Socio-Economic Productive Capacities and Energy Efficiency: Global Evidence by Income Level and Resource Dependence

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Abstract

This study tests the effects of productive capacities in socio-economic factors (human capital, transport, information-communication technology, institutions, private sector, and structural change) on energy efficiency in a sample of 125 countries. Energy efficiency is assessed by energy productivity (gross domestic product per unit of total primary energy supply) and energy intensity (total primary energy supply per capita). The world sample is divided into four income groups and an income-heterogeneous control group of non-renewable resource-dependent economies. The study utilizes cross-sectionally dependent and stationary panel data over the period 2000-2018. The analysis of variance shows that higher income groups monotonically have higher productive capacities and energy intensity. The regression results from appropriate fixed-effects and random-effects modeling reveal varied driver and barrier influences of the socio-economic factors on energy efficiency improvements (higher energy productivity and lower energy intensity). In some cases, predictors scale up both energy productivity and energy intensity indicating the issue of the rebound effect. Higher human capital capacity stimulates energy efficiency except for middle-income groups. Higher transport capacity reduces energy productivity, except for upper-middle-income economies, and tends to increase energy intensity for low-income and middle-income groups. The deployment of information-communication technologies is positively associated with energy productivity, except for low-income economies. Energy productivity performance of resource-dependent economies is improved by higher productive capacities in institutions and private sectors but impaired by structural change, whereas structural change drives energy efficiency in low-income economies. Additionally, the growth of gross national income per capita worsens energy efficiency for resource-dependent economies. Bidirectional feedback causalities are established between energy efficiency and its predictors in most cases. The heterogeneous findings are discussed for providing research and policy implications.

Introduction

Economic growth of resource-scarce industrialized economies has been threatened by increasing cost of energy shocks (Esseghir and Khouni 2014; Velasco-Fernández, Dunlop, and Giampietro 2020), while some resource-abundant developing economies have been facing varied challenges of overdependence on non-renewable energy resources (Havranek, Horvath, and Zeynalov 2016; Zallé 2019). According to global trends in energy efficiency (OECD 2021) and economic growth (UNCTAD 2021a; World Bank 2021) data after the 1970s' oil crises, some industrialized countries have been getting economic growth benefits from energy productivity improvements, albeit at an insufficient level, while economic activities in many resource-abundant developing countries have been yet heavily relying on the extractive resources. Despite the well-evidenced fact that ecological problems driven by the depletion of energy resources and relevant environmental pollution have been exerting great pressure on the world economy, both production and consumption of the world have been increasingly demanding more energy. Furthermore, world energy production still largely depends on non-renewable fossil sources with a steady share of about 80%.

Global energy projections foresee neither a persistent decrease in the demand for energy nor a precise transition to renewable energy in the coming decades (IEA 2019; IEA 2020). From the policy perspective on the world's energy future, the International Energy Agency's (IEA) current policies scenario reveals that energy demand rises by 1.3% each year from 2018 to 2040, if the world continues along with its present policies. In this scenario, the demand for energy will increase by about 34% from 14,314 million tons of oil equivalent in 2018 to 19,177 million tons of oil equivalent in 2040, followed by an about 24% increase in carbon dioxide (CO₂) emissions from 33.2 gigatons in 2018 to 41.3 gigatons in 2040 (IEA 2019). In line with the recognition of these stylized facts, many local and global energy policies have been prioritized to conserve energy resources and mitigate environmental degradation. These global efforts can be broken down into two essential groups: A renewable energy transition to adopt low carbon clean

alternatives to fossil energy (Murshed 2020; Altinoz and Dogan 2021; Nathaniel, Yalçiner, and Bekun 2021) and an overall improvement of energy efficiency as higher energy productivity and lower energy intensity (Sutherland 1994; Dunlop 2019; Goh and Ang 2020; Irfan 2021).

Energy efficiency is about less energy usage while both producing and consuming goods and services. Given the limited availability of non-renewable energy resources and the shortcoming of renewable energy supply, energy efficiency brings a variety of economywide and worldwide benefits by reducing the depletion of energy sources and environmental problems. More recently, energy efficiency is also linked to environmental quality and examined by taking both social and economic factors into account. Therein, widely examined socio-economic factors include structural change, globalization, institutional quality, technological advancement and innovation, population dynamics and household demographics, urbanization, environmental agreements, energy policies, cultures, customer preferences, education, enterprise characteristics, and so on for individual countries and different country groups (Neumayer 2002; Cornillie and Fankhauser 2004; Hang and Tu 2007; Liddle 2014; Martinez 2016; Atalla and Bean 2017; Sineviciene, Sotnyk, and Kubatko 2017; Nyangon and Byrne 2021).

An increasing number of studies have examined empirically the potential determinants of energy productivity and energy demand, as well as energy consumption, with a specific interest in the environmental degradation and carbonization effects of economic growth and income (Chang 2015; Atalla and Bean 2017; He and Lin 2019). Relatively fewer studies have considered socio-economic determinants such as human capital (Zallé 2019; Nathaniel, Yalçiner, and Bekun 2021), transport and logistic performance (Liu et al. 2018; Li et al. 2021), digital transformation and information-communication technology advancement (Sadorsky 2012; Schulte, Welsch, and Rexhäuser 2016; Yan, Shi, and Yang 2018), institutional quality (Castiglione, Infante, and Smirnova 2015; Sun et al. 2019; Azam, Liu, and Ahmad 2021), private sector and business environment (Chang 2015; Rieger 2019), and structural change (Nepal, Jamasb, and Tisdell 2014; Atalla and Bean 2017; Sineviciene, Sotnyk, and Kubatko 2017). These studies, however, tend to suffer from the missed effects as they do not capture the overall impacts of the exogenous socio-economic factors due to omitted variables and one-data measures.

Conventionally, energy efficiency is measured by either energy productivity (output per energy supply) or its inverse, i.e., energy intensity (energy supply per output) (Goldemberg 1996; UNIDO 2011; IEA 2019). Consistently, most of the relevant studies consider only either energy productivity (Atalla and Bean 2017; Yan, Shi, and Yang 2018) or energy intensity and energy consumption (Chang 2015; Murshed 2020) relying on the reverse meaning. This approach, however, does not capture potential rebound (take-back) effects, which indicates that more energy may be consumed because of the financial gains enabled by the energy productivity increase (Galvin 2015; Nyangon and Byrne 2021). The rebound effect is important as it can occur when one factor increases both energy productivity and energy intensity, showing that the improvement of the overall energy efficiency will be more difficult than commonly assumed by the contested suggestions of the current oversimplified approaches. Global energy demand also depends upon the preferences of the population and the economic decisions of business organizations and individuals. Thus, energy efficiency measured by output per energy supply or its inverse ignores the consumption side of energy and fails to fully capture the overall energy efficiency performance of countries. The existing studies cover individual countries (Takase and Murota 2004; He and Lin 2019; Nyangon and Byrne 2021) or some groups of countries classified by region (Esseghir and Khouni 2014; Liu et al. 2018; Li et al. 2021), income level/ development stage (Chang 2015; Sun et al. 2019), or some economic blocs such as OECD (Schulte, Welsch, and Rexhäuser 2016) and BRICS (Nathaniel, Yalçiner, and Bekun 2021), which do not provide world evidence.

The review of extant literature explains that available empirical evidence is scarce and blurry and thus obstructing the identification of a common set of determinants and limiting the preparation of policies. We believe that this is due to

the need to pay more attention to socio-economic factors. By addressing the interdependence of energy efficiency and productive capacities, we suggest that productive capacities in socio-economic factors may be affecting the energy efficiency performance of countries by also interacting with their income level and resource dependence. From the socio-economic and socio-technical perspective, most of the previous studies, notably cross-country research, miss the problem of the co-existence of unobservable latent effects which can be captured indirectly by using multidimensionally constructed index-based measures. Thanks to the world level availability of the internationally comparable and harmonized Productive Capacities Index (PCI) metrics provided by the United Nations Conference on Trade and Development (UNCTAD), the present study examines the impacts of productive capacities in human capital, transport, information-communication technology (ICT), institutions, private sector, and structural change on energy efficiency for a world sample of 125 countries. The study distinctively contributes to the literature in mainly three respects. First, it considers both energy productivity (output per energy supply) and energy intensity (energy supply per capita) dimensions of energy efficiency. This distinction enables the exploration of potential rebound effects which also explain some of the ambiguity and controversiality of the existing evidence. Second, unlike most of the previous work, this study adopts a holistic approach and uses multidimensionally constructed composite indices of socio-economic factors. Third, it covers the world sample and provides evidence for specific country groups designated by both income level and resource dependence, the latter of which extends the implications of the resource curse hypothesis to the energy efficiency context.

In the rest of the study, the next section defines energy efficiency and socio-economic productive capacities and explains their measurements. After we outline our review of the most relevant literature, we describe country sampling and econometric modeling of the study. The section devoted to analyses and results begins by presenting descriptive results, then inspects cross-sectional dependence and stationarity of series, and ends with sequent analyses including analysis of variance, regression analysis, and causality test. Finally, the last section concludes with a discussion of findings and study limitations to give some policy and research insights.

Definitions

Energy efficiency

The concept of energy efficiency is multidimensional and represented in diverse fields. Regardless of which discipline defines, energy efficiency simply means the use of less energy to produce the same or more quantity of output (Dunlop 2019; Goh and Ang 2020; Velasco-Fernández, Dunlop, and Giampietro 2020). Therefore, it can be simply measured by a ratio of output to energy input. This indicator can be used interchangeably with energy productivity, especially at the macro-level. Energy use per output, i.e., the inverse of energy productivity, is widely recognized as energy intensity (Cornillie and Fankhauser 2004; Takase and Murota 2004; Atalla and Bean 2017). In practice, either energy productivity or energy intensity is often taken as a proxy for energy efficiency (Cornillie and Fankhauser 2004; Goh and Ang 2020). These output measures, however, are insufficient as they ignore the consumption side.

Unlike the one-indicator studies, we assess energy efficiency by considering both energy productivity and energy intensity. From a production-side perspective and within an energy supply approach, energy productivity is, as usual, proxied by gross domestic product (GDP) per unit of total primary energy supply (TPES). However, we have gauged energy intensity as TPES per capita, not per GDP, to control for the energy consumption patterns of societies, i.e., the ways people use energy to do things to meet their needs. TPES is defined as production and imports of energy minus energy exports and international bunkers, plus or minus stock changes (OECD 2017; OECD 2021).

This distinction helps in capturing the difference between the productive use of energy sources (increased energy productivity) and the use of fewer energy resources (declined energy intensity) (Sutherland 1994). According to these descriptions, a country may increase energy productivity by either producing more at the same energy use or using less energy for the same production, or both. Energy intensity can be reduced by reducing overall energy-related consumption or changing consumption behaviors towards more energy-efficient products. Based on these conditions, the present study combines higher energy productivity and lesser energy intensity with overall energy efficiency to better track the potential rebound effects.

Productive Capacities

Large-sample studies lack internationally comparable data of socio-economic capacities. However, recently, the UNCTAD (2021a, 2021b) provides the Productive Capacities Index (PCI) relying on the premise that productive capacities are essential for generating inclusive economic growth and achieving sustainable development. As the leading initiative to measure productive capacities multidimensionally in all economies, the PCI measures enable us to evaluate how much productive capacity has been utilized or untapped in countries. The PCI initiative can also help policy-makers formulate energy efficiency policies and benchmark their achievements. The PCI metrics vary between 1 (the lowest productive capacity) and 100 (the highest productive capacity). The PCI project currently covers 193 economies for the period 2000–2018 based on 46 indicators (UNCTAD 2021a). The overall PCI is further divided into some categories, which, among others, are shown in Table 1.

Table 1
Selected categories of UNCTAD productive capacities

Categories	Coverage
Human capital (<i>PCIhc</i>)	The education, skills, and health conditions of the population; research and development expenditures; the number of researchers, and fertility (higher fertility rate reduces human capital score).
Transport (<i>PCItr</i>)	The availability and quality of roads and railway networks and air connectivity to transport people or products between destinations.
ICT (<i>PCIitc</i>)	The accessibility, integration, use, and security of communication systems and servers (fixed-line and mobile phones, and internet accessibility) within the population.
Institutions (<i>PCIins</i>)	Political stability; regulatory quality; success in fighting criminality, corruption, and terrorism, and safeguard of citizens' freedom of expression and association.
Private sector (<i>PCIps</i>)	The ease of international trade (time and monetary costs to export and import); the support to business in terms of domestic credit; velocity of contract enforcement; and time required to start a business.
Structural change (<i>PCIsc</i>)	The movement of resources from low to high productive economic activities both within and between sectors. This shift is captured by the sophistication and diversification of exports, the intensity of fixed capital, and the shares of industry and services in domestic production.
<i>Source:</i> UNCTAD (2021a) (2021b)	

Relevant Literature

Many studies have contributed to the evaluation of energy efficiency performance using different indicators and analytical techniques within both the country-level and multi-country empirical settings. In these studies, income level is one of the widely used predictors of energy efficiency. Higher per capita income, on the one hand, can provide possibilities for investing in new technologies which improve energy efficiency while, on the other hand, it increases the energy demand. As the relative importance of the contradictory income effects tends to vary across countries, the existing literature does not provide a consensus on the nexus between income and energy efficiency. An analysis by Chang (2015) on a sample of 53 countries for the period 1999–2008 shows that energy consumption increases with the income growth in relatively lower-income emerging and developing economies, while energy consumption pattern changes in high-income advanced economies depending on different levels of income. Atalla and Bean (2017) investigate the drivers of energy productivity (output per unit of energy use) changes in 39 countries during 1995–2009 and find that higher income is associated with greater energy productivity improvement. Sineviciene, Sotnyk, and Kubatko (2017) identify GDP growth as a key factor increasing both energy efficiency and energy consumption for the panel of 11 post-communist countries in Eastern Europe during 1996–2013. Azam, Liu, and Ahmad's (2021) results reveal that GDP growth increases energy consumption as well as environmental pollution. The EKC hypothesis premises that when the level of economic development is high, people begin to pay more attention to environmental protection. Within the EKC framework, environmental degradation is sometimes measured by proxies of energy intensity. For example, based on the 2003–2017 data of China's provinces, He and Lin (2019) find that the income elasticity of emission pollution is positive (negative) when the energy intensity is higher (lower). Besides, as found by Esseghir and Khouni (2014) for 38 Union for the Mediterranean countries from 1980 to 2010, energy use and economic growth may also be related bidirectionally. Furthermore, energy consumption may cause income growth as discovered by Soytaş and Sari (2003) in the cases of Turkey, France, Germany, and Japan.

To the best of our knowledge, there is no study using PCI metrics to measure socio-economic indicators and examine their impacts on energy efficiency. Yet, the most relevant body of the literature has been reviewed to highlight the potential contributions of this study.

Although it is well known that resource distortions mainly emanate from human activities, studies on energy efficiency have little considered the impact of human development. The human capital level of societies is important not only for their consumption but also for their producers as companies have their owners and employees from the population. More specifically, well-educated people (consumers) know better how and why to save energy, which is important in especially resource-dependent countries. Zallé (2019) analyzes data from 29 countries from 2000 to 2015 and shows that investing in human capital helps in turning the curse of natural resources into a blessing. Meanwhile, resource dependence can also worsen human capital, albeit raising physical capital, as evidenced by Blanco and Grier (2012) for 17 Latin American countries during the 1975–2004 period. Nathaniel, Yalçiner, and Bekun (2021) show that human capital does not mitigate environmental deterioration and find a feedback causality between human capital and ecological footprint for BRICS (Brazil, Russia, India, China, South Africa) countries. Based on the analysis covering the 1992 to 2016 period, Pata, Aydin, and Haouas (2021) verify that resource abundance damages the environment but human development lowers environmental pollution for 10 countries with a large ecological footprint.

The relevant literature focuses on the improvement of energy efficiency in transport and logistics services by addressing the substantial portion of transport-induced environmental pollution. The transport effect on energy efficiency is not clear since transport itself is an energy-intensive sector with a high share (around 28% for the 2000–

2018 period) in final energy consumption in the world (IEA 2010; IEA 2020). Li et al.'s (2021) study find complex results for different country groups over the period 2007–2019. Their findings reveal that green logistics performance enhances the environmental pollution in One Belt and Road Initiative countries, Central Asia, and the Middle East and North Africa economies while it improves the environmental quality in Europe and East and Southeast Asia regions. These variations are also observed between the dimensions of transportation and logistics performance. For example, a study by Liu et al. (2018) uses data from 42 Asian countries between 2007 and 2016 and reveals that international shipment in logistics performance decreases CO₂ emissions while timeliness of logistics intensifies the CO₂ emissions.

The access to digital systems and ICT devices has been growing worldwide. The spread of ICT use has set great expectations of energy efficiency improvement relying on the ICT-induced changes in social practices and socio-technical structures (Galvin 2015). However, the energy efficiency contribution of ICT adoption is questionable because of the co-occurrence of its absolute energy intensity effects and the relative energy productivity effects. For the first effect, the internet and the production, usage, and disposal of ICT goods directly consume energy. The facilitation of ICT development and sustainment of digital utilities also require energy-intensive large infrastructures. The second effect is about the channels through which the ICT-driven digital transformation may increase the total factor productivity, and stimulate the transition to a service economy by replacing energy-inefficient production technologies and energy-intensive obsolete communications systems (Galvin 2015; Lange, Pohl, and Santarius 2020), while ICT-led digital transition again needs more energy. For the income channel of rebound effect at both individual and country level, additional income generated through ICT-enabled energy productivity may lead to an increase in the energy demand (Takase and Murota 2004). Thus, the net energy efficiency effect of ICT remains conditional on the relative importance of the contradictory sequent effects. Salahuddin and Alam (2016) show that ICT use stimulates electricity consumption in OECD countries during the period 1985–2012. However, using a 13-year and 27-industry dataset of 10 OECD countries Schulte, Welsch, and Rexhäuser (2016) find that ICT development is associated with a significant reduction in total energy demand. Based on a panel dataset of 50 economies over the 1995–2013 period, Yan, Shi, and Yang (2018) conclude that ICT development is significantly related to energy productivity improvement. Adopting an ICT trade approach and using the post-2000 data of South Asian countries, Murshed (2020) shows that ICT trade reduces energy intensity. On the contrary, for emerging economies, Sadorsky (2012) ascertains a positive relationship between the use of ICT components and electricity consumption. On the equivocality of evidence, Takase and Murota (2004) compare two high-income countries and find that the promotion of information technologies conserves more energy in Japan, whereas it leads to increases in energy use for the United States. ICT adoption also interacts with the institutional framework and together mediate the relationships between resource abundance and economic growth. For example, utilizing data from 1984 to 2016 for 43 Organization of Islamic Cooperation countries, Erum and Hussain (2019) demonstrate that ICT diffusion determines the impacts of corruption on economic growth. They affirm that natural resources impede economic growth in countries with low ICT competence, whereas the nexus is positive in high ICT diffusion countries.

It is long argued that well-governed state intervention, strong institutions, and good democracy, which are tightly correlated, are necessary conditions to increase the environmental awareness of societies and the efficacy of environmental policies (Neumayer 2002; Castiglione, Infante, and Smirnova 2015). This mechanism is also true for energy efficiency performance within the institutional theory (Neumayer 2002; Ward 2008; Azam, Liu, and Ahmad 2021), which argues that environmental problems have socio-economic and anthropocentric causes and effects at both the organizational level and country-level (Hoffman and Jennings 2015). Over the period 1996–2010 for 33 high-income countries including advanced, emerging, and former-transition economies, Castiglione, Infante, and Smirnova (2015) confirm a negative link between the enforcement of the rule of law and environmental pollution.

Natural resource-rich developing countries tend to suffer from slow economic growth and development, which are commonly attributed by the resource curse hypothesis to lower institutional quality. Consistently, based on an analysis covering the 2000–2015 period, Zallé (2019) finds better control of corruption as an appropriate policy action to take advantage of natural resources in African countries. A study by Sun et al. (2019) ascertains a significant contribution of institutional quality on energy efficiency enhancement in a large sample of developed and developing countries between 1990 and 2014. Ozturk, Al-Mulali, and Solarin (2019) also confirm that better control of corruption enhances the energy efficiency for all income groups of 60 countries for the period of 2000–2017. By conducting a patent analysis for large multinational companies in the energy, water, and land resources fields in Europe, Japan, and the United States over the period 2002–2017, Aldieri, Makkonen, and Vinci (2020) find that institutional quality enhances the technical efficiency of firms through a transition from more to less pollutive technologies. Some studies, albeit fewer, find the disconnection and even undesired association between environmental quality and institutional quality. For example, using panel data of 61 countries from 2003 to 2016, Akhbari and Nejati (2019) show that corruption and anti-corruption do not affect carbon emissions in developed countries. Furthermore, using data from 66 developing countries between 1991 and 2017, Azam, Liu, and Ahmad (2021) determine institutional quality leading to increases in environmental pollution caused by energy consumption.

In the business literature, organizational commitment to energy efficiency practices is no longer seen as a hindrance in reaching business targets. In this micro-level win-win approach, coherent incorporation of environmental responsibility into economic goals benefits both business and the environment (Porter and Van der Linde 1995; Shrivastava 1995; Ambec and Lanoie 2008; Brinkerink, Chegut, and Letterie 2019; Aldieri, Makkonen, and Vinci 2020). However, market failures, the lack of finance, inadequate policy framework, and insufficient energy infrastructure continue to set barriers to investment in energy efficiency and therefore government supports are needed to facilitate private investment in energy efficiency. Meanwhile, whether private companies become (voluntarily) or made (by governmental policies) more energy-efficient is a longstanding debate. In the context of intrinsic versus extrinsic motivation, as it is widely believed that governments are responsible to cope with environmental problems, most of the literature has focused on the impacts of environmental policies, rather than the possible direct impact of the development of the private sector. In the empirical studies, the development of private sectors is represented by different indicators including financial development, stock market performance, and business environment. As a country-specific study, Rohdin, Thollander, and Solding's (2007) questionnaire analysis shows that respondents from the Swedish foundry industry perceive the limited access to capital as the most important barrier to energy efficiency. Chang (2015) analyzes a sample of 53 countries for the period 1999–2008 and explores that energy consumption increases with both private and domestic credit that are used as financial development indicators. Rieger (2019) determines pro-business regulations raising CO₂ emissions in developing countries during the 2005–2014 period. Besides the importance of the overall size of the private sector, the expansion of companies also matters for their energy efficiency based on the economy of scale argument. For example, Brinkerink, Chegut, and Letterie (2019) show that Netherlands' manufacturing industries become more energy-efficient after their large capital expenditures over the 2000–2008 period. Martinez (2016) also shows that enterprise size has a positive influence on energy efficiency among German and Colombian non-energy intensive sectors between 1998 and 2005. The international trade theory and international business literature suggest that exporting encourages energy-saving innovation at both country and firm levels. Consistently, Montalbano and Nenci (2019) provide some evidence supporting the 'learning energy efficiency by exporting' paradigm in some cases of a large sample of firms located in 30 Latin American and Caribbean countries. It is also important to note that the economic performance of companies is obstructed by environmental problems (Soppelsa, Lozano-Gracia, and Xu 2021) and improved by the commitment to environmental protection (Efobi et al. 2019), which together favor the win-win strategy.

Structural change, which is commonly evaluated by the comparisons of sectoral shares in the national economy, plays a decisive role in energy efficiency. For the transition economies, structural change also contains a transformation from central planning to marketization. Cornillie and Fankhauser (2004) show that progress in enterprise restructuring is an important driver for more efficient energy consumption of the transition economies of Central and Eastern Europe and the former Soviet Union. Similarly, for the 1990–2010 period of a group of the transition economies, Nepal, Jamasb, and Tisdell's (2014) study confirms that transition reforms improve energy efficiency. Studies often support the suggestion that industrial production, on average, is less energy-efficient than the service sector. For example, Sineviciene, Sotnyk, and Kubatko (2017) demonstrate that structural change determined by industry share in the national economy (industrialization), significantly decreases energy efficiency for the Eastern European post-communist countries during 1996–2013. Consistently, Atalla and Bean (2017) verify that economic shifts away from industry to service-led sectors improve overall energy productivity, and growth of industrial production lowers energy productivity in 39 countries during 1995–2009. On the other hand, further structural change may also counterbalance the previous contribution of structural change. For example, during the period 2006–2015 in Italy, Trotta (2020) show that energy savings enabled by reduced energy consumption in the traditional industrial, transport, and agricultural sectors are partially offset (rebound effect) by energy intensity increases in the freight transport, services, and residential sectors.

The review of the literature outlines that the findings are heterogeneous and sensitive to the proxies and measures as well as to samples and methods. Notwithstanding the ever-growing literature, there is still a lack of empirical studies investigating the socio-economic determinants of energy efficiency at the world level along with some country groups designated by income and resource dependence. Although the theory strongly suggests that improvements of productive capacities in the involved socio-economic factors provide mechanisms to foster environmental performance, the existing evidence particularly on energy efficiency indicators calls for more proof.

Sample And Model

After excluding some countries with missing data and significant outliers, the study covers a world sample of 125 economies over the period 2000–2018. These countries have been distinguished between four income groups based on gross national income (GNI) per capita converted to current United States dollars (USD) using the World Bank's Atlas method. However, changes in economic growth, inflation, exchange rates, population, as well as methodological revisions to national accounts influence GNI per capita. Therefore, the World Bank updates the per capita GNI thresholds annually to keep the income levels fixed in real terms (World Bank 2021).

Large sample panel studies with different income groups usually take the available country classification in a given year by ignoring the movements of some countries to different (upper or lower) income categories within the examined period. The periodical averages of the annual thresholds are shown in Table 2, where it is seen that the annual income thresholds changed considerably from 2000 to 2018. The consideration of these updates and between-groups movements is important for capturing individual consumption behaviors, especially in our energy intensity case. Therefore, we have regrouped countries by GNI per capita based on the average income thresholds of the examined period (2000–2018).

Table 2
Historical updates in the Atlas GNI per capita thresholds (current USD)

Period Group	2000–2004 avg.	2005–2009 avg.	2010–2014 avg.	2015–2018 avg.	2000–2018 avg.*
LIEs	< 766	< 938	< 1,032	< 1,014	< 933
LMIEs	766-3,039	938-3,713	1,032-4,069	1,014 – 3,970	933-3,683
UMIEs	3,040 – 3,099	3,714 – 11,479	4,070 – 12,569	3,971 – 12,285	3,684 – 11,388
HIEs	> 9,399	> 11,479	> 12,569	> 12,285	> 11,388
* The study's country grouping is based on the average income thresholds of the 2000–2018 period.					

Source

Elaboration on World Bank (2021) data archive.

The resource endowment theory indicates that the natural resource abundance of countries affects their environmental performance. Empirically, it means that resource abundance should be reflected in cross-country studies (Altinoz and Dogan 2021). On the other hand, it is well evidenced that resource abundance does not necessarily mean resource dependence (Havranek, Horvath, and Zeynalov 2016; Hailu and Kipgen 2017; Shahbaz et al. 2019). Combining the resource abundance and resource dependence, we have designated a specific country group of non-renewable natural resource-dependent economies (NRDEs) by taking three criteria into account. Firstly, the countries are in the resource-rich group in the classification of IMF (2012), which defines a country to be resource-rich when the country has at least 20% share of either natural resource revenue in total fiscal revenue or natural resource exports in total exports. The classification of IMF is based on the average of the 2006–2010 period which fits well the average of the period (2000–2018) of our study. Secondly, we have considered the extractives dependence index (EDI) introduced by Hailu and Kipgen (2017) and measured by the economic dependence of countries on the extractive sectors consisting of oil, gas, and mineral resources. Countries in our NRDEs group have an extractives dependence index greater than 20. Hailu and Kipgen (2017) constituted the EDI compositely based on the share of export earnings from extractives in total export earnings, the share of the revenues from extractives in total fiscal revenue, and the extractive industry value-added in GDP. We have referred to the most recent (2011) EDI values. Lastly, we have also considered the revealed comparative advantage (RCA) indices (greater than 2) and net export (positive) in crude oil (petroleum) and natural gas sectors, computed based on the UNCTAD (2021a) data as an average of the 2000–2018 period. Consequently, our NRDEs are both resource-abundant and resource-dependent as well as they have both higher comparative advantage and positive net export in at least one of oil and natural gas resources. The final sampling of countries by income level and resource dependence are shown in Table 3.

Table 3
Country sub-samples of the study

<p>Low-income economies (LIEs) (12 countries)</p> <p>Bangladesh, Cambodia, Dem. Rep. of the Congo, Ethiopia, Kenya, Kyrgyzstan, Mozambique, Niger, Tajikistan, Tanzania, Togo, Zimbabwe</p>
<p>Lower-middle-income economies (LMIEs) (27 countries)</p> <p>Angola, Benin, Bolivia, Cameroon, Côte d'Ivoire, Egypt, Ghana, Haiti, Honduras, India, Indonesia, Lao People's Democratic Republic, Moldova, Mongolia, Morocco, Nicaragua, Nigeria, Pakistan, Philippines, Rep. of Congo, Senegal, Sri Lanka, Ukraine, Uzbekistan, Viet Nam, Yemen, Zambia</p>
<p>Upper-middle-income economies (UMIEs) (48 countries)</p> <p>Albania, Algeria, Argentina, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Croatia, Dominican Republic, Ecuador, El Salvador, Equatorial Guinea, Gabon, Georgia, Guatemala, Hungary, Iran, Jamaica, Jordan, Kazakhstan, Latvia, Lebanon, Lithuania, Malaysia, Mauritius, Mexico, Namibia, North Macedonia, Panama, Paraguay, Peru, Poland, Romania, Russia, South Africa, Suriname, Thailand, Tunisia, Turkey, Turkmenistan, Uruguay</p>
<p>High-income economies (HIEs) (38 countries)</p> <p>Australia, Austria, Bahrain, Belgium, Brunei Darussalam, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Iceland, Ireland, Israel, Italy, Japan, Rep. of Korea, Kuwait, Luxembourg, Malta, Netherlands, New Zealand, Norway, Oman, Portugal, Saudi Arabia, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Trinidad and Tobago, United Arab Emirates, United Kingdom, United States</p>
<p>Non-renewable natural resource-dependent economies (NRDEs) (33 countries)</p> <p>Algeria, Angola, Azerbaijan, Bahrain, Bolivia, Botswana, Brunei Darussalam, Cameroon, Chile, Rep. of Congo, Dem. Rep. of Congo, Côte d'Ivoire, Equatorial Guinea, Gabon, Ghana, Indonesia, Iran, Kazakhstan, Lao People's Dem. Rep., Mexico, Mongolia, Niger, Nigeria, Norway, Oman, Peru, Russia, Saudi Arabia, Suriname, Trinidad and Tobago, United Arab Emirates, Yemen, Zambia.</p>

Our study proposes that productive capacities, measured by the productive capacities index (PCI), as well as GNI per capita (*GNIpc*) affect energy efficiency represented by energy productivity (*EnProd*) and energy intensity (*EnInt*). After disaggregating the components of PCIs into human capital (*PCIhc*), transport (*PCItr*), ICT (*PCIict*), institutions (*PCIins*), private sector (*PCIps*), and structural change (*PCIsc*) and including a regression constant (α_0) and an error term (u), the final panel regression model takes the following form in Eq. 1.

$$\begin{aligned}
 (EnProd_{c,t}); (EnInt_{c,t}) = & \alpha_0 + \beta_1(GNIpc_{c,t}) + \beta_2(PCIhc_{c,t}) + \beta_3(PCItr_{c,t}) + \beta_4(PCIict_{c,t}) \\
 & + \beta_5(PCIins_{c,t}) + \beta_6(PCIps_{c,t}) + \beta_7(PCIsc_{c,t}) + e_c f_t + u_{c,t}
 \end{aligned} \quad (1)$$

where, c shows countries ($c = 1, \dots, 125 = C$) and t denotes yearly time units ($t = 2000, \dots, 2018 = T = 19$), while f is the latent common factors with e varying effects. Finally, β_k ($k = 1 - 7$) parameters are the coefficients to be estimated. Energy productivity (*EnProd*) is measured by GDP per unit of TPES as thousand USD at constant (2015) prices. The constant (real) term better measures the true productivity by adjusting for the effects of price inflation. Energy intensity (*EnInt*) is gauged by TPES per capita as tons of oil equivalent. The data of both energy efficiency indicators are taken from the environment database of OECD (2021). GNI per capita (*GNIpc*) is measured as current USD per capita (thousand) based on the Atlas method which better captures living standards. *GNIpc* and PCI datasets are taken from the World Bank (2021) and UNCTAD (2021a), respectively. The regression model in Eq. 1 is estimated for the world sample and five sub-sample panels.

Analyses And Results

Descriptive statistics and correlations

Summary descriptive statistics of variables and Pearson correlation coefficients are reported in Table 4. At the world level, over the covered period, the mean *EnProd* is 9.271 thousand USD per unit of TPES varying between 28.784 (in the year 2018 of Malta from HIEs) and 1.347 (in the year 2003 of Turkmenistan from UMIEs). The mean value of *EnInt* is 2.459 tons of oil equivalent with a maximum value of 18.241 (in the year 2018 of Iceland from HIEs) and a minimum value of 0.113 (in the year 2011 of Niger from LIEs and NRDEs). The highest *GNlpc* (104.560 USD) is that of Norway (in 2014), while Ethiopia has the lowest *GNlpc* (110 USD in 2000).

PCI scores considerably change across sub-samples as well. The Republic of Korea has the highest (89.128 in 2018) *PCIhc* score, whereas Niger has the lowest index (18.661 in 2000). The United States (47.960 in 2007) and Niger (4.002 in 2001) have, respectively, the highest and lowest *PCltr* scores. For *PClict*, Iceland (32.564 in 2018) has the best performance, while The Democratic Republic of the Congo has the worst performance (2.757 in 2000). Finland (99.728 in 2004) has the highest level and Yemen (13.059 in 2018) has the lowest score in *PClins*. For *PClps* scores, Iceland has the highest index (96.867 in 2006) and Tajikistan has the lowest score (37.966 in 2018). Lastly, the United States holds the highest (48.674) *PClsc* score, while Ethiopia's score is the lowest (6.734 in 2000).

Additionally, correlations between energy efficiency indicators and their potential predictors vary significantly across country groups. As expected, energy productivity and energy intensity are negatively correlated, albeit not that strong, in all sub-samples.

Table 4
Descriptive statistics and correlations

	Descriptive statistics			Correlations		Descriptive statistics			Correlations	
	Mean	Max.	Min.	<i>EnProd</i>	<i>EnInt</i>	Mean	Max.	Min.	<i>EnProd</i>	<i>EnInt</i>
	World sample (C: 125; Obs.: 2375)					LIEs (C: 12; Obs.: 228)				
<i>EnProd</i>	9.271	28.784	1.347	1	– 0.231*	5.623	16.435	1.596	1	– 0.454*
<i>EnInt</i>	2.459	18.241	0.113	– 0.231*	1	0.398	0.842	0.113	– 0.454*	1
<i>GNlpc</i>	13.375	104.560	0.110	0.236*	0.649*	0.626	1.750	0.110	0.452*	0.304*
<i>PClhc</i>	50.855	89.128	18.661	0.227*	0.541*	34.719	45.910	18.661	0.414*	0.326*
<i>PCltr</i>	15.912	47.960	4.002	0.194*	0.564*	10.626	16.210	4.002	0.304*	0.363*
<i>PClict</i>	10.727	32.564	2.757	0.246*	0.590*	4.337	9.484	2.757	0.266*	0.386*
<i>PClins</i>	56.803	99.728	13.059	0.289*	0.547*	35.368	49.066	18.662	0.154*	– 0.417*
<i>PClps</i>	78.038	96.867	37.966	0.321*	0.395*	66.037	81.308	37.966	0.056*	– 0.120
<i>PClsc</i>	20.397	48.674	6.734	0.259*	0.343*	13.853	19.292	6.734	0.213*	0.567*
	LMIEs (C: 27; Obs.: 513)					UMIEs (C: 48; Obs.: 912)				
<i>EnProd</i>	8.831	23.187	1.406	1	– 0.471*	10.024	26.867	1.347	1	– 0.638*
<i>EnInt</i>	0.675	3.009	0.116	– 0.471*	1	1.665	5.210	0.440	– 0.638*	1
<i>GNlpc</i>	1.616	5.010	0.270	0.310*	0.272*	6.036	17.460	0.600	0.234*	0.360*
<i>PClhc</i>	39.426	55.958	21.243	–0.044	0.563*	49.421	62.548	27.189	0.018	0.181*
<i>PCltr</i>	12.429	25.873	6.884	– 0.133*	0.217*	14.530	31.028	7.592	0.177*	0.039
<i>PClict</i>	5.769	16.748	2.803	0.111*	0.392*	9.516	22.047	2.919	0.121*	0.294*
<i>PClins</i>	40.498	60.270	13.059	0.212*	– 0.015	52.357	84.419	20.157	0.309*	– 0.159*
<i>PClps</i>	73.538	86.711	50.003	0.380*	– 0.165*	77.736	89.666	52.055	0.244*	– 0.207*
<i>PClsc</i>	16.929	25.947	9.336	0.157*	0.264*	20.567	43.467	11.543	0.023	0.047
	HIEs (C: 38; Obs.: 722)					NRDEs (C: 33; Obs.: 627)				
<i>EnProd</i>	9.784	28.784	1.829	1	– 0.644*	8.374	24.414	1.829	1	– 0.407*

* shows the statistical significance of correlation coefficients at the level of 5%

	Descriptive statistics			Correlations		Descriptive statistics			Correlations	
<i>EnInt</i>	5.381	18.241	1.364	– 0.644*	1	2.700	14.901	0.113	– 0.407*	1
<i>GNlpc</i>	35.028	104.560	4.160	0.373*	0.087	9.096	104.560	0.130	–0.003	0.580*
<i>PClhc</i>	65.880	89.128	39.235	0.233*	– 0.208*	41.567	69.618	18.661	–0.022	0.499*
<i>PCltr</i>	21.801	47.960	9.132	0.150*	0.150*	13.074	34.845	4.002	– 0.153*	0.757*
<i>PClct</i>	17.795	32.564	4.254	0.276*	– 0.017	7.764	21.055	2.757	–0.080	0.623*
<i>PClins</i>	80.772	99.728	44.808	0.290*	– 0.183*	46.935	93.170	13.059	0.084	0.482*
<i>PClps</i>	85.408	96.867	71.609	0.177*	– 0.132*	73.251	88.638	50.676	0.129*	0.471*
<i>PClsc</i>	24.712	48.674	15.441	0.245*	– 0.392*	16.844	28.158	9.182	0.056	0.420*
* shows the statistical significance of correlation coefficients at the level of 5%										

Cross-sectional Dependence And Stationarity

Stationarity, which means that disturbances of series do not depend on the observed time units is a decisive diagnostic for the selection of an appropriate analysis method. The stationarity of series may be investigated through several panel unit root tests grouped into two generations. The first group tests assume cross-sectional independence, while the second-generation tests take possible cross-sectional dependence (CD) into account. Hence, CD, which refers to the possible spatial or spillover effects of some unobserved common factors, should be detected to choose a proper unit roots test. We have employed Pesaran's (2021) CD and scaled LM tests together with Baltagi, Feng, and Kao's (2012) bias-corrected scaled LM tests to check CD. These tests are based on a null hypothesis of the absence of CD. The results reported in Table 5 reject the null hypothesis and indicate the appropriateness of the second-generation panel unit root tests.

Table 5
Results of cross-sectional dependence tests

Tests →	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
<i>Variables ↓</i>	World sample (Obs.: 2375)			LIEs (Obs.: 228)		
<i>EnProd</i>	471.023*	467.551*	140.767*	30.650*	30.317*	16.150*
<i>EnInt</i>	412.303*	408.831*	34.280*	30.034*	29.701*	5.379*
<i>GNlpc</i>	841.627*	838.155*	332.149*	84.487*	84.154*	32.033*
<i>PClhc</i>	778.004*	774.532*	290.510*	84.949*	84.616*	32.133*
<i>PCltr</i>	332.901*	329.429*	95.398*	28.360*	28.027*	4.914*
<i>PClict</i>	1002.45*	998.975*	363.430*	95.649*	95.316*	34.114*
<i>PClins</i>	229.494*	226.022*	8.864*	25.776*	25.443*	3.569*
<i>PClps</i>	475.531*	472.058*	123.270*	51.101*	50.768*	1.493
<i>PClsc</i>	221.181*	217.709*	32.467*	37.632*	37.299*	14.326*
	LMIEs (Obs.: 513)			UMIEs (Obs.: 912)		
<i>EnProd</i>	98.565*	97.815*	19.471*	155.079*	153.746*	45.909*
<i>EnInt</i>	107.942*	107.192*	26.395*	146.867*	145.533*	55.404*
<i>GNlpc</i>	195.299*	194.549*	74.058*	351.809*	350.475*	133.120*
<i>PClhc</i>	180.421*	179.671*	68.312*	281.802*	280.469*	100.404*
<i>PCltr</i>	76.487*	75.737*	13.583*	180.230*	178.897*	61.210*
<i>PClict</i>	223.061*	222.311*	79.094*	398.448*	397.115*	141.553*
<i>PClins</i>	46.437*	45.687*	1.982*	94.380*	93.047*	2.487*
<i>PClps</i>	104.124*	103.374*	27.928*	203.907*	202.574*	55.620*
<i>PClsc</i>	63.019*	62.269*	14.945*	72.233*	70.899*	11.895*
	HIEs (Obs.: 722)			NRDEs (Obs.: 627)		
<i>EnProd</i>	185.496*	184.441*	58.767*	89.104*	88.188*	6.232*
<i>EnInt</i>	139.325*	138.269*	28.814*	98.285*	97.368*	25.538*
<i>GNlpc</i>	246.723*	245.668*	98.644*	232.218*	231.302*	89.323*
<i>PClhc</i>	222.665*	221.609*	86.600*	247.485*	246.569*	92.394*
<i>PCltr</i>	64.144*	63.089*	26.122*	110.054*	109.138*	38.460*
<i>PClict</i>	306.999*	305.944*	110.397*	266.009*	265.092*	95.473*
<i>PClins</i>	65.651*	64.595*	6.310*	63.777*	62.861*	-0.217

* shows the cross-sectional dependence of the series at the level of 5%

Tests →	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
<i>PClps</i>	119.145*	118.089*	37.983*	129.821*	128.904*	23.458*
<i>PClsc</i>	52.112*	51.057*	5.682*	42.944*	42.027*	8.607*
* shows the cross-sectional dependence of the series at the level of 5%						

We have applied the cross-sectionally augmented Dickey-Fuller (CADF) panel unit root test (Pesaran 2007). The results reported in Table 6 reject the null hypothesis of the existence of unit roots in both detrended and trended specifications and indicate stationarity of variables at the level.

Table 6
Results of CADF panel stationarity test

Samples→ ↓Variables	World sample (Obs.: 2375)		LIEs (Obs.: 228)		LMIEs (Obs.:513)	
	Detrended	Trended	Detrended	Trended	Detrended	Trended
<i>EnProd</i>	−5.258*	−5.787*	−4.773*	−5.632*	−4.857*	−5.102*
<i>EnInt</i>	−4.061*	−11.155*	−5.385*	−5.244*	−2.553*	−17.708*
<i>GNlpc</i>	−4.672*	−6.074*	−3.293*	−4.741*	−2.351*	−3.839*
<i>PClhc</i>	−5.702*	−5.835*	−8.052*	−21.172*	−5.248*	−5.473*
<i>PCltr</i>	−4.858*	−4.888*	−4.516*	−3.902*	−4.119*	−4.317*
<i>PClict</i>	−4.956*	−4.895*	−1.934*	−2.707*	−5.052*	−5.362*
<i>PClins</i>	−6.046*	−6.103*	−2.851*	−2.945*	−6.273*	−5.666*
<i>PClps</i>	−5.187*	−6.126*	−3.292*	−3.875*	−5.336*	−5.818*
<i>PClsc</i>	−4.839*	−5.377*	−4.666*	−5.771*	−4.062*	−4.529*
↓Variables	UMIEs (Obs.: 912)		HIEs (Obs.: 722)		NRDEs (Obs.: 627)	
	Detrended	Trended	Detrended	Trended	Detrended	Trended
<i>EnProd</i>	−2.684*	−5.097*	−3.035*	−4.955*	−4.156*	−4.358*
<i>EnInt</i>	−6.606*	−6.753*	−5.523*	−5.882*	−4.346*	−4.111*
<i>GNlpc</i>	−1.609*	−2.978*	−2.382*	−2.978*	−3.131*	−3.898*
<i>PClhc</i>	−2.743*	−9.246*	−2.175*	−9.555*	−3.639*	−3.851*
<i>PCltr</i>	−4.520*	−4.307*	−5.138*	−5.092*	−4.536*	−4.392*
<i>PClict</i>	−1.798*	−4.692*	−3.167*	−4.810*	−3.708*	−3.803*
<i>PClins</i>	−2.640*	−9.638*	−8.821*	−9.742*	−4.446*	−4.224*
<i>PClps</i>	−2.419*	−6.011*	−2.317*	−5.906*	−4.087*	−4.336*
<i>PClsc</i>	−3.624*	−5.661*	−6.115*	−7.672*	−2.974*	−8.824*
* shows the stationarity of the series at the level of 5%. Optimal lag length varies from 1 to 3						

Analysis Of Variance (Anova)

When countries are classified, the mean values of groups should be significantly different. The one-way ANOVA is largely used to determine whether the means of groups are equal or different. ANOVA proposes the null hypothesis that all the means of compared groups are equal. Despite the rejection of the null hypothesis indicates that at least one group is different from the others, it does not specify which group is different. Thus, the ANOVA tests are followed by a post hoc test. The ordinary ANOVA procedure has strict assumptions of equal group size, homogenous variances, and normal distribution, none of which are met in our study. Alternatively, as a rank-based nonparametric ANOVA procedure, the Kruskal-Wallis test is robust to the violations of these assumptions and less sensitive to outliers in data. When the Kruskal-Wallis test rejects the null hypothesis, Dunn's post hoc test is an appropriate nonparametric pairwise comparison (Dinno 2015).

We have followed a nonparametric ANOVA procedure of the Kruskal-Wallis and Dunn's tests and reported the results in Table 7. The Kruskal-Wallis test finds a significant difference in all variables for all sub-samples. Dunn's pairwise comparisons also showed that each group is different from others (with a few exemptions) regarding each variable. The ANOVA results show that the LIEs group not only has the lowest income but also it has the lowest performance in all productive capacities. In general, productive capacities, as well as energy intensity, depict a monotonic function of income level since their means significantly ascend as the income levels of groups ascend. Even though it contains different countries from each income level, NRDEs' group is different from income groups in most variables. NRDEs' group is strictly surpassing LIEs' sub-sample but underperforming HIEs' sub-sample in terms of productive capacities, in which NRDEs' sub-sample is more similar to UMIEs' group. Relatively greater mean values of both energy productivity and energy intensity imply the possibility of the rebound effect notably in UMIEs and HIEs.

Table 7
ANOVA results of comparisons of sub-samples

Variables	Groups	Means (level)	Multiple comparisons		Dunn's pairwise comparisons (only significant comparisons are reported)
			Means (rank)	Kruskal–Wallis stat.	
<i>EnProd</i>	LIEs	5.623	717	282*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	8.831	1439		(LIEs < HIEs)*; (LIEs < NRDEs)*
	UMIEs	10.024	1726		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	9.784	1629		(UMIEs > NRDEs)*; (HIEs > NRDEs)*
	NRDEs	8.374	1365		
<i>EnInt</i>	LIEs	0.398	374	1714*	(LIE < LMIEs)*; (LIE < UMIEs)*
	LMIEs	0.675	705		(LIE < HIEs)*; (LIE < NRDEs)*
	UMIEs	1.665	1511		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	5.381	2464		(LMIEs < NRDEs)*; (UMIEs < HIEs)*
	NRDEs	2.700	1440		(HIEs > NRDEs)*
<i>GNlpc</i>	LIEs	0.626	266	2029*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	1.616	699		(LIEs < HIEs)*; (LIEs < NRDEs)*
	UMIEs	6.036	1528		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	35.028	2572		(LMIEs < NRDEs)*; (UMIEs < HIEs)*
	NRDEs	9.096	1336		(UMIEs < NRDEs)*; (HIEs > NRDEs)*
<i>PClhc</i>	LIEs	34.719	510	1690*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	39.426	843		(LIEs < HIEs)*; (LIEs < NRDEs)*
	UMIEs	49.421	1686		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	65.880	2454		(LMIEs < NRDEs)*; (UMIEs < HIEs)*
	NRDEs	41.567	1035		(UMIEs < NRDEs)*; (HIEs > NRDEs)
<i>PCltr</i>	LIEs	10.626	775	1226*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	12.429	1054		(LIEs < HIEs)*; (LIEs < NRDEs)*
	UMIEs	14.530	1483		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	21.801	2414		(UMIEs < HIEs)*; (UMIEs > NRDEs)* (HIEs > NRDEs)*
	NRDEs	13.074	1108		
<i>PClct</i>	LIEs	4.337	521	1519*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	5.769	867		(LIEs < HIEs)*; (LIEs < NRDEs)* (LMIEs < UMIEs)*; (LMIEs < HIEs)*

* shows the statistical significance of the compared mean differences at the level of 1%

	UMIEs	9.516	1563		(LMIEs < NRDEs)*; (UMIEs < HIEs)*
	HIEs	17.795	2452		(UMIEs > NRDEs)*; (HIEs > NRDEs)*
	NRDEs	7.764	1193		
<i>PClins</i>	LIEs	35.368	569	1606*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	40.498	894		(LIEs < HIEs)*; (LIEs < NRDEs)*
	UMIEs	52.357	1494		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	80.772	2522		(LMIEs < NRDEs)*; (UMIEs < HIEs)*
	NRDEs	46.935	1174		(UMIEs > NRDEs)*; (HIEs > NRDEs)*
<i>PClps</i>	LIEs	66.0367	543	1288*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	73.5379	1086		(LIEs < HIEs)*; (LIEs < NRDEs)*
	UMIEs	77.7362	1536		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	85.4081	2393		(UMIEs < HIEs)*; (UMIEs > NRDEs)* (HIEs > NRDEs)*
	NRDEs	73.2513	1113		
<i>PClsc</i>	LIEs	13.853	492	1318*	(LIEs < LMIEs)*; (LIEs < UMIEs)*
	LMIEs	16.930	1040		(LIEs < HIEs)*; (LIEs < NRDEs)*
	UMIEs	20.567	1725		(LMIEs < UMIEs)*; (LMIEs < HIEs)*
	HIEs	24.712	2293		(UMIEs < HIEs)*; (UMIEs > NRDEs)* (HIEs > NRDEs)*
	NRDEs	16.844	1010		
* shows the statistical significance of the compared mean differences at the level of 1%					

Regression Analysis

A panel data with both cross-country and temporal dimensions may have group effects, time effects, or both. These effects are mostly modeled through the pooled regression, fixed-effects, and random-effects approaches to panel regression analysis. The pooled regression model builds on the country homogeneity and pools all of the included countries by averaging any unobserved (latent) heterogeneities, which is not a typical feature of our panel data. The fixed-effects model arises from the assumption that the unobserved country effects are correlated with the included regressors, and thus it is more applicable when all designated countries are sampled and potential omitted effects are likely included. The underlying assumption of the random-effect model is that the missed effects are uncorrelated with the involved regressors and they may be included in the disturbance of the model, which more likely occurs when sampled countries are randomly drawn from a large population (Greene, 2012; Baltagi 2013). Besides this antecedent information, these possible effects may be determined statistically by performing several traditional tests including the Lagrange Multiplier (LM) omitted random-effects tests of Breusch and Pagan (1980) and Honda (1985; 1991), the F-test (redundant fixed-effects test), and the Hausman's (1978) correlated random-effects test. If the null hypothesis is accepted in the LM tests and the F-test, the pooled regression is favored over the random-effects model and fixed-effects model, respectively. For the Hausman test, if the null hypothesis (the individual effects are uncorrelated with the other regressors) is accepted, the random-effects model is favored over the fixed-effects model

(Greene, 2012; Baltagi 2013; Martinez 2016). We have estimated energy efficiency models in Eq. 1 based on the inferences of these effect tests. In all estimations, covariances and standard errors have been computed by weighting countries (period cluster) and correcting degrees of freedom to produce robust-to-heteroskedasticity coefficients.

The results of the panel regression estimations of energy productivity and energy intensity models are respectively reported in Table 8 and Table 9. Statistically significant coefficients show that the impacts of the involved predictors tend to change over the sub-samples on a driver-barrier basis. Per capita GNI is positively associated with energy productivity in all income groups. This result is in line with the findings of Atalla and Bean (2017). In general, the magnitudes of the positive income effect on energy productivity decline gradually from LIEs to HIEs, albeit statistical insignificance in the case of UMIEs. We found a negative association between per capita GNI and energy productivity for NRDEs. Growth in GNI per capita tends to enlarge energy intensity for middle-income countries and NRDEs. This finding concurs with that of Chang (2015). Overall, our findings show that income growth increases both energy efficiency and energy consumption in general. This finding confirms the results of Sineviciene, Sotnyk, and Kubatko (2017) and indicates the presence of an offsetting mechanism raised by rebound effects.

The increased productive capacity in human capital stimulates energy efficiency by leading to higher energy productivity and lower energy intensity for LIEs and HIEs. Considered the adverse link between energy efficiency and environmental pollution, these results support that of Pata, Aydin, and Haouas (2021). However, for the middle-income groups, higher human capital capacity means lesser energy efficiency. We evidenced a negative impact from the growth of human capital to energy intensity in the case of NRDEs. From the resource dependence approach, this result provides some support to that of Zallé (2019). Higher transport capacity is not good for energy productivity in sub-samples except for UMIEs. Moreover, it tends to increase energy intensity for all income groups. This evidence underlines the necessity of energy-saving transport modes and green logistics practices as evidenced by Li et al. (2021). However, we found a negative nexus between transport capacity and energy intensity for NRDEs, revealing that transport advancement may help in the mitigation of energy intensity even in resource-dependent countries where energy prices, on average, are relatively lower. Higher ICT capacity improves energy productivity for the sub-samples (except for LIEs). This result is consistent with the conclusion of Yan, Shi, and Yang (2018). Nevertheless, ICT capacity-energy intensity nexus is found positive (except for middle-income groups). This supports the findings of Sadorsky (2012) and Salahuddin and Alam (2016) but contradicts that of Schulte, Welsch, and Rexhäuser Schulte (2016) and Murshed (2020).

Table 8
Panel least squares estimate of energy productivity (*EnProd*) model

Samples→ ↓Predictors	World	LIEs	LMIEs	UMIEs	HIEs	NRDEs
<i>GNlpc</i>	0.008 (0.008)	2.145* (0.547)	0.466* (0.148)	0.029 (0.054)	0.020** (0.009)	−0.050* (0.015)
<i>PClhc</i>	0.034** (0.014)	0.075* (0.027)	−0.064** (0.030)	−0.126* (0.035)	0.108* (0.022)	0.010 (0.034)
<i>PCltr</i>	−0.049** (0.020)	−0.001 (0.027)	−0.109* (0.025)	0.073** (0.031)	−0.149* (0.036)	−0.092* (0.028)
<i>PClct</i>	0.229* (0.018)	−0.257** (0.108)	0.251* (0.051)	0.243* (0.045)	0.182* (0.031)	0.159* (0.035)
<i>PClins</i>	0.063* (0.010)	0.004 (0.020)	0.022 (0.020)	0.086* (0.015)	0.009 (0.021)	0.092* (0.023)
<i>PClps</i>	−0.016 (0.013)	−0.033*** (0.019)	0.075* (0.027)	−0.006 (0.024)	−0.181* (0.036)	0.055** (0.025)
<i>PClsc</i>	0.061* (0.022)	0.147* (0.047)	0.013 (0.061)	0.093** (0.042)	0.039 (0.033)	−0.173** (0.075)
<i>Constant</i>	2.144*** (1.126)	2.811 (1.722)	3.890*** (2.106)	6.726* (2.226)	15.782* (3.437)	2.950 (2.415)
Goodness-of-fit and model specification statistics						
<i>R</i> ² ;	0.903;	0.515; 0.499	0.314; 0.305	0.890;	0.345; 0.339	0.830;
<i>Adjusted R</i> ²	0.898			0.883		0.819
<i>F-stat.</i>	159.887*	33.363*	33.058*	128.849*	53.792*	73.508*
<i>Breusch-Pagan LM</i>	15508.54*	1500.23*	2825.930*	5450.898*	4570.082*	3168.068*
<i>Honda LM</i>	124.533*	38.733*	53.159*	73.830*	67.602*	56.286*
<i>F-test</i>	145.715*	309.522*	104.861*	113.029*	129.674*	77.918*
<i>Hausman test</i>	45.451*	2.519	8.745	13.821**	10.288	12.076***
<i>Estimated effect</i>	Fixed-effect	Random-effect	Random-effect	Fixed-effect	Random-effect	Fixed-effect
*, **, and *** show the statistical significance of the estimated regression coefficients at the levels of 1%, 5%, and 10%, respectively. Panel corrected (cross-section weighed and degrees of freedom-corrected) robust standard errors are in parentheses.						

Institutional capacity is positively associated with energy productivity for NRDEs, as well as for UMIEs, but it does not have a significant effect on energy intensity in any case. This neutral effect is similar to that of Akhbari and Nejati (2019) but contradicts both evidence that reveals either a positive (Ozturk, Al-Mulali, and Solarin 2019; Sun et al. 2019) or negative (Azam, Liu, and Ahmad 2021) relationship between different institutional quality and resource efficiency indicators. An increase in private sector capacity improves energy productivity in LMIEs and NRDEs, while it worsens energy productivity in LIEs and HIEs. The first case supports the findings of Rohdin, Thollander, and Solding's (2007) study. Moreover, the development of private sectors raises energy intensity in LIEs, confirming the results of Chang (2015) and Rieger (2019) from energy consumption and environmental pollution perspectives, respectively.

Table 9
Panel least squares estimate of energy intensity (*EnInt*) model

Samples→ ↓ Predictors	World	LIEs	LMIEs	UMIEs	HIEs	NRDEs
<i>GNlpc</i>	0.002 (0.004)	0.007 (0.027)	0.075* (0.015)	0.060* (0.010)	0.004 (0.005)	0.030* (0.008)
<i>PClhc</i>	−0.021* (0.007)	−0.003** (0.001)	0.017* (0.003)	0.015* (0.005)	−0.055* (0.016)	−0.023** (0.012)
<i>PCltr</i>	0.029* (0.011)	0.005* (0.001)	0.007* (0.003)	0.012* (0.004)	0.032 (0.026)	−0.036*** (0.021)
<i>PClct</i>	0.024* (0.009)	0.027* (0.006)	−0.030* (0.008)	−0.012 (0.008)	0.034*** (0.019)	0.064* (0.019)
<i>PClins</i>	−0.001 (0.004)	0.0003 (0.001)	−0.001 (0.002)	−0.004 (0.003)	−0.016 (0.018)	−0.010 (0.008)
<i>PClps</i>	−0.006 (0.005)	0.002** (0.001)	0.002 (0.002)	−0.002 (0.005)	−0.050*** (0.028)	−0.003 (0.006)
<i>PClsc</i>	0.004 (0.008)	−0.008* (0.003)	−0.0003 (0.007)	0.008 (0.009)	−0.022 (0.017)	−0.030 (0.021)
<i>Constant</i>	3.223* (0.601)	0.289* (0.079)	−0.128 (0.215)	0.687 (0.428)	13.583* (3.381)	4.618* (0.794)
Goodness-of-fit and model specification statistics						
<i>R</i> ² ; <i>Adjusted R</i> ²	0.968; 0.966	0.438; 0.420	0.955; 0.952	0.947; 0.943	0.928; 0.924	0.965; 0.963
<i>F-stat.</i>	511.059	24.472*	309.894*	280.864*	199.619*	420.672*
<i>Breusch-Pagan LM</i>	15775.54*	1252.734*	3034.168*	5911.520*	4643.822*	2450.370*
<i>Honda LM</i>	125.601*	35.394*	55.083*	76.886*	68.146*	49.501*
<i>F-test</i>	271.178*	271.734*	189.105*	209.739*	168.135*	190.319*
<i>Hausman test</i>	128.687*	7.289	17.964**	25.816*	12.884***	105.073*
<i>Estimated effect</i>	Fixed-effect	Random-effect	Fixed-effect	Fixed-effect	Fixed-effect	Fixed-effect
*, **, and *** show the statistical significance of the estimated regression coefficients at the levels of 1%, 5%, and 10%, respectively. Panel corrected (cross-section weighed and degrees of freedom-corrected) robust standard errors are in parentheses.						

The structural change supports the energy productivity performance of LIEs and UMIEs, while it impedes NRDEs' energy productivity. The structural change also means a lesser energy intensity for LIEs. The positive nexus between structural change and energy efficiency improvement supports the findings of Cornillie and Fankhauser (2004), Nepal, Jamasb, and Tisdell (2014), and Sineviciene, Sotnyk, and Kubatko (2017) who assessed structural change by different indicators. Overall, improvements in productive capacities of some socio-economic indicators are found with potential rebound effects, which indicate that some or all of the realized energy productivity gains may be counterbalanced by increases in energy intensity, and vice versa. Similar mechanisms of the rebound effects are also explained by Galvin (2015) and Lange, Pohl, and Santarius (2020).

Causality Analysis

Rebound effects may be also enabled by feedback loops. Therefore, lastly, we have attempted to find out bidirectional causalities between energy efficiency indicators and the involved predictors by testing the null hypothesis of homogeneous non-causality based on the approach of Dumitrescu and Hurlin (2012). This procedure produces a standardized Zbar statistic which is robust to the presence of cross-country dependence and country heterogeneity. The Zbar statistics reported in Table 10 ascertain bidirectional causalities from (to) the examined predictors to (from) energy productivity and energy intensity in most cases.

Table 10
Results of Dumitrescu-Hurlin pairwise causality test (*Zbar* statistics)

Samples→	<i>World</i>	<i>LIEs</i>	<i>LMIEs</i>	<i>UMIEs</i>	<i>HIEs</i>	<i>NRDEs</i>
↓ Null hypothesis	Causalities between energy productivity (<i>EnProd</i>) and predictors					
<i>GNlpc</i> ↔ <i>EnProd</i>	10.567*	4.250*	6.381*	7.627*	2.826*	7.211*
<i>EnProd</i> ↔ <i>GNlpc</i>	5.595*	4.331*	3.616*	3.267*	0.994	4.203*
<i>PClhc</i> ↔ <i>EnProd</i>	7.937*	4.265*	0.705	5.974*	4.690*	2.818*
<i>EnProd</i> ↔ <i>PClhc</i>	3.996*	−0.793	3.997*	2.291**	1.749***	2.919*
<i>PCltr</i> ↔ <i>EnProd</i>	5.903*	3.156*	1.564	4.823*	2.193**	4.129*
<i>EnProd</i> ↔ <i>PCltr</i>	5.030*	0.233	1.571	5.305*	1.705***	0.297
<i>PClict</i> ↔ <i>EnProd</i>	9.672*	2.371**	3.793*	7.326*	4.779*	8.946*
<i>EnProd</i> ↔ <i>PClict</i>	7.061*	1.237	7.513*	4.640*	0.563	4.551*
<i>PClins</i> ↔ <i>EnProd</i>	2.397**	0.195	3.871*	0.803	0.072	2.317**
<i>EnProd</i> ↔ <i>PClins</i>	6.180*	2.302**	2.592*	4.190*	3.021*	2.881*
<i>PClps</i> ↔ <i>EnProd</i>	4.637*	2.119**	3.379*	2.227**	1.868***	2.147**
<i>EnProd</i> ↔ <i>PClps</i>	6.612*	6.882*	0.835	1.765***	5.438*	2.839*
<i>PClsc</i> ↔ <i>EnProd</i>	5.746*	3.848*	3.221*	3.447*	1.669***	1.771***
<i>EnProd</i> ↔ <i>PClsc</i>	7.552*	2.301**	6.244*	2.991*	3.778*	5.060*
	Causalities between energy intensity (<i>EnInt</i>) and predictors					
<i>GNlpc</i> ↔ <i>EnInt</i>	13.323*	3.310*	7.288*	4.734*	10.840*	7.106*
<i>EnInt</i> ↔ <i>GNlpc</i>	5.189*	2.886*	2.198**	5.283*	0.000	4.495*
<i>PClhc</i> ↔ <i>EnInt</i>	7.989*	2.507**	3.454*	2.721*	7.112*	1.695***
<i>EnInt</i> ↔ <i>PClhc</i>	7.110*	−1.416	3.708*	5.995*	3.829*	5.216*
<i>PCltr</i> ↔ <i>EnInt</i>	7.859*	2.056**	2.114**	6.604*	3.894*	4.350*
<i>EnInt</i> ↔ <i>PCltr</i>	6.762*	1.984**	1.082	4.812*	4.829*	3.640*
<i>PClict</i> ↔ <i>EnInt</i>	14.359*	3.734*	6.281*	6.193*	11.690*	10.117*
<i>EnInt</i> ↔ <i>PClict</i>	5.898*	3.544*	4.274*	4.252*	0.325	6.145*
<i>PClins</i> ↔ <i>EnInt</i>	2.077**	−0.539	1.884***	1.130	1.211	1.792***
<i>EnInt</i> ↔ <i>PClins</i>	4.664*	1.706**	1.769***	2.671*	3.008*	2.582*
<i>PClps</i> ↔ <i>EnInt</i>	12.296*	4.817*	8.581*	2.656*	9.375*	6.991*
<i>EnInt</i> ↔ <i>PClps</i>	3.837*	1.483	1.115	4.091*	0.589	2.524**

*, **, and *** show the statistical significance of causalities at the levels of 1%, 5%, and 10%, respectively. Lag length is 2.

Samples→	<i>World</i>	<i>LIEs</i>	<i>LMIEs</i>	<i>UMIEs</i>	<i>HIEs</i>	<i>NRDEs</i>
<i>PClsc</i> ↔ <i>Enlnt</i>	4.342*	0.794	4.540*	0.420	3.130*	2.209**
<i>Enlnt</i> ↔ <i>PClsc</i>	5.283*	1.148	4.239*	2.737*	2.288**	1.991**
*, **, and *** show the statistical significance of causalities at the levels of 1%, 5%, and 10%, respectively. Lag length is 2.						

The bidirectional causalities between per capita GNI and energy efficiency indicators (except for HIEs) do not contradict the results of Esseghir and Khouini (2014) and Nathaniel, Yalçiner, and Bekun (2021). More specifically, the evidenced bidirectional causalities are in line with the results of Irfan (2021) who estimated a bidirectional Granger causality between economic growth and energy efficiency for 34 developing economies. Again, the one-way causality running from per capita GNI to energy intensity in HIEs is consistent with the results of Soytaş and Sari (2003), who found a unidirectional causality from GDP to energy consumption for some developed countries.

Conclusion

Engagement in energy efficiency efforts provides many benefits in all contexts from individuals and households to countries and the world. From the policy perspective to environmental issues, efficient use of limited energy resources is the responsibility of all countries. However, despite the growing recognition of the need for responsible production and consumption, global energy efficiency improvement in practice is not at an optimal level.

From the research perspective, despite the strong predictions in the theory, the available empirical results are scarce and provide unclear evidence. Some barriers and drivers of energy efficiency have been identified at both country and cross-country levels, albeit without consensus. The effects of countries' socio-economic productive capacities on their energy efficiency trajectories are decisive but often underrepresented. Addressing the shortcomings of the relevant literature, this study examined the impacts of productive capacities in human capital, transport, ICT, institutions, private sector, and structural change on energy efficiency in a large sample of 125 countries. Energy efficiency is assessed by energy productivity (output per unit of total primary energy supply) and energy intensity (total primary energy supply per capita) within a holistic approach. The world sample is divided into low-income, lower-middle-income, upper-middle-income, and high-income economies, as well as a control group of non-renewable resource-dependent economies with a high economic dependence on extraction of energy resources. The study applied ANOVA, regression modeling, and causality test to a cross-country dependent and stationary panel dataset from 2000 to 2018.

Findings And Implications

The results of the ANOVA procedure confirmed that country groups with higher (lower) income levels also have higher (lower) energy intensity and socio-economic productive capacities. This pattern reveals a linear monotonic function in the between-group context. For the within-group effects, we applied linear regression analysis. The regression estimations of two energy efficiency performance measures (higher energy productivity and lower energy intensity), showed that different factors drove energy efficiency with varied effects for different country groups. To explore the directions of the effects we also employed a causality test which established bidirectional causalities between energy efficiency and its predictors in most cases. Group-specific findings and relevant implications of the study are as follows.

(i) LIEs: The ANOVA findings showed the low-income economies' group had the lowest levels in all included The regression results showed that per capita income growth stimulates energy productivity most for this group, implying that low-income countries require a combination of economic growth policies and energy-saving production Our findings indicated that one of the useful ways to achieve this was to increase human capital capacity as it improves overall energy efficiency by increasing energy productivity and decreasing energy Even though transport and ICT enhancement, as well as the development of the private sector, are crucial for spurring progress on economic activities in low-income economies, all these variables are negatively associated with energy efficiency in these We found a positive effect from structural change to energy efficiency, suggesting an overall relocation of resources from less productive and low energy-efficient to more productive and high energy-efficient economic activities in these Overall, energy efficiency policies in low-income countries should be directed to human capital development, structural transformation, and economic growth.

(ii) LMIEs and UMIEs: Energy efficiency trajectories of middle-income countries may shed light on future directions of low-income For the middle-income groups, income growth has two contradicting effects on energy efficiency as it tends to enhance both energy productivity and energy This offset mechanism, which is possibly resulted from the rebound effect can be turned into net energy efficiency gains through investing in energy-saving technologies and/or changing consumption patterns of These countries may be attracting energy-inefficient investments from other Thus, enforcement of stringent resource policies may help in energy efficiency Recently, middle-income countries, which also include emerging economies, have improved their human However, the increased human capital capacity is an important barrier to energy efficiency for these This finding can be explained by the dynamic interaction between human capital and energy intensity: in the lower level of human capital, the energy demand is relatively lower, but after some level, human capital is improved by using more Human capital components such as education, training, and research-development practices may be redesigned to include environmental awareness, for example by educating people about the environmental consequences of their lifestyle Furthermore, the negative nexus between energy productivity and human capital is related to the overall energy-dependent production structure of these relatively fast-industrializing countries, where human capital is an important driver of these countries' energy-intensive industrial Improvement in ICT productive capacities of middle-income countries was found as a driver of energy productivity, while it also reduces energy intensity for lower-middle-income This evidence indicates the potential benefits from the integration of digital transformation into long-term energy efficiency Although these countries, on average, have been making considerable efforts to improve their transport capacity and logistics performance, higher transport productive capacity was found with an energy-intensifying This underlines energy-saving transportation practices (green transport and green which also stimulate energy productivity for upper-middle-income countries, albeit a negative impact on lower-middle-income countries' energy productivity Upper-middle-income countries may keep encouraging structural change and institutional development, while lower-middle-income countries are to support the private sector to improve energy In line with the ANOVA results, the regression results changed considerably for the lower-middle-income and upper-middle-income Therefore, given a large number of countries in these groups, prospective world sample studies may consider classifying middle-income countries into more sub-categories to have more homogeneous groups.

(iii) HIEs: For the high-income countries' sub-sample, which has the highest levels in all productive capacities, income growth means higher energy The high-income group has by far the highest level of human capital and gets significant energy efficiency benefits from the increased human capital Increased ICT capacity has a contribution to energy productivity but also increases energy These counteracting effects indicate a need to support production systems by ICT-based digital transformation, while the existing ICT components should be replaced by more energy-efficient High-income countries should keep promoting the development of private sectors to reduce energy However,

private sectors should be controlled and motivated to be more energy-productive as we found higher private sector capacity hindering energy Production activities in high-income countries are strongly linked to transportation within global supply-chains and value-added These countries both produce and use transport equipment Given the evidenced negative nexus between transport capacity and energy productivity, high-income countries may increase the adoption of more energy-efficient production technologies and transportation modes.

(iv) NRDEs: The sub-sample of nonrenewable resource-dependent countries enabled us to control the relationships for resource Growth of per capita income reduces energy productivity for only this Furthermore, higher per capita income was found intensifying individual energy use, indicating that economic growth strategies should be redesign towards energy Given the considerable contribution of resource extraction to the economic growth in resource-dependent countries, policy-makers in these countries should focus on decoupling economic growth from extractive To do so, oil extraction sectors may be discouraged by taxes and these tax revenues may be used to incite non-resource Since the human capital-energy intensity nexus is negative, resource-dependent countries may ease energy intensity by investing in education/training, skill/talent development, and research activities, as well as in better health system Improved transport capacity in these countries scales down both energy productivity and energy intensity (rebound effect). The net energy efficiency contribution may be achieved through a replacement of personal energy-intensive transportation modes by public transports and energy-saving In addition, energy intensity may be stepped down by stringent energy standards expanded to energy-efficient Higher ICT capacity encourages energy productivity performance but ICT improvement is coupled to energy intensity for this sub-The potential ICT rebound effect reveals the need for the conveyance of the fact that energy sources are not limitless to resource-abundant Environmental awareness programs, as well as binding energy standards enforced by taxes or fines, may work well in increasing the societal commitment to energy In the context of energy policy, institutional quality matters for energy The resource-dependent countries' group is behind the upper-middle-income and high-income groups in terms of institutional capacity, which we found as a potential driver of energy efficiency, significantly from the energy productivity Thus, stronger institutional framework features such as regulatory quality, anti-corruption, good governance, and freedom should be improved in resource-dependent For this sub-sample, one can expect that private sectors are concentrating on extractive sectors and paying less attention to energy However, we found that these countries might get energy productivity benefits from the development of the private Since the structural change obstructs energy productivity, additional industrial policies will be required to develop the energy-efficient private sector in non-resource Overall, the mixed findings open the ground to future research on the energy consumption behaviors of enterprises and individuals in resource-rich economies.

(v) World sample: Energy efficiency, environmental quality, and resource conservation are interconnected and among the major global Therefore, this study also aimed to provide evidence and policy implications at the world The statistically insignificant effect of per capita income in regression analysis has an economically significant implication that the neutral effect may be improved towards disconnecting economic growth from excessive use of energy The global findings may explain some driving and inhibiting forces of socio-economic factors to how this decoupling can be The development of human capital has a dual contribution (high energy productivity and low energy on energy efficiency suggesting global initiatives to integrate energy policies and human capital development Notably, since the 2000s, international production, trade, and investments are increasingly managed by global value chains, in which many countries contribute to the different stages of the production process of a great number of Global value chains also need well-operating global supply chains facilitated by good logistics and quality Knowing this, many countries have been investing in the improvement of transport and logistics However, this trend may impair the energy efficiency trajectory of the world as we found the improved transport capacity associated with low energy productivity and higher energy The latter effect is easier to explain that transport inherently scales up the energy intensity as the increased mobility of people and products uses more Therefore, the policy suggestion is

simple that countries need to transform their transport and logistics into the energy-efficient modes enforced by energy efficiency standards for transport. However, the controversial negative nexus between transport and energy productivity requires an in-depth insight that better transport across the world brings about new demand for goods and services which might be supplied at a cost of increasing energy. Likewise, improved transport enables to carry new energy sources between destinations both within and between. Additionally, since better transport may affect energy demand by changing energy prices, further studies alternatively may consider measuring energy intensity in monetary terms to control for energy cost.

It is long argued that ICT advancement and digital transformation improve energy efficiency at the world level. We confirmed this argument only from the energy productivity side, indicating that ICT-enabled technologies and services may foster decoupling production from energy use. However, the increased ICT capacity also causes higher energy intensity which indicates the increasing energy burden of ICT development. This rebound effect infers that the production of modern digital ICT technologies entails supports to replace energy-intensive ones. The complexity of the ICT-energy efficiency nexus, and the motivational drivers of behavioral changes towards the use of more energy-efficient ICT components, leave a research domain for future studies. Our results also showed that increased capacity in institutions and structural change stimulated energy productivity globally. These pieces of evidence argue that global energy initiatives and environmental studies require the incorporation of economic structure and institutional quality into energy policies.

Overall, our study calls into question the use of a one-data indicator of energy efficiency. We suggest that energy policies at all global, regional, and country levels should be addressed for energy productivity and energy efficiency separately. It is certain that the one-size-fits-all solution to global energy inefficiency concerns will fail due to the presence of strong country heterogeneity. Since the energy-saving practices of individuals may be affected by their expectations for financial savings, energy efficiency strategies should enable the comparisons of future monetary gains with the present cost of energy-saving practices. In addition to companies' training programs, educational institutions should also include energy efficiency subjects in their curriculums at all levels to strengthen the public awareness and acceptance of the alarming climate impacts of the global depletion of finite energy sources.

Limitations And Future Research

It should be noted that we did not distinguish any kinds of energy as we dealt with the overall energy efficiency. Future studies may make distinctions, for example between renewable and non-renewable or fossil and non-fossil energy resources, as well as between electric and non-electric energy. The energy intensity concept we gauged as per capita energy supply embodies some geographic characteristics such as climate and location, and demographic factors such as population and house/family size. These omitted links call for micro-level studies which control for specific demographics of individuals, employees, and companies within countries. Finally, we focused on the environmental impact of energy intensity and thereby measured it in physical amount as oil equivalent. Further studies may also use monetary metrics to capture the price and cost impacts. These considerations will better explain feedback loops and rebound effects running between energy productivity (production-side), energy intensity (consumption-side), and socio-economic indicators.

Declarations

Ethics approval and consent to participate: Not applicable. This study does not report on or involve the use of any animal or human data or tissue. It used open access data which is not involving human participants, human data or human tissue.

Consent for publication: Not applicable. This study does not contain data from any individual person.

Availability of data and materials: The datasets generated and/or analyzed during the current study are available in the [Google-Drive] repository, [<https://drive.google.com/file/d/1C2bK7diOTDbIFqGulblYX5DpoRviY5oE/view?usp=sharing>] and they are available from the authors on request.

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