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ORIGINAL RESEARCH

Shadow economy and energy efficiency: utilising goal programming for sustainability assessment

Samar S. Alharbi[1] · **Sabri Boubaker**[2,3,4] · **Thanh Ngo**[5,6] · **Mui Kuen Yuen**[7]

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Abstract

This paper combined different methods of operations research, goal programming, and unsupervised machine learning into a single framework to examine energy efficiency across the globe. Using the latest data from 131 countries in 2017, our empirical findings reveal different patterns of energy efficiency among countries and country groups under both the meta-frontier and group-frontiers. We found an inequality in production technology for many countries, which made it difficult for them to improve their energy efficiency. Importantly, our analysis also reveals that the size of the shadow economy has a small but negative impact on energy efficiency. Consequently, we suggest that governments should (i) pay more attention to the shadow economy, (ii) increase investments in education and human capital, and (iii) strengthen their institutions.

Keywords Meta-frontier · Data envelopment analysis (DEA) · Goal programming (GP) · Euclidean common set of weights (ECSW) · Sustainability · Machine learning (ML)

1 Introduction

Global energy consumption and energy efficiency (EE) are critical topics in today's world, holding significant implications for economic growth, environmental sustainability, and geopolitical dynamics (Belaïd & Massié, 2023; Sueyoshi et al., 2017). According to the

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✉ Thanh Ngo
T.Ngo@massey.ac.nz

[1] College of Administrations and Finance, Saudi Electronic University, Dammam, Saudi Arabia

[2] Métis Lab, EM Normandie Business School, Clichy, France

[3] International School, Vietnam National University, Hanoi, Vietnam

[4] Swansea University, Swansea, UK

[5] School of Aviation, Massey University, Palmerston North, New Zealand

[6] VNU University of Economics and Business, Hanoi, Vietnam

[7] School of Accountancy, Economics and Finance, Massey University, Palmerston North, New Zealand

International Energy Agency (IEA, 2023), global energy demand is projected to continue its upward trajectory in the coming years, mainly due to population growth, urbanization, and industrialization. On the one hand, it places increasing pressure on energy resources and production/utilization. On the other hand, concerns about climate change and the finite nature of fossil fuel reserves have led to a growing emphasis on EE and the transition to cleaner and more sustainable energy sources. It is noted that fossil fuels—including coal, oil, and natural gas—still dominate the global energy mix, accounting for a significant share of energy consumption, whereas the contribution of renewable energy sources such as solar, wind, hydroelectric, and geothermal is gradually expanding but still modest (IEA, 2023).

EE is increasingly gaining popularity as a crucial tool for addressing climate objectives and reducing greenhouse gas emissions (Belaïd & Massié, 2023; Filippini & Hunt, 2015; Yu & He, 2020). Furthermore, implementing EE measures can enhance energy security and affordability and alleviate the burden on vulnerable populations in terms of reduced carbon intensity, lower energy costs, and improved citizens' well-being and health (Chu et al., 2024; Wu et al., 2023). Improved EE can be simply defined as a reduction in the energy required to produce a specific level of economic output (Ang et al., 2023). This definition aligns with the nonparametric DEA approach, which assesses the efficiency of decision-making units (DMUs)—such as countries—based on their ability to generate the highest outputs (e.g., GDP) given a set of inputs (e.g., energy consumption), their ability to achieve a given level of outputs using the fewest inputs, or both (Boubaker et al., 2023a; Ngo & Tsui, 2021; Yu et al., 2022). Consequently, there has been a significant increase in the number of DEA studies focusing on EE (Mardani et al., 2017; Sueyoshi et al., 2017). However, as Mardani et al. (2017) highlight in their review, most studies primarily examine EE at the firm or regional levels, with limited research conducted on a cross-country scale (Gómez-Calvet et al., 2016; Wang et al., 2024). Accordingly, a global analysis of EE under advanced techniques such as data-driven machine learning (ML) and meta-frontier (MF) DEA is necessary.

This study aims to contribute to the existing literature in three main ways. *First*, we examine a cross-sectional dataset comprising 131 countries, representing the largest sample size examined to date. Among previous studies, Gómez-Calvet et al. (2016) only focus on 27 European countries, while Li and Wang (2014) include 95 countries in their analysis. As such, our research can provide a more comprehensive analysis of global EE. *Second*, we extend the DEA MF approach—as introduced by O'Donnell et al. (2008) and subsequently popularly applied in Kerstens et al. (2019) and Cheng et al. (2020), among others—by employing Ward's (1963) hierarchical clustering technique as an unsupervised ML method to classify countries into different groups. This approach avoids the common practice of dividing countries solely based on their income levels or developmental states, as seen in Yu-Ying Lin et al. (2013) and Li and Wang (2014). Additionally, within each cluster or group, we argue that an Euclidean common set of weights (ECSW) should be used for comparing countries, as suggested by Contreras (2020) and Hammami et al. (2022), instead of the traditional dynamic weights of DEA. Boubaker et al. (2023b) specifically highlight that while dynamic weights can provide flexibility in DEA, using different weights corresponding to different frontier surfaces might render the comparison of DMUs inappropriate. Therefore, such a combination utilizes the advantages of different advanced techniques of DEA (as a model of operations research), ECSW (as a model of goal programming; GP), MF, and ML. *Third*, we are the first to investigate the relationship between EE variations across our sample and the level of the shadow economy (SE) (Zolkover & Terziev, 2020).

While a limited number of studies explore the SE's relationship with energy consumption (Canh et al., 2021; Sohail et al., 2021), green economy/growth (Dada et al., 2023; Saafi et al., 2023), and the environment and sustainability (Butt et al., 2023), its relationship with EE remains unexplored.

The next section provides a brief review of the literature on EE, the SE, and their indirect linkages. Section 3 explains the methodologies (including DEA, ECSW DEA, MF DEA, and Ward's clustering technique) and data employed in this research. Section 4 then discusses our empirical findings, before Sect. 5 concludes.

2 Literature review

This section provides brief literature reviews on energy efficiency, shadow economy, and the indirect linkage between them.

2.1 Energy efficiency

EE has garnered significant attention in the academic literature due to its potential to address environmental concerns, promote sustainable development, and enhance energy security. A simple search on Energy Economics journal—a premier field journal for energy economics and energy finance—using "energy efficiency" as the keyword returns 236 articles published in 2023 alone. Similar search results in the Energy Policy and Energy Efficiency journals also highlight a jump from 56 (in 2000) to 227 articles (in 2023) for the former and 28 (in 2008) to 87 articles (in 2023) for the latter journal.

EE is commonly defined as the ability to achieve a desired output level while minimizing energy input. It encompasses both technological and economic dimensions. Its conceptualization involves considering technical efficiency—which focuses on optimizing the conversion of energy inputs into useful outputs—and economic efficiency, exploring the cost-effectiveness of energy use (Linares & Labandeira, 2010; Sorrell & O'Malley, 2004). Sueyoshi et al. (2017) review argues that EE can also be referred to as energy saving and conservation, representing a measure of managing and restraining growth in energy consumption. Several methodologies are employed to measure EE, including energy intensity ratios, energy productivity indicators, and frontier-based approaches such as Data Envelopment Analysis (DEA) (Cheng et al., 2020; Filippini & Hunt, 2015). For instance, according to Yu and He (2020) review of 1206 journal articles on EE under the microscope of DEA using the Web of Science database, the number of publications increased from only one article in 1992–280 in 2018. Notably, one of the most popular research areas among such studies is comparisons among industries and regions, with few focusing on country comparisons (Sueyoshi et al., 2017; Yu & He, 2020). This is consistent with Mardani et al. (2017) finding only found twelve cross-country studies among 144 DEA EE articles (i.e., 8.3%) published during the 2006–2015 period, ranging from the smallest sample of nine countries (Cui et al., 2014) to the largest sample of 95 countries (Li & Wang, 2014).

Recent research conducted by Wang et al. (2024) utilizes a small sample of the ten major global energy-consuming countries, namely China, the United States, India, Russia, Japan, Canada, Germany, Brazil, Iran, and South Korea. The study emphasizes that these countries bear the majority of the responsibility for energy conservation and emission reductions, and any progress they achieve in terms of EE will have a significant impact on mitigating global climate change. However, given that a larger sample size would yield more accurate and robust findings and conclusions, we aim to expand our sample to include the largest possible cross-country data for evaluating EE. Nevertheless, it is important to acknowledge a relevance trade-off, whereby as the number of variables in the DEA model increases, more observations or countries might become missing or unavailable and need to be excluded from the analysis. Thus, we follow the traditional DEA approach employed by Li and Wang (2014), Li and Lin (2015), Cheng et al. (2020), and Wang et al. (2024) in selecting three inputs (capital, labour, and energy consumption) and one output (GDP) for our DEA model. Further details regarding this approach are provided in Sect. 3.4.

2.2 Shadow economy

The SE—also known as the informal or underground economy—has attracted significant attention in academic research due to its pervasive nature and implications for economic development, taxation, and governance (Schneider & Enste, 2000, 2013). Essentially, the SE refers to economic activities operating outside of formal regulations, taxation, and official statistics. It encompasses a variety of informal, unreported, or illegal activities, such as undeclared work, informal businesses, and illicit trade. For instance, Lewis (1955) argued that underemployment in urban areas could be called the informal sector. Meanwhile, the International Labour Organisation (ILO, 1972) emphasized that the informal sector should comprise a wide range of wage earners and self-employed persons who are missing from official statistics. In this sense, Frey et al. (1982), Tanzi (1983), and Feldbrugge (1984) were among the pioneering studies to explore the concept of SE, focusing on defining the phenomenon (Frey & Weck, 1983) and devising methods to measure its relative size within national accounts (Schneider, 1986). More recently, Schneider and Enste (2013) emphasized the separation of the (dual) economy into official and unofficial sectors resulting in the inclusion of all market transactions (i.e., transactions that cannot be recorded in the national account statistics due to practical problems and insufficient methods and those whose value-added is not revealed) under the SE. A common (and recent) understanding of SE is that it comprises all economic activities that are hidden from official authorities due to monetary, regulatory, and institutional reasons (Medina & Schneider, 2019). Accordingly, our study utilizes the dataset of Medina and Schneider (2019), in which 157 countries were examined in terms of their SE activities.

Since it is difficult to define and measure the SE, governments face challenges as it undermines tax revenues, hampers economic growth, and affects social welfare (Schneider & Enste, 2013; Sohail et al., 2021; Zolkover & Terziev, 2020). Consequently, recent research focuses on examining the size of the SE and its determinants. For instance, Ruge (2010) analyze data from 35 countries, including 28 OECD members, finding that a country's level of development, administrative system, and tax complexity can reduce the size of the SE. Conversely, social security payments and labour market regulations have the opposite effect. Similarly, using data from 145 countries, Goel and Nelson (2016) discover that GDP and government size can help to limit the SE, while inflation can contribute to its growth. In a more comprehensive analysis, Zhanabekov (2022) expands the number of determinants to 34 and reveals that institutional quality—including regulations and GDP—

is among the SE’s primary determinants. Therefore, we also incorporate GDP and institutional variables in our analysis.

2.3 The relationship between EE and SE

Research on the SE increasingly examines its impacts on the formal economy and economic growth (Schneider & Enste, 2000) and—more recently—sustainability issues (Chatti & Majeed, 2023). It is argued that solely relying on formal GDP statistics to represent overall economic activities—especially in energy-intensive and heavily-polluted sectors such as the manufacturing, equipment, and chemical industries—inaccurately proxies economic development (Butt et al., 2023). In this regard, the SE could play a significant role in providing the missing pieces of the economic growth puzzle and shed light on EE and sustainable development. Furthermore, it is also argued that firms can exploit tax evasion and lax environmental standards under the umbrella of the SE, allowing them to continue producing goods and services without concern for the environment (Sohail et al., 2021). Specifically, Elgin and Oztunali (2014) find that the SE might have both deregulation and scale effects on the environment. The deregulation effect enables firms to be more flexible in choosing production technologies, often resulting in cheaper, inferior, and less efficient options that lead to greater pollution. Conversely, the scale effect allows firms to operate at smaller scales, which tend to be less polluting. Depending on the relationship between these two effects, the impacts of the SE on the environment might exhibit an inverse U-shaped relationship, similar to the Environmental Kuznets Curve (EKC). For more information on the EKC, readers are encouraged to explore the works of Pan et al. (2020), Ngo et al. (2022), and Naimoglu and Akal (2023), among others.

While numerous studies explore the relationship between economic growth (i.e., the formal sector) and EE (Pan et al., 2020; Wang et al., 2024), there is a growing trend in recent research to examine the linkages between the SE (i.e., the informal sector) and various sustainability issues, including energy consumption and renewable energy (Canh et al., 2021; Chu et al., 2024; Sohail et al., 2021), environmental degradation and emissions/pollution (Butt et al., 2023; Dada et al., 2023), and sustainable development (Saafi et al., 2023). However, given that—to the best of our knowledge—no study has specifically examined the impacts of the SE on EE, our paper aims to fill this research gap considering the nonlinear relationship discussed above.

2.4 Summary

Accordingly, the recent research gaps that this study aims to address are reflected and summarized as follows.

- There is a rich body of DEA literature on EE; however, global and large-scale cross-country analyses are still limited.
- Studies on SE are also intensive, but they do not focus on the relationship between SE and EE.
- Therefore, it is justified to use DEA/OR to examine the global EE under the impacts of SE using advanced techniques such as machine learning, goal programming, and metafrontier.

3 Methods and data

This section outlines our methodological approach, as depicted in Fig. 1. Following the data collection process, we use the slacks-based measure (SBM) DEA, Ward clustering, and the ECSW DEA to estimate MF efficiency and the ECSW group-frontier efficiency, respectively, with the meta-technology ratio (MTR) calculated accordingly. Subsequently, we use a truncated regression approach to examine the impacts of the Z variables on EE.

3.1 Meta-frontier data envelopment analysis

DEA is a popular nonparametric approach to measure energy EE (Cui et al., 2014; Li & Lin, 2015; Wang et al., 2024). The basic principle of DEA—as introduced in Charnes et al. (1978) and Banker et al. (1984)—is that a set of DMUs sharing the same technical/production frontier can be benchmarked against this frontier and relatively compared against each other. DMUs on the frontier are deemed as efficient (with efficiency scores of 1.000) while those under the frontier are inefficient (with efficiency scores less than 1.000) (Boubaker et al., 2023a; Hammami et al., 2022). Given a set of n DMUs, each one uses k inputs x_i ($i = 1,2,..,k$) to produce m outputs y_r ($r = 1,2,..,m$), Charnes et al. (1978) propose that DEA can be used to estimate the best-frontier efficiency of the j_0–th DMU as:

$$EF_{j_0}^{B} = max_{u,v}\frac{\sum_{r=1}^{m} u_r y_{rj_0}}{\sum_{i=1}^{k} v_i x_{ij_0}} \tag{1}$$

subject to

$$\frac{\sum_{r}^{m} u_r y_{rj}}{\sum_{i}^{k} v_i x_{ij}} \le 1, j = 1,2,..,n$$
$$u_r, v_i \ge \varepsilon, \forall i, r$$

where $EF_{j_0}^{B}$ is the efficiency score of the DMU j_0 ($j=1,2,..,n$), v_i and u_r are the optimal weights assigned to the relevant inputs and outputs of this DMU, and ε is a non-Archimedean value designed to enforce positivity on the weights.

However, as O'Donnell et al. (2008) discuss, DMUs from different industries, regions and/or countries often operate under different production functions due to differences in the availability of production resources (e.g., capital, labour, land, and buildings) and the macroeconomic environment (e.g., politics, institutions, regulations, and infrastructure). In this case, a cross-industry or -country evaluation of DEA would be inaccurate and thus researchers have to examine different groups of DMUs using separated production frontiers (Knox Lovell & Pastor, 1997; O'Donnell & Van Der Westhuizen, 2002). Battese et al. (2004) and O'Donnell et al. (2008) propose the remedy of examining both the group-frontiers (similar to the separated frontiers for each country or industry) and the MF that envelops these group-frontiers (similar to the cross-industry or -country frontier). Figure 2 illustrates the case of three DMUs (A, B, and C) regarding two group-frontiers (GF1 for A and B, and GF2 for C) and a single MF, whereas the corresponding group-frontier and MF efficiency scores of DMU B are defined as follows.

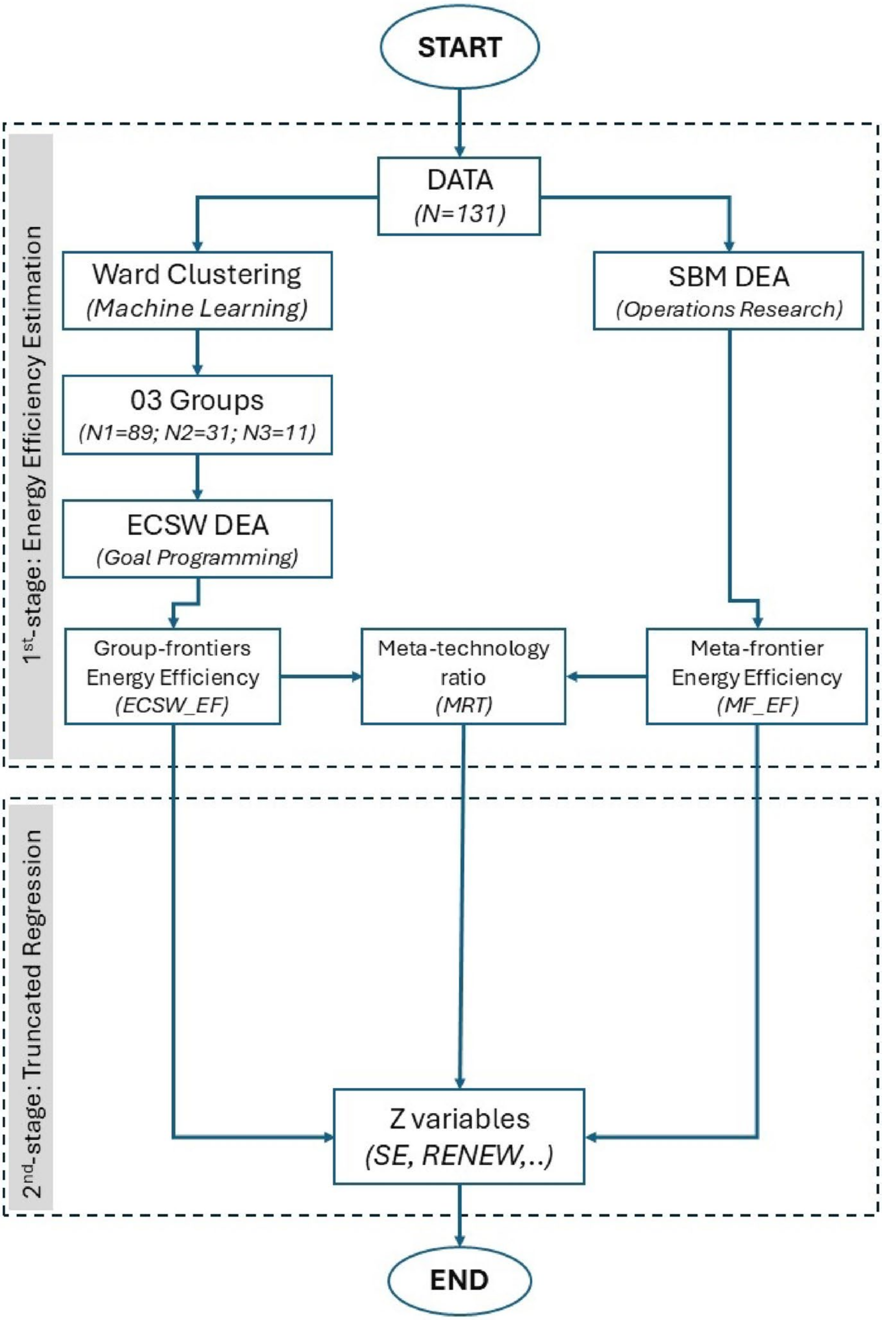

Fig. 1 Conceptual framework

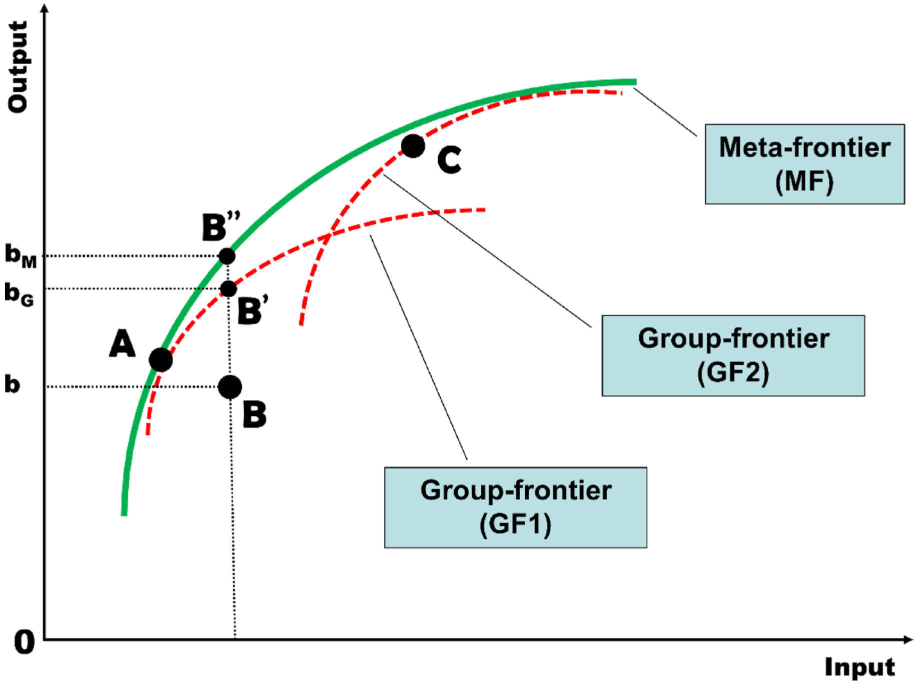

Fig. 2 Basic principle of meta-frontier DEA

Meta-frontier efficiency (output-oriented, regarding MF—see Fig. 2*):*

$$EF_B^{MF} = \frac{Output\,level\,of\,B}{Output\,level\,of\,B"} = \frac{0b}{0b_M} \tag{2}$$

Group-frontier efficiency (regarding GF1):

$$EF_B^{GF1} = \frac{0b}{0b_G} \tag{3}$$

Accordingly, the meta-technology ratio (MTR) of B is:

$$MTR_B = \frac{EF_B^{MF}}{EF_B^{GF1}} = \frac{\frac{0b}{0b_M}}{\frac{0b}{0b_G}} = \frac{0b_G}{0b_M} \tag{4}$$

As discussed in Walheer (2018), this ratio provides a measure of the gap between the technology available to all DMUs and the technology available to a group of DMUs. By definition, as the MF envelopes all $\mathrm{GF_k}$, $0b_M$ is always greater than $0b_G$ and thus MTR_B is always smaller than 1.00. Moreover, by definition, the MF and group-frontier efficiency scores and the MTR of A are all unity. Meanwhile, as C lies on GF2, its group-frontier efficiency score is 1.00, although its MF efficiency and MTR are less than unity.

Furthermore, it is noted that while traditional DEA can evaluate the efficiency of DMUs in terms of minimizing the input given certain outputs or maximizing the outputs given certain inputs (Banker et al., 1984; Charnes et al., 1978), it is much more important if one can minimize the inputs and maximize the outputs at the same time (Boubaker et al., 2023a). In this sense, the slacks-based measure (SBM) of Tone (2001) is a suitable model for our analysis where countries aim to improve their EE regarding the minimum input used (e.g., energy consumption) to obtain the most output (e.g., GDP). Accordingly, the SBM efficiency of the country j_0-th in our sample is calculated as follows.

$$EF_{j_0} = \min \frac{1 - \frac{1}{k}\sum_{i=1}^{k} s_i^- / x_{ij_0}}{1 + \frac{1}{m}\sum_{r=1}^{m} s_r^+ / y_{rj_0}} \tag{5}$$

subject to

$$\begin{aligned} &\sum_{i=1}^{k} \lambda_j x_{ij} + s_{ij_0}^- = x_{ij_0} \\ &\sum_{r=1}^{m} \lambda_j y_{rj} - s_{rj_0}^+ = y_{rj_0} \\ &j \ = \ 1, \ 2, \ .., \ n \\ &\lambda_j, s_i^-, s_r^+ \geq 0 \end{aligned}$$

For our study, we follow Li and Wang (2014), Cheng et al. (2020), and Wang et al. (2024)—among others—in selecting three inputs (capital, labour, and energy consumption) and one output (GDP) for our EE DEA model. In this sense, our argument is in line with those studies, arguing that a country's EE is determined by the level of resources—especially energy consumption—used to produce the economic output of GDP (Zhang et al., 2018). However, unlike those studies, we do not incorporate undesirable outputs such as emissions and pollution for three main reasons. First, our main purpose is to introduce a novel method of data-driven MF using a common set of weights in DEA. Second, there is an ongoing debate on how to treat those undesirable factors, such as using them as inputs or using their reciprocals as outputs, as well as their impacts on the DEA results (Boubaker et al., 2023a; Liu et al., 2010; Sueyoshi et al., 2017), whereby we leave this issue for future research. Third—and most importantly—data for emissions is limited to the pre-2015 period (The World Bank, 2023), while we aim to analyze 2017 utilizing the recent updates on the SE from Medina and Schneider (2019).

3.2 The Ward's clustering method: a data-driven unsupervised machine learning approach

As discussed earlier, one important step of MF DEA is to divide DMUs into different groups and define the group-frontiers accordingly. For our study, one can refer to the MF as a global benchmark and the group-frontiers as cluster-based benchmarks.[1] This task is convenient for firm-level studies because one can categorize them based on their industries, sectors,

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[1] We are thankfully for an anonymous reviewer to point it out.

regions, or countries of operation. For instance, Chen and Yang (2011) divide the banking industries in Taiwan and China into two group-frontiers based on their location/nation, while Li and Lin (2015) divide 30 provinces in China into eastern, central, and western regions. Studying the aggregation of the MTR in Europe, Walheer (2018) examine ten sectors (e.g., agriculture, mining, and manufacturing), each comprising nineteen countries (e.g., Austria, Ireland, and Sweden), thus defining the group-frontiers based on sectors of operation rather than geographical locations. Zhang et al. (2018) divide the sixteen countries involved in the Clean Development Mechanism (CDM) into host and investment countries, and Yu et al. (2022) divide 39 Spanish airports into major (hub) airports and small local airports.

Nevertheless, such division or categorization is a priori based on assumptions about the characteristics of the DMUs. For instance, Li and Lin (2015) assume that Chinese provinces within the same region (i.e., east, west, and central China) operate under the same group-frontier in terms of EE. However, questions emerge when exploring provinces at the boundaries of those regions, e.g., one could categorize Jilin and Heilongjiang as central China, similar to the case of Liaoning. Similarly, the study of Yu et al. (2022) assumed that the 39 airports in Spain should operate under two distinguished group-frontiers, one for major airports and one for small local airports. However, a closer examination of Table 7 by Yu et al. (2022) showed that the aircraft traffic movements (ATMs) are an important factor in defining the status of an airport, ranging from 14,580 to 469,750 operations for major airports to 2110–50,550 operations for small local airports. However, the overlap between these ranges prompts questions about how certain airports should be grouped: for instance, should we categorize airports such as Almeria and Fuerteventura with ATMs of 18.280 and 44.552 thousand operations, respectively,[2] as major or small airports?

It is important to note that DEA measures the (relative) technical efficiency of the DMUs involved, i.e., how they utilize their inputs to produce the outputs. In this sense, the technical production frontier is defined by the inputs and outputs data. From the broad viewpoint of the MF, one might argue that the DMUs operate under the same technology of using the same inputs and outputs setting, e.g., all airports use terminals, runways, and ATMs as inputs to produce annual passenger movement and cargo (Yu et al., 2022), or all provinces use capital, labour, and energy consumption to produce GDP (Li & Lin, 2015). From the specific viewpoint of the group-frontier, we further argue that DMUs sharing similar input–output settings tend to exhibit similar scales and production technology. We refer to this as a data-driven approach to define the group-frontiers.

In the era of data-driven analysis, various ML techniques are available to partition large datasets into smaller clusters or groups. Cluster analysis is an unsupervised ML method used to group similar observations, data points, or feature vectors based on shared characteristics (Jain, 2010), which can be referred to as "the art of finding groups in data" (Kaufman & Rousseeuw, 2009). Cluster analysis techniques can be broadly categorized as hierarchical and non-hierarchical, with the former being closely related to the principles of MF DEA. In particular, hierarchical clustering algorithms recursively identify nested clusters within the dataset, following either an agglomerative mode (where each data point starts in its own cluster and progressively merges the most similar pairs of clusters to create a hierarchy) or a divisive mode (where all data points begin in one cluster and clusters are successively divided into smaller ones) (Jain, 2010). Flores-Hernández et al. (2022) identify six groups among 310 microenterprises in El Salvador based on their strategic management practices,

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[2] The data is also reported in Table 2 of Lozano et al. (2013).

while Wang et al. (2023a) classify 281 cities into five clusters based on the coupling coordination levels between population-crop yield, population-cropland soil erosion, and crop yield-cropland soil erosion. Wang et al. (2023b) conduct clustering analysis to group the 30 provinces of China into five classes based on similarities in their consumption of coal, petroleum, natural gas, and electric and heat power, and Çağlar and Gürler (2022) group 110 countries into five clusters based on their progress towards the Sustainable Development Goals (SDGs).

Nonetheless, our paper is the first to incorporate cluster analysis into the MF framework. We select Ward's clustering method (Ward, 1963) because it is the only one among the agglomerative clustering algorithms that divides groups based on the classical Euclidean sum-of-squares criterion[3] to minimize within-group dispersion at each binary fusion, resulting in compact and homogeneous clusters (Murtagh & Legendre, 2014). Additional advantages of the Ward method include the ability to produce balanced clusters and preserve the underlying structure of the data, its flexibility with various types of data and variables, and its computational efficiency (Kaufman & Rousseeuw, 2009).

Given a set of n objects (or DMUs, in DEA terminology) defined by A attributes $x_{ab}\,(a = 1,..,A; b = 1,..,B)$, the objective of cluster analysis is to find M clusters ($M < B$) such that the members of a cluster are similar to each other but differ from those outside this cluster (Ward, 1963). Mathematically, if we define E_p as the error-sum-of-squares for cluster p, i.e., the within-group Euclidean squared deviations about the mean x_{ap}^{m}, and E as the total within-group-error-sum-of-squares, then at each stage the Ward method will find the two clusters whose fusion yields the minimum increase in E:

$$E_p = \sum\nolimits_{b=1}^{Bp} \sum\nolimits_{a=1}^{A} \left(x_{abp} - x_{ap}^{m}\right)^2 \tag{6}$$

$$E = \sum\nolimits_{p=1}^{M} E_p \tag{7}$$

3.3 Common set of weights (CSW) for DEA group-frontiers: a goal programming approach

Traditional DEA models benefit from their dynamic weights setting in which each DMU or country can select the weights u and v that maximize their efficiency score (see Eq. (1)). However, different weights imply different frontier surfaces, which might render the comparison of those DMUs inappropriate (Boubaker et al., 2023b).

According to Kao and Hung (2005), there is a consensus among practitioners that using dynamic weights to classify DMUs as efficient or inefficient is acceptable. However, when ranking the DMUs, most practitioners might disagree when different sets of weights are used. It becomes possible to compare and rank the performances of DMUs on a standardized basis by employing a common set of weights (CSW). Such CSW DEA models have been extended and applied to the banking sector (Hammami et al., 2022; Kao & Hung, 2005), professional tennis players (Ramón et al., 2012), manufacturing

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[3] Note that we also utilize the Euclidean distance in defining the common set of weights for the group-frontiers, as explained in the following section.

(Shabani et al., 2019), and even provinces (Omrani et al., 2019) and countries (Yang et al., 2018).

Cook and Zhu (2007) also argue that in many real-world applications where DEA is applied, DMUs can be grouped under the same management (team) and thus experience common multipliers or weights. In this sense, this CSW helps to minimize the maximum discrepancy among the within-group DMUs from the (group) frontier (Cook & Zhu, 2007). In later research, Cook et al. (2017) extend this idea to evaluate the research performance of public Spanish universities, with those belonging to the same region forming a within-group-frontier. Although this idea is similar to the MF setting, it has never been incorporated in MF studies. More importantly, the CSW proposed by Cook and Zhu (2007) and Cook et al. (2017) is based on the L_1 distance between the inefficient DMUs and the frontier, while it is argued that the Euclidean L_2 distance is more appropriate (Hammami et al., 2022). Therefore, this study employs the ECSW proposed by Hammami et al. (2022).

Given the previous steps, assume that we have already computed the MF and (data-driven) group-frontier efficiency scores for all DMUs involved. Our aim now is to define the ECSW for each group-frontier under the assumption that DMUs belonging to the same group should be evaluated under the same weights, whereby this argument has not been applied to previous MF studies. In particular, for the *j*-th DMU, we define:

$$\Delta X_j = \sum_{i=1}^{k} v_{ij}x_{ij} - \sum_{i=1}^{k} v_{ij}^{ECSW}x_{ij} \tag{8}$$

$$\Delta Y_j = \sum_{r=1}^{m} u_{rj}y_{rj} - \sum_{r=1}^{m} u_{rj}^{ECSW}y_{rj} \tag{9}$$

where (u_r, v_i) are the group-frontier DEA dynamic weights calculated from Eq. (1) above and $\left(u_{ij}^{ECSW}, v_{ij}^{ECSW}\right)$ are the Euclidean CSW that we are trying to achieve. In this sense, Eq. (8) measures the input distance and Eq. (9) represents the output distance between the DEA and ECSW coordination of the within-group DMU_j. Accordingly, the Euclidean distance between the two is:

$$GR_{DIST\,j} = \sqrt{\Delta X_j^{\,2} + \Delta Y_j^{\,2}} \tag{10}$$

The optimal ECSW—if it exists—is the set of weights that can minimize the sum of $GR_{DIST\,j}$ for all DMUs within that group. Hence, we have a GP problem of:

$$\min\left(GR_{DIST\,1} + GR_{DIST\,2} + .. + GR_{DIST\,s}\right) \tag{11}$$

subject to

$$\frac{\sum_{r=1}^{m} u_{rj}^{ECSW} y_{rj}}{\sum_{i=1}^{k} v_{ij}^{ECSW} x_{ij}} \leq 1, j = 1, 2, .., s$$
$$u_{ij}^{ECSW}, v_{ij}^{ECSW} \geq \varepsilon, \forall i, r$$

where s is the number of DMUs in the group ($s < n$). Note that the group-frontier ECSW efficiency scores of the DMUs within the group are also defined in the first constraint of Eq. (11).

3.4 The relationship between SE and EE: a truncated regression approach

The group-frontier Euclidean CSW efficiency scores (*ECSW_GR_EF*), the meta-frontier efficiency (*MF_EF*), and their corresponding meta-technology (*MTR*) are further examined to ascertain whether the SE influences EE. Besides SE, we also follow the previous literature by including other control variables in the research. For instance, macroeconomic factors such as economic growth, industrial structure, and energy prices have been found to affect EE (Antonietti & Fontini, 2019), while technological advancements—including the adoption of energy-efficient technologies and practices—also play a crucial role in improving EE (Paramati et al., 2022; Yu, 2020). In addition, institutional factors such as energy regulations, standards, and policies have also been identified as significant drivers of EE improvements (Sun et al., 2019, 2022). Consequently, our model includes the total renewable energy (RENEW) as examined in Hwang (2023) and Naimoglu and Akal (2023); governmental spending on education (EDU_SPENDING) as in Capasso et al. (2019) and Ngo et al. (2022); foreign direct investment (FDI) (Zhang et al., 2018); and a set of institutional factors including Control of Corruption (CC), Government Effectiveness (GE), Political Stability and Absence of Violence/Terrorism (PS), Regulatory Quality (RQ), Rule of Law (RL), and Voice and Accountability (VA) (Ofori & Figari, 2023).

More importantly, it is noted that our dependent variables (e.g., ECSW_GR_EF and MF_EF) are, by definition, bounded between the (0,1] intervals. Accordingly, OLS regressions to examine the impacts of those control variables on our EE measures are biased (Simar & Wilson, 2007). Although there are several remedies for this situation (Boubaker et al., 2023b; Johnson & Kuosmanen, 2012; Thaker et al., 2021), we follow Ouenniche and Carrales (2018) and Ngo and Tsui (2021) in using the traditional truncated regression based on the fact that (i) it is simple to use but can still provide a general picture of the relationship between our variables and (ii) the combination of SBM, Ward clustering, and ECSW models makes it complicated to perform the Simar and Wilson (2007)'s bootstrap.

Accordingly, EE can be explained by:

$$EE = \beta_0 + \beta_i Z_i + \varepsilon \tag{12}$$

where EE is measured by *MRT*, *MF_EF*, and *ECSW_GR_EF* as defined in Eqs. (4), (5), and (11), respectively; Z is a vector of explanatory variables, including the *SE* index (more details in Sect. 3.5 below); β is a vector of parameters to be estimated; and ε is the statistical error.

3.5 Data and variables

As discussed in Sect. 3.1, to estimate the energy efficiency of countries across the globe, we rely on three inputs (CAPITAL, LABOUR, and ENERGY) and one output (GDP). Similar to Wang et al. (2024), we extract data from the World Development Indicators (WDI)(The World Bank, 2023) in terms of the Gross capital formation (constant 2015 US$) to proxy for CAPITAL; Labour force (total) to proxy for LABOUR; and GDP (constant 2015 US$). Although the WDI also provides information on energy consumption, they are almost entirely missing for our sample, and thus we extracted the data for Total energy consumption (in Quad Btu) from the IEA (2023) to proxy for ENERGY.

For the determinants of EE (discussed in Sect. 3.3), data for the SE is extracted from Medina and Schneider (2019) with the most recent values for 2017. Therefore, our dataset is cross-country data of the same year. Meanwhile, the total renewable energy production is obtained from the International Renewable Energy Agency (IRENA, 2023) and is used to proxy for RENEW. Data for government expenditure on education, FDI, and institutional variables (e.g., Control of Corruption and Regulatory Quality) are all extracted from the WDI (The World Bank, 2023). Matching the three datasets for SE (Medina & Schneider, 2019), total energy consumption (IEA, 2023), and others (The World Bank, 2023) resulted in a sample of 131 countries/observations for 2017. The sampled countries are further illustrated in Fig. 2 of Sect. 4.1 whilst their descriptive statistics are presented in Table 1 below. Stata version 17 (StataCorp, 2021) is used for all analyses.

4 Results and discussions

4.1 Meta-frontier data envelopment analysis

The data-driven Ward clustering analysis on our sample of 131 countries divided them into three groups. As summarized in Table 2 and illustrated in Fig. 3, group 1 comprises the majority of the sample with 89 countries (e.g., Albania, Cambodia, and Ukraine) whose input/output settings were on the lower side, i.e., maximum gross capital formation of less than 38 billion US$, a labour force of less than 56 million, and total energy consumption of less than four Quad Btu (to produce less than 141 billion in GDP). Meanwhile, group 2 features 31 ‘mid-level’ countries (e.g., Finland, Greece, and Vietnam), and group 3 includes eleven ‘high-class’ countries (e.g., Canada, India, and Japan), which on average consumed 489.60 billion US$ of gross capital, had a labour force of 93.88 million, overall consumed 12.08 Quad Btu of energy, and produced 2,188.42 billion US$ in GDP. While this classification is close to the development status (e.g., developed, emerging, and underdeveloped) defined by the World Bank or International Monetary Fund (IMF), we argue that our approach is more accurate regarding the data. For instance, India now belongs to Group 3 since its inputs/outputs are comparable to other countries in that group, rather than being in Group 2 or even Group 1.

Accordingly, an MF DEA analysis is conducted for the 131 countries, while three ECSW DEA models are applied for the three relevant group-frontiers. Table 3 reports the estimated results for the MF efficiency, Euclidean CSW efficiency scores, and MTR.

Table 1 Descriptive statistics

	Unit	N	Mean	SD	MIN	MAX
DEA variables						
Inputs						
CAPITAL	billion 2015 US$	131	66.63	155.60	0.05	1102.32
LABOUR	million persons	131	15.44	47.08	0.04	496.93
ENERGY	Quad Btu	131	1.77	4.00	0.00	31.96
Output						
GDP	billion 2015 US$	131	292.27	666.68	0.49	4369.04
Determinants of energy efficiency						
SE	Index	120	27.37	11.36	5.40	55.80
RENEW	Mega Watts	115	129.40	281.75	0.01	1677.37
EDU_SPENDING	% of government expenditure	123	4.80	1.93	0.00	12.75
FDI	net inflow, % of GDP	129	2.85	12.08	−117.42	33.56
CC	Index	131	0.00	0.98	−1.58	2.37
GE	Index	131	0.02	0.93	−2.19	2.03
PS	Index	131	−0.07	0.84	−2.35	1.44
RQ	Index	131	0.04	0.92	−1.71	1.92
RL	Index	131	0.01	0.93	−1.67	2.06
VA	Index	131	0.05	0.93	−1.72	1.75

CAPITAL Gross capital formation, *LABOUR* Labour force, *ENERGY* Total energy consumption, *GDP* Gross domestic product, *SE* Shadow economy, *RENEW* Total renewable energy production, *EDU_ SPENDING* Government expenditure on education, *FDI* Foreign direct investment, *CC* Control of corruption, *GE* Government effectiveness, *PS* Political stability and Absence of violence/terrorism, *RQ* Regulatory quality, *RL* Rule of law, *VA* Voice and accountability. N stands for Number of observations. SD stands for Standard deviation. And 1 Btu (British thermal unit) is equivalent to about 0.293 Wh

Table 2 Three country groups under the Ward clustering method

	CAPITAL	LABOUR	ENERGY	GDP
Unit:	billion 2015 US$	million persons	Quad Btu	billion 2015 US$
Group 1: 89 countries				
Mean	7.35	4.92	0.26	32.08
SD	8.36	7.69	0.43	32.00
MIN	0.05	0.04	0.00	0.49
MAX	37.88	55.82	3.54	140.70
Group 2: 31 countries				
Mean	86.76	17.83	2.46	366.42
SD	45.71	21.15	1.81	166.04
MIN	27.52	2.43	0.62	168.31
MAX	199.00	72.84	9.18	807.60
Group 3: 11 countries				
Mean	489.60	93.88	12.08	2,188.42
SD	280.26	138.49	7.63	1,054.39
MIN	204.56	20.47	5.43	1,027.66
MAX	1,102.32	496.93	31.96	4,369.04

CAPITAL Gross capital formation, *LABOUR* Labour force, *ENERGY* Total energy consumption, *GDP* Gross domestic product, *SD* stands for Standard deviation

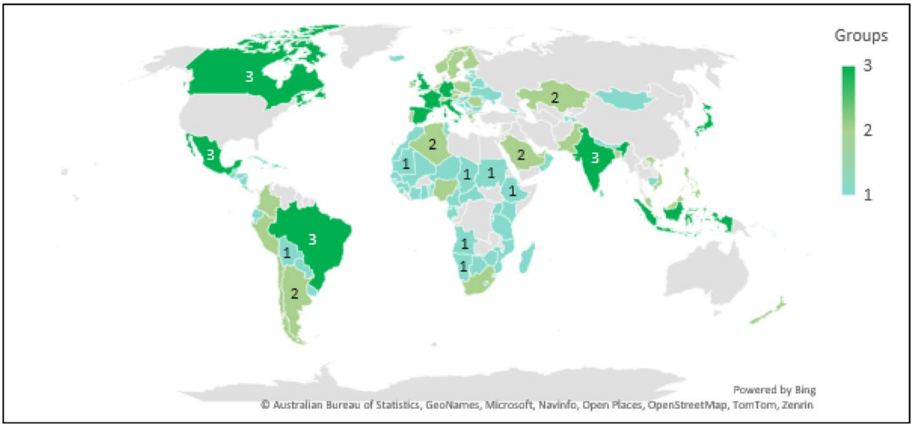

Fig. 3 Distribution of the three group-frontiers

Table 3 DEA results on the energy efficiency of 131 countries in 2017

	MF_EF	ECSW_GR_EF	MTR
Group 1: 89 countries			
Mean	0.5157	0.9110	0.5686
MIN	0.1928	0.6246	0.2077
MAX	1.0000	1.0000	1.0000
N_EF	2	46	3
Group 2: 31 countries			
Mean	0.5996	0.9730	0.6176
MIN	0.2251	0.7942	0.2251
MAX	1.0000	1.0000	1.0000
N_EF	2	11	2
Group 3: 11 countries			
Mean	0.5800	0.8825	0.6666
MIN	0.2428	0.5748	0.3440
MAX	0.9798	1.0000	0.9798
N_EF	0	1	0
All samples: 131 countries			
Mean	0.5410	0.9233	0.5884
MIN	0.1928	0.5748	0.2077
MAX	1.0000	1.0000	1.0000
N_EF	4	58	5

MF_EF Energy Efficiency under Meta-frontier, *ECSW_GR_EF* Energy efficiency under group-frontiers using the Euclidean Common Set of Weights, *MTR* Meta-technology ratio, *N_EF* Number of efficient countries (i.e., EF = 1.0000)

Interestingly, we initially find that the middle group of 31 countries has higher EE scores in both the MF and group-frontier analyses, with the highest mean and minimum scores. By contrast, Group 3 only has one country that belongs to the ECSW group-frontier and none on the MF, and its members are also not considered as the top performers with average efficiency scores of only 0.5800 and 0.8825 for the MF and group-frontier estimates, respectively. However, it is understandable that countries with higher input/output settings (such as Group 3) might not end up with higher efficiency scores as those scores are the relative efficiency regarding the best-practice fron-

Table 4 The determinants of energy efficiency

	MF_EF		ECSW_GR_EF		MTR	
	Coefficient	SD	Coefficient	SD	Coefficient	SD
SE	−0.00185*	0.00112	−0.01777*	0.00949	−0.01932*	0.01007
SE^2	−0.00003	0.00009	0.00020	0.00014	0.00022	0.00015
RENEW	−0.00002	0.00004	−0.00003	0.00006	−0.00002	0.00007
EDU_SPENDING	0.00203	0.00622	0.01910*	0.01030	0.02295**	0.01093
FDI	−0.00034	0.00080	−0.00174	0.00132	−0.00160	0.00141
CC	0.05808	0.03801	0.17377***	0.06292	0.15278**	0.06674
GE	−0.03057	0.04330	−0.16758**	0.07167	−0.16362**	0.07604
PS	−0.04277*	0.02423	−0.01589	0.04010	0.00922	0.04254
RQ	−0.10593**	0.04157	0.01431	0.06881	0.09372	0.07300
RL	0.12021*	0.06163	−0.05553	0.10201	−0.14974	0.10822
VA	−0.00531	0.02494	0.05478	0.04129	0.06458	0.04380
Constant	0.89671***	0.09495	0.95990***	0.15717	1.04766***	0.16673

MF_EF Energy Efficiency under Meta-frontier, *ECSW_GR_EF* Energy efficiency under group-frontiers using the Euclidean Common Set of Weights, *MTR* Meta-technology ratio, *SE* Shadow economy, SE^2 Shadow economy squared, *RENEW* Total renewable energy production, *EDU_SPENDING* Government expenditure on education, *FDI* Foreign direct investment, *CC* Control of corruption, *GE* Government effectiveness, *PS* Political stability and Absence of violence/terrorism, *RQ* Regulatory quality, *RL* Rule of law, *VA* Voice and accountability. *, **, and *** denote the significance levels at 10%, 5%, and 1%, respectively

tiers enveloped by other countries. In this sense, it also indicates the existence of the diminishing marginal utility of production in advanced economies, where the marginal increase in outcomes—and thus efficiency—is lower than the marginal cost of inputs (Brookes, 2000; Das et al., 2020; Jakob, 2006).

In addition, the MTR reaches its lowest mean score of 56.86% in Group 1, suggesting that this group faces the largest gap between the technology available to all countries (i.e., regarding the MF) and the technology available to Group 1's countries. As expected, the MTR gaps are smaller for countries from Groups 2 and 3. We argue that there is not only inequality in resources (e.g., inputs and output) but also in technology for many countries regarding their EE.

4.2 Determinants of energy efficiency: the important role of shadow economy

Due to the mismatch in the explanatory variables (see Table 1), only 101 observations remain for use in our regression analyses. Table 4 reports the truncated regression results of Eq. (12),[4] whereby several important findings and discussions can be drawn as follows.

First, it is statistically confirmed that the size of the SE has a negative impact on the country's EE at both the global (i.e., MF EE) and group levels (i.e., EE under group-frontiers using the ECSW), although the magnitudes/coefficients are small and only significant at the 10% level. However, we cannot find evidence of an EKC-like effect, i.e., an inverted U-shape relationship between SE and EE. Indeed, the positive coefficients of SE^2 for both energy efficiency under group-frontiers using the ECSW and MTR equa-

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[4] Estimated results using OLS and Tobit regressions are consistent with the truncated regression results reported in Table 4 and thus are not reported here but are available upon request.

tions—although statistically insignificant—suggest that the relationship between the SE and EE might follow a U-shape curve, whereby the SE drags EE down until a certain level then it starts to help improve it. We argue that in this case the deregulation effect of SE comes first (for the decreasing part), whereas the scale effect comes later (for the increasing part of the U-shape curve), as discussed in Elgin and Oztunali (2014).

Second, we find that government spending on education (EDU_SPENDING) does helps to improve EE. Since education spending can proxy for a country's human capital and research and development, one could follow Capasso et al. (2019) in arguing that increased government spending on education could enhance productivity and efficiency—especially in terms of energy consumption—and improve EE. Such empirical evidence is also found in a single-country (Greece) study by Zografakis et al. (2008), a G5 (Canada, Germany, France, Japan, and the US) study by Caglar and Ulug (2022), an OECD study by Geller et al. (2006), and this time, in our study with 131 countries.

Third, institutions play different roles in the relationship between SE and EE, whereas political stability and regulatory quality can hinder MF EE, while government effectiveness is also an obstacle for EE under group-frontiers using the ECSW and its MTR. Note that the political stability variable reflects perceptions of the likelihood of political instability and/or politically motivated violence (including terrorism), regulatory quality measures perceptions of the ability of the government to monitor and promote private sector development, and government effectiveness captures perceptions of the quality of public services and policy formulation/implementation and the credibility of the government's commitment to those policies (The World Bank, 2023). In this sense, it is understandable that a higher PS might lead to lower EE because higher political risk can increase energy demand and consumption, whereas the aspect of renewable and efficient energy usage becomes less important (Wang et al., 2022). For RQ, we argue that the threshold effects of (environmental) policy do hold for our sample, whereas the regulation stringencies in most countries have exceeded the optimal level, resulting in a low incentive for EE in practice. For instance, Guo and Yuan (2020) showed that due to a high level of policy stringency, the effective incentives for promoting EE across 26 out of 30 Chinese provinces were limited. Another possible explanation for RQ is that regulatory improvement could become a reason for fast industrial progress (Wenlong et al., 2023), thus contributing to higher energy consumption. Meanwhile, if evaluated using a common base of the ECSW group-frontiers, the differences in GE across groups and within a certain group play an important (but negative) influence on EE. For instance, the average GE for Groups 1, 2, and 3 are −0.304, 0.691, and 0.735, respectively. Given that the three groups accordingly consist of 89, 31, and 11 countries, respectively, one can argue that this negative influence is largely driven by Group 1, whereas the positive effects from Groups 2 and 3 were overridden, as evidenced in Chang et al. (2018) and Kulin and Johansson Sevä (2021). In contrast, the variable CC shows positive relationships with ECSW_GR_EF and MTR, suggesting that countries should improve their control of corruption to enhance EE. Such finding is in line with previous studies such as Ozturk et al. (2019) and Lu et al. (2021).

Overall, the production of renewable energy (i.e., RENEW) and net FDI inflows do not show significant impacts on EE. For the former factor, we argue that its size remains limited (for instance, Table 1 reports that the average total energy consumption (ENERGY) is 1.77 Quad Btu, which is equivalent to more than 518 million MWh, while the average total renewable energy production (RENEW) is only around 130 MW, resulting in an insignificant contribution to EE. For the latter, our finding is in line with Yasmeen et al. (2022) and Long et al. (2023), who found the impacts of FDI depend on several factors, including the investment type, location, and implementation.

5 Conclusions

We have extended the operations research literature and developed a data-driven multiple-criteria decision analysis (MCDA) meta-frontier (MF) model to examine the energy efficiency (EE) of 131 countries across the globe, as well as its determinants, including the shadow economy (SE), government spending on education (EDU_SPENDING), institutions (such as Control of Corruption, CC, and Regulation Quality, RQ), and so on. In this sense, this study contributes to the understanding of the United Nations (2024)' Sustainable Development Goals, including SDG4 Quality Education (regarding education spending), SDG8 Decent Work and Economic Growth (regarding economic development and shadow economy), and SDG16 Peace, Justice and Strong Institutions (regarding institutional quality). For this purpose, we combined the Slacks-Based Measure (Tone, 2001) and MF (O'Donnell et al., 2008) of DEA, the Euclidean Common Set of Weights (Hammami et al., 2022) of MCDA, and Ward clustering (Ward, 1963) of unsupervised machine learning into a single framework. This is a methodological contribution of this study.

Empirically, our findings reveal several interesting arguments regarding the EE measure and its determinants. First, it is observed that the middle group comprising 31 countries exhibits higher EE scores in both the MF and group-frontier analyses. The eleven countries from the group with the highest level of inputs and outputs do not emerge as top performers, whereby we argue that this might reflect the marginal effect of input–output utilization. This is also related to the technological gaps across the sampled countries, where an inequality in production technology exists for many countries (e.g., Group 1 versus Group 3), making it difficult for countries to improve their EE. Second, our analysis also reveals that the size of the SE has a minor negative impact on EE, although no evidence of an Environmental Kuznets Curve-like effect is found. Instead, a U-shaped relationship is observed, suggesting that the SE initially hinders EE until a certain level, after which it starts to help improve EE. Other factors that significantly influence EE include government spending on education, political stability, regulatory quality, control of corruption, and government effectiveness. We therefore suggest that governments should (i) pay more attention to the SE, especially regarding the nation's EE; (ii) increase investment in education and human capital; and (iii) strengthen their institutional factors.

While our model can be applied to other fields (e.g., banking or manufacturing efficiency) and/or incorporate advanced techniques and methods such as network DEA (Lozano et al., 2013), bootstrap regression (Boubaker et al., 2023a; Simar & Wilson, 2007), productivity change over time (Ang et al., 2023; Ngo & Nguyen, 2012), or other ML techniques (Boubaker et al., 2023b; Thaker et al., 2021), there are other research avenues to further deepen our understanding of the relationship between SE and EE. For instance, one could analyze the specific mechanisms through which the shadow economy affects energy efficiency. Comparative studies across countries or regions with varying levels of development, institutional quality, and energy profiles (Wang et al., 2022; Wenlong et al., 2023) can provide insights into the role of specific contextual factors in shaping these relationships. Additionally, examining the effects within specific sectors or industries can help identify sector-specific policy implications. Finally, an extension to incorporate environmental issues of EE such as carbon dioxide and greenhouse gas emissions (Belaïd & Massié, 2023; Ngo et al., 2024; Wu et al., 2023; Zuniga Gonzalez & Jaramillo-Villanueva, 2024) could underscore the role of energy efficiency in the sustainable development context.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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