leone, Rwanda, Paraguay, Burundi, Zimbabwe, Bhutan, Burundi, Chad, and Lesotho) seems to be located in this region.

4.3.2. Energy efficiency performance by level of development

Fig. 2 shows the temporal energy efficiency performance of the high-income, upper-income, lower-middle-income, and lower-income groups using the regression results in Table 7, which categorize the countries according to their level of development (i.e., low income, lower-middle income, upper-middle income, and high income). Fig. 2 shows that in the early 1980s, the high-income group had a greater energy efficiency performance than the other income groups. However, from the early 2000s, this potential fell precipitously. Compared to the other income groups, the high-income group's time trend for energy efficiency shows an undulating pattern, whereas the other income groups' time trend shows an increasing trend. More specifically, the energy efficiency of the lower- and upper-middle-income groups grew sharply over the years, with the energy efficiency of the lower-income group growing past all other income groups after the year 2000. A further point to consider is that while other income groups have experienced a downtrend since 2009, the lower income bracket continues to experience an upward trend. In summary, our results indicate that the lower-income group has enormous energy efficiency growth potential.

5. Conclusions, policy implications and further research

5.1. Conclusions

This study examined the effect of economic globalization on technical energy efficiency for a global sample consisting of 141 countries. The study addressed identification concerns related to measurement of variables, heterogeneity bias and infrequent temporal variations in the data. Our identification strategy involved using more refined measures of economic globalization and energy

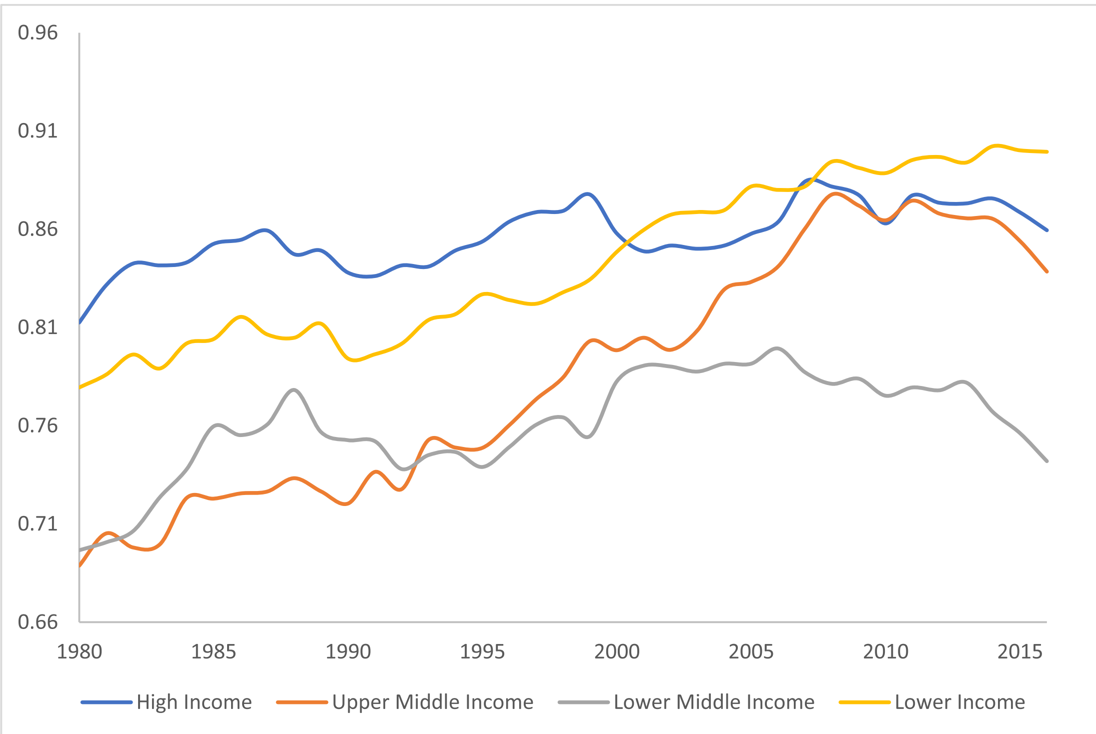

Fig. 2. Trend of energy efficiency for high-income, lower-middle income and upper-middle income group from 1980 to 2016.

efficiency; performing regressions at greater levels of time variations in the data, and running regressions for different income level groups. Our results have demonstrated that failing to account for these identification issues distorts the causal ability of economic globalization to energy efficiency. The following specific results emerged from the study:

(1) Economic globalization positively drives energy efficiency. Without accounting for the control variables, the coefficient of economic globalization suffered from upward bias, suggesting serious caution about the causal ability of existing studies. Economic globalization drives energy efficiency by promoting green and low-polluting commodities, novel production processes, technological spillover, and managerial skills to countries. The increasing number of foreign companies and the various advances in technology may potentially limit the indiscriminate use of energy resources as inputs in production lines, hence increasing energy efficiency. Thus, economic globalization that results in positive externalities such as increased R&D, new knowledge, and eco-friendly technologies due to foreign investment and trade can significantly positively affect energy efficiency.
(2) However, we note that infrequent temporal variations in the data as well as business cycle effects and heterogeneity bias do drive the result. The result showed that the energy saving potential of economic globalization is likely in upper-middle and lower-middle income countries and not in high and low-income countries, suggesting that in analyzing the effect of economic globalization on energy efficiency, the level of economic development matters.
(3) Regarding the other variables, we found that increasing the price of energy and higher population growth can bring about a meaningful reduction in energy inefficiency. The former suggests that pricing or market mechanisms can be relied upon as instruments to stimulate energy efficiency. The latter implies that economies that experience higher population growth may be benefiting from the economies of scale in the use of energy resources. However, urbanization does not promote energy efficiency.

This research also aimed to measure economy-wide energy efficiency using stochastic frontier analysis and the shepherd distance function proposed by Zhou et al. (2012).

(4) The findings show significant differences in energy efficiency performance between countries, ranging from 0.18 to 0.95 with a mean of 0.77, indicating that energy efficiency can be improved. In other words, 23% of global energy consumption could be saved.
(5) High-income countries such as the United States, Germany, Japan, and France lead in terms of country-level variations in energy efficiency performance. In contrast, low-income countries' average energy efficiency performance is very low, particularly in Chad, Djibouti, Burundi, Equatorial Guinea, Rwanda, Paraguay, Aruba, Maldives, and Bhutan.
(6) Given the high levels of technical energy inefficiency in the lower-income group, our findings indicate that this income group has a comparatively large opportunity for energy savings.

5.2. Policy implications

Considering these outcomes, we recommended the following policy implications to help improve energy efficiency and reduce energy-related carbon emission reduction across the globe:

(1) Most countries have become more globalized in recent years, and some stand to benefit from the new technologies that this trend has spawned. As a result, policymakers should not fret over the potentially adverse effects of globalization on energy consumption and the environment. Governments should work to promote globalization by opening up to and attracting foreign investment. These investments will bring cutting-edge methods of production, advanced industrial technology, and fresh perspectives to the home country.
(2) Furthermore, given the ease with which climate change information and awareness are already available, it appears that the positive environmental consequences of globalization will outweigh the negative.
(3) In addition, the growing adoption of corporate globalization will ensure that firms become more active in transferring clean technology from industrialized to underdeveloped countries.
(4) Evidence that improved energy efficiency has been linked to a growth in energy prices should provide empirical backing for the government's decision to cut subsidies for energy services to increase energy efficiency.
(5) There is still an opportunity to advance energy efficiency globally, as the average potential energy savings score is 23%. Because the efficiency value derived by the SFA model is relative, no country has achieved a level of energy efficiency that is completely efficient. All countries, particularly emerging ones, should improve their industrial production to make it more energy-efficient. For example, increasing awareness, facilitating information dissemination, and strengthening capacity for promoting energy efficiency measures and systems in the industrial sector can contribute to overall energy efficiency improvement. More importantly, it is critical to foster energy conservation and CO_2 emission reduction in industries that consume a lot of energy and emit pollution.

5.3. Future research

(1) The current study presents important lessons on identification issues connecting energy efficiency to economic globalization. Specifically, it highlights the need to control for temporal variation in the data, heterogeneity bias and business cycle effects, as these can influence the causal ability of economic globalization to energy efficiency.
(2) While the current study seems to have shown the relationship between economic globalization and energy efficiency, further analysis of the mechanism of the impact of economic globalization and energy efficiency may be useful for future studies.
(3) It would be exciting to read a future study investigating the implications of various forms of globalization (for example, social, political, economic and overall globalization) on efficiency from a global point of view.
(4) Future work on this topic could use time-series analysis to investigate the outcomes of economic globalization on energy efficiency in highly industrialized and emerging countries like China, Russia, Brazil, and India.

Declaration of Competing Interest

We confirm that this research is our original work, including all materials and data obtained during the study, and that it is free of plagiarism. Additionally, we can confirm that the article has not already been published or considered by another journal.

Data availability

Data will be made available on request.

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