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A DEA Approach for Assessing the Energy, Environmental and Economic Performance of Top 20 Industrial Countries

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Abstract: Due to growing concerns of global warming, reducing carbon emissions has become one of the major tasks for developing countries to meet the national demand for energy policies. The objective of this study is to measure the energy consumption, carbon emission and economic-environmental efficiency in terms of the environmental performance of the top 20 industrial countries by employing a data envelopment analysis (DEA) model from 2013 to 2017. This study used the trilemma of energy efficiency, CO_2 emission efficiency, and environmental efficiency, and also the contribution included the quantitative analysis of 20 industrial countries The results show that the energy efficiency of Australia, China, Japan, Saudi Arabia, and Poland are the best performing countries, whereas Mexico, Indonesia, Russia, and Brazil are identified as least efficient among all 20 countries. Furthermore, Russia's energy intensity has a maximum score while Poland has a minimum score. Additionally, in the case of CO_2 emission efficiency, Brazil, France, and Saudi Arabia are considered as efficient while nine country's scores were less than 0.5. The results show that most countries exhibit higher performance in economic efficiency than environmental efficiency. The study provides valuable information for energy policy-makers.

Keywords: energy consumption efficiency; CO_2 emission efficiency; economic-environmental efficiency; Slack-based DEA; top 20 industrial countries

1. Introduction

The pattern of global energy consumption is underway to develop the low carbon energy sources to fleet the national economy. There is a challenging issue to keep the global warming up to maximum of 1.5 °C, and unfortunately the natural resources are finite; simultaneously, the energy consumption is a basic pillar to produce environmental degradation factors to achieve an economic output. Growing concerns about energy consumption, economic output, environmental impacts and considerations of self-sufficient supply of energy security are major drivers of industrialized economies to control their level CO_2 emissions and also need to control the dependence of oil and gas [1]. Over the past three decades, global surface temperatures have increased significantly. According to a recent report by Intergovernmental Panel on Climate Change (IPCC), global warming of the atmosphere and oceans, snow and ice reduction, and sea level rise are mainly related to increased greenhouse gas (GHG) concentrations caused by human activities. The key drivers of global warming are GHG emissions from transport, fossil fuel consumption, buildings, industry, cement production, land use change (such as deforestation), and waste [2,3]. Most of the global emissions accounted for ~72% of CO_2, but methane, nitrous oxide and other gases have a significant share of 19%, 6%, and 3%, respectively, and also global energy-related CO_2 emissions represented ~80% of global GHG emissions [4]. At the same time, the burning of fossil fuels accounts for two-thirds of global carbon emissions which is the most substantial proportion of greenhouse gas emissions. Therefore, a reduction in carbon emissions has become one of the essential tasks for countries in developing national energy policies around the world [5,6].

Most modern techniques of energy production and consumption create environmental problems locally, regionally, and globally. Moreover, these techniques contribute to reducing the quality of life, hazarding human health, and the well-being of present and future humans. The annual average concentration of CO_2 in the atmosphere reached 400 ppm, 40 percent higher than the pre-industrial carbon dioxide level of 280 ppm in 2016. Since 1980, CO_2 emissions have increased by 50% [7]. As GHG emissions cause global climate change, there is growing concern about energy use and carbon dioxide emissions. Therefore, it is essential to systematically and regularly monitor and measure the environmental performance of economies around the world [8]. These measurements not only provide brief information for assessing growth, but also serve as a guide for countries to set environmental goals for international agreements such as the EU Climate and Energy Package. They can also remind countries to mitigate environmental issues and pressures. On November 6, 2017, the Agreement of the Conference of the Parties (COP) 24 on climate change came into force, with the aim of controlling the increase in global average temperature to 2 °C above pre-industrial levels and continuing the effort to limit the temperature increase to 1.5 °C [9].

Over the past two decades, many studies have been published on energy efficiency, carbon dioxide emissions, and environmental efficiency addressing these topics either individually or in combination. Data envelopment analysis (DEA) is a nonparametric approach proposed by Charnes, Cooper and Rhodes in 1978 to measure the relative efficiency of multiple inputs and outputs of a set of comparable entities [10]. Many practical and theoretical applications of DEA research have been reported [11–13]. Song et al. [14] applied a bootstrap DEA technique to evaluate the energy performance of BRICS countries. Even in their DEA analysis, they do not include carbon dioxide emissions but they established the relationship among CO_2 emissions and energy consumption separately in their research. In addition, there are some examples of "studies that focus on energy efficiency, regardless of carbon dioxide emissions contained in their analysis". On the contrary, different studies have incorporated carbon emissions in their energy efficiency analyses [15–17]. In addition to these energy efficiency studies, there are several research paper that focus not only on energy efficiency, but also on CO_2 emissions [18–20] and environmental performance [21,22].

All the studies mentioned above use nonparametric techniques to evaluate the economic efficiency of energy consumption and carbon emission. Economic energy efficiency is defined as the efficiency with which an economy converts energy related inputs into economic output and bad outputs. The consumption of fossil fuel energy generates undesirable output (CO_2 emissions) in addition to the desirable output. The assessment of environmental performance is impractical without considering the undesirable outputs. Huang and Li [23] applied an improved undesirable input and output two phase DEA model to measure environmental efficiency. Zhou et al. [24] measure the CO_2 emission control method in China using the several centralized DEA model to allocate carbon emissions under different strategies, it is found that it is more suitable for China to implement a modest emission reduction policy as early as possible in more developed regions. Fanyi Meng et al. [25] applied and compared different DEA model to measure the regional energy and carbon emission efficiency of China, and conclude that energy and carbon emission efficiency remains stable in 1996–2000 then declined in 2000–2005. Meng et al. [26] applied a non-radial DEA model to estimate the environmental performance of China's industrial sector. In [27], a non-radial DEA method and non-radial Malmquist index were applied for modeling multilateral comparisons and the change in the environmental performance of OECD economies. This study investigate that the environmental performance of OECD countries improved over time. Wu et al. [28] measured the energy and CO_2 emissions performance by using nonparametric DEA approach in their analysis. In another study, Yu et al. [29] measured the total factor carbon emission performance of top carbon emitters using the Malmquist CO_2 emission performance index (MCPI) approach. The environmental performance of investment in terms of renewable energy at the macroeconomic level in European countries was studied in [30]. Wang et al. [31] measured the improvement in energy efficiency of twenty five countries using a slack-based DEA approach and Malmquist Productivity Index (MPI). The multiple-criteria decision analysis (MCDA) DEA method was applied in [32] to construct a slacks-based composite indicator for 109 countries worldwide, and the authors of [33] evaluated the effect of clean energy use on total factor efficiencies of 87 countries from 2004 to 2010. Most studies found in the literature measured the energy efficiency or CO_2 emission efficiency of the country or region, but they did not consider economic development.

This paper undertakes an evaluation of energy consumption, carbon emission and economic-environmental efficiency of the top 20 industrial countries by using traditional output oriented DEA model over the period of 2013 to 2017. This study contributes to the existing literature on energy consumption, CO_2 emissions, and economic-environmental efficiency and DEA modeling. Further, the study calculates how much CO_2 emissions and primary energy use can be reduced. Unlike others, we used the trilemma of energy efficiency, CO_2 emission efficiency, and environmental efficiency. Our contribution also included the quantitative analysis of 20 industrial countries. Finally, the study recommends directions for structural reforms and policy changes that will not only deliver measurable results for economic performance in the coming years, but may also be of interest to researchers, policy-makers, and other readers. Section 2 discusses the methodology used in this research. Section 3 presents empirical results and the discussion. Finally, Section 4 concludes the paper and provides several policy recommendations.

2. Methodology

This section first presents a method for assessing the energy consumption and carbon emissions efficiency of the top 20 industrial countries as shown in Figure 1. Additionally, in this section, we measured the potential energy saving targets and the reduction of CO_2 emission of inefficient countries for efficiency improvement. In the second section, two models were used: first, we used the undesirable outputs orientation DEA technique proposed in [34] to measure the environmental efficiency and, second, we used the SBM-DEA model presented in [13] to explore the economic efficiency.

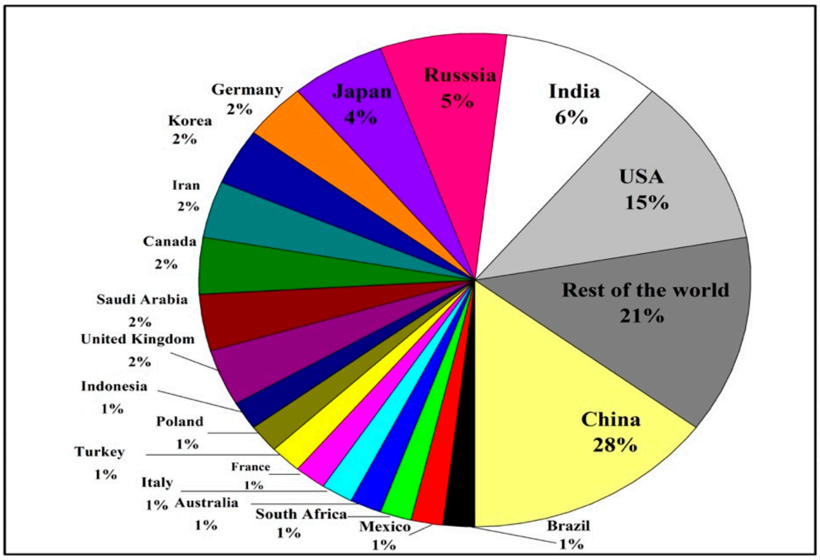

Figure 1. Top 20 CO_2 emitter countries.

We consider that there are k number of countries denoted by DMU_k $(k = 1, 2, \ldots, \text{K})$. In the process of measuring national or regional environmental efficiency, or energy efficiency, each country employs energy consumption and population as inputs to generate desirable and undesirable outputs, while GDP and carbon emission are generally exercised as desirable output and undesirable outputs respectively [13,35]. To explore the energy consumption, CO_2 emission, and environmental economic efficiency of the top 20 industrial countries, we use population as non-energy input and primary energy use as an energy input, while using GDP as a desirable output and CO_2 emission as an undesirable output.

2.1. Environmental DEA Technology

Here, we consider a production process in which both desirable outputs (Y) and undesirable outputs (U) are produced with the consumption input (X). Suppose that the vectors of inputs, desirable outputs, and undesirable outputs are presented as follows, $X = (x_1, x_2, \ldots, x_n)$, $Y = (y_1, y_2, \ldots, y_m)$, $U = \left(u_1, u_2, \ldots, u_j\right)$, and the production technology function T can be defined as

$$T = \{(X, Y, U) : X\ can\ produced\ (Y, U)\} \tag{1}$$

The assumptions imposed on T proposed by [36] are below.

(i) if $(X, Y, U) \in T$ and $0 \le \theta \le 1$ then $(X, \theta Y, \theta U) \in T$
(ii) if $(X, Y, U) \in T$ U = 0 then Y = 0

According to assumption (i), the outputs are weakly disposable; this suggests the reduction in undesirable outputs is not free. Similarly, the proportional decrease in desirable outputs and undesirable outputs is possible. Assumption (ii) indicates that when desirable outputs are produced, some undesirable outputs must also be produced.

The piecewise linear manufacturing technology T is clearly defended: in the case of nonparametric specification, it can be widely used in empirical studies. This kind of production technology T could be named as environmental DEA technology described in [37], as this technology is designed in the framework of DEA model. Suppose there are $k = 1, 2 \ \ldots \ldots \ K$ DMUs. So, for DMU_k the vectors of inputs, desirable outputs and undesirable outputs are presented as $x_k = (x_{1k}, x_{2k}, \ldots, x_{Nk})$, $y_k = (y_{1k}, y_2, \ldots, y_{Mk})$, $u_k = \left(u_{1k}, u_{2k}, \ldots, u_{jk}\right)$ respectively. Environmental DEA technology that exhibits a constant rate of return (CRS) can be expressed as follows.

$$T = \{(x, y, u)\} : \sum_{k=1}^{K} z_k x_{nk} \le x_n \ n = 1, 2, \ldots, N \tag{2}$$

$$\sum_{k=1}^{K} z_k y_{mk} \ge y_m \qquad m = 1, 2, \ldots, M \tag{2a}$$

$$\sum_{k=1}^{K} z_k u_{jk} = u_j, \qquad j = 1, 2, \ldots, J \tag{2b}$$

$$z_k \ge 0,\ k = 1, 2, \ldots, K$$

It can be tested that Model 1 fulfills all the properties as discussed above, e.g., the outputs are weak disposable and the desirable and undesirable outputs are null-joint.

2.2. Method for Measuring Energy Consumption and CO_2 Emission Efficiency

Many environmental performance indices (EPI) have been developed by using environmental DEA technology with different types of energy efficiency measurements, but the undesirable outputs orientation-based DEA model is particularly attractive [13]. This model provides a standardized and aggregated efficiency measurement for environmental performance. The primary energy consumption efficiency is developed by Model 3:

$$PEI_1 = \theta_1^* = \ min\ \theta \tag{3}$$

$$\text{s.t} \sum_{k=1}^{K} z_k x_{nk} \leq x_{n0},\ n = 1, 2, \ldots, N \tag{3a}$$

$$\sum_{k=1}^{K} z_k e_k \leq \theta \mathrm{e}_0 \tag{3b}$$

$$\sum_{k=1}^{K} z_k y_{mk} \geq \mathrm{y}_{m0},\ m = 1, \ldots, M \tag{3c}$$

$$\sum_{k=1}^{K} z_k u_{jk} = \mathrm{u}_{j0},\ j = 1, \ldots, J \tag{3d}$$

$$z_k \geq 0,\ k = 1, \ldots, K$$

where PEI_1 measures the primary energy consumption of economies (DMUs). Model 3 indicates that the undesirable outputs are weak disposable. The constraint (3a) tries to reduce the energy input to its maximum that means the minimum energy input level of each DMU. The constraint (3c) indicates that the desirable output (GDP) and the resulting undesirable output (CO_2 emission) must be at least the same as the current level, whereas constraint (3d) indicates the undesirable output.

We know that the GDP is produced with consumption labor, capital, and energy; it produces CO_2 emission. To adequately address the efficiency assessment problem, CO_2 emission will be modeled based on weak disposability of undesirable output. Therefore, model 4 concentrates on the minimum emission level of CO_2. The CO_2 emission efficiency calculation is presented as follows.

$$PEI_2 = \theta_2^* = \min \theta \tag{4}$$

$$\text{s.t} \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z_k x_{nk}} \leq \mathrm{x_{n0}},\ \mathrm{n} = 1, 2 \ldots, \mathrm{N} \tag{4a}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z_k y_{mk}} \geq \mathrm{y_{m0}},\ \mathrm{m} = 1, \ldots, \mathrm{M} \tag{4b}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z_k c_k} = \theta \mathrm{c_0}, \tag{4c}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z_k u_{jk}} = \mathrm{u_{j0}},\ \mathrm{j} = 1, \ldots, \mathrm{J} \tag{4d}$$

$$\mathrm{z_k} \geq 0,\ \mathrm{k} = 1, \ldots, \mathrm{K}$$

where PEI_2 measures the CO_2 emission efficiency of DMUs. In Model 4, the constraint (4a) indicates that the resulting inputs must be equal to or less than the current level, whereas constraint (4b) indicates that the resulting desirable output must be equal to or greater than the current level. Constraint (4d) indicates that other undesirable output remains the same.

2.3. Method for Calculating Potential Energy Saving and Carbon Reduction

Environmental policies could result in wasted inputs and a loss of desirable outputs that impact results in energy consumption savings and carbon emission reduction. According to the DEA theory, energy consumption and carbon emissions objectives can be achieved based on the outcomes of efficiency results by using the DEA target setting method. Therefore, by estimating the gap between actual and target outcomes, DEA can be used to investigate potential energy savings and carbon reductions in inefficient economies [38]. For inefficient countries, the following formula can be used to measure potential energy savings and CO_2 reductions.

$$PES_k = (1 - \theta^*_{1k}) \times e_k \tag{5}$$

$$PCR_k = 1 - \theta^*_{2k} \times u_k \tag{6}$$

2.4. Method for Measuring Economic-Environmental Performance

In earlier studies, Model 7 is the undesirable output orientation-based DEA model proposed by Tyteca (1996), in which the subscript "0" indicates that the DMU_0 is under evaluation, which is particularly attractive. As compared to Model 4, in Model 7 an adjustment factor λ is applied to all undesirable outputs where only CO_2 emission adjustments are allowed.

$$PEI_3 = \theta^*_3 = \min \theta \tag{7}$$

$$\text{s.t} \sum_{k=1}^{K} z_k x_{nk} \leq x_{n0},\ n = 1, 2, \ldots, N \tag{7a}$$

$$\sum_{k=1}^{K} z_k y_{mk} \geq y_{m0},\ m = 1, 2 \ldots, M \tag{7b}$$

$$\sum_{k=1}^{K} z_k u_{jk} = \theta u_{j0},\ j = 1, 2, \ldots, J \tag{7c}$$

$$z_k \geq 0 \text{ and } k = 1, 2\ \ldots, K$$

PEI_3 is the environmental efficiency; although, Model 7 does not include the slacks of the inputs and desirable outputs. It means that the efficiency scores of the two DMUs are the same (1), even though a DMU leads the other in certain inputs and desirable outputs. One DMU at least is not fully efficient from a DEA perspective. It is reasonable to single out the inefficient DMUs and combine them into the economic-environmental index. The SBM-DEA model was proposed by Cooper et al. (2000) and was further enhanced by Zhou et al. (2006) who followed the concept and measured the slacks-based environmental performance index. We followed the SBM model of Zhou for the formulation of economic-environmental performance:

$$\rho^* = \min \frac{1 - \frac{1}{N}\sum_{n=1}^{N} s_n^- / s_{n0}}{1 + \frac{1}{M}\left(\sum_{m=1}^{M} \frac{s_m^+}{y_{m0}} + \frac{s_{uk}^-}{\theta^*_3 u_0}\right)} \tag{8}$$

$$\text{s.t} \sum_{k=1}^{K} z_k x_{nk} + s_{nk}^- = x_{n0},\ n = 1, 2\ \ldots, N \tag{8a}$$

$$\sum_{k=1}^{K} z_k y_{mk} - s_{mk}^+ = y_{m0},\ m = 1, \ldots, M \tag{8b}$$

$$\sum_{k=1}^{K} z_k u_{jk} + s_{uk}^- = \theta^*_3 u_{j0},\ j = 1, \ldots, J \tag{8c}$$

$$z_k \geq 0,\ k = 1, \ldots, K\ s_n^-, s_n^+ \geq 0$$

where θ^* indicates the slacks-based economic efficiency. In Model 8, the slacks s^-_{nk} and s^-_{uk}, indicate the excess in inputs and undesirable outputs. The slacks s^+_{mk} indicate the shortage in desirable outputs. These slacks variables are used to estimate and identify the economic inefficiency causes. Thus, Model 8 can be used to assess the economic inefficiency of DMU_0. A greater the value of θ^* means that in terms of pure economic performance, DMU_0 performs better. If there are no slacks (i.e., $s^-_n = s^-_u = s^-_m = 0$) in inputs and desirable outputs, then $\theta^* = 1$, which means there are no economic inefficiencies. However, Model 8 yields the economic efficiency score by using the optimal undesirable output levels obtained from Model 5.

Zhou et al. (2006), in their work measured the composite index for economic and environmental efficiencies by simply multiplying the two efficiency values. However, we used the sum of both efficiency values obtained from Models 7 and 8 to measure the economic-environmental efficiency (EEE), measured as

$$EEE = \theta^*_3 + \rho^* \tag{9}$$

2.5. Regression Analysis

We investigated whether there is a relationship between economic-environmental efficiency (EEE) and country-specific variables by using multiple linear regression model [39]. The EEE is the dependent variable and the explanatory variables used in this study are GDP per capita, carbon intensity, energy intensity, and the openness index. The explanatory variable GDP per capita is repeatedly used in previous studies [40,41]. The second variable, energy intensity affects a country's carbon dioxide emissions. CO_2 emission intensity is included as an explanatory variable and measured as the ratio of CO_2 emissions produced to the GDP of each country [42,43]. Finally, the openness index is calculated as the ratio of total exports and imports to GDP. The multiple linear regression model that describes the relationship between EEE and its determinants can be expressed as follows,

$$\mathrm{EEE_{it}} = \beta_0 + \beta_1 \mathrm{GDPPC}_{it} + \beta_2 \mathrm{EI}_{it} + \beta_3 \mathrm{CI}_{it} + \beta_4 \mathrm{OPENI}_{it} + \sum_{i=1}^{20} \gamma_i \mathrm{COUN_{it}} + \varepsilon \tag{10}$$

where EEE, GDPPC, CI, EI, and OPENI denote the environmental economic efficiency, GDP per capita, CO_2 emission intensity, energy intensity, and openness index of country i at year t, respectively. We let $COUN_{it}$ be a dummy variable that takes a value of one to specify the country under evaluation; otherwise, its value is zero. Also, ε is a random error term such that $\varepsilon \sim N\left(0, \sigma^2_i\right)$. The regression model is presented with a variable intercept and a constant slope. These regression models are common when evaluating panel data because they provide a simple but reasonable alternative that provides intercept and constant slope.

3. Results and Discussion

We collect data on four variables, namely, energy consumption, CO_2 emission, GDP, and population for the top 20 industrial countries for the period of 2013–2017. The data on GDP, population and energy consumption is attained from "World Development Indicators" (World Bank) [44], whereas the data related to CO_2 emission is acquired from the International Energy Agency (IEA) [45]. Data for variables openness index and GDP per capita is collected from the World Bank indicators (2018) and the openness index is calculated as the ratio of total exports and imports to GDP. Energy consumption and CO_2 emission are calculated in millions of tons of oil equivalent (Mtoe), whereas the GDP is measured in 2010 US dollars. Table 1 lists the description of all the variables used in this study.

During the period in the study, the highest growth rate with respect to energy consumption was observed in the Turkey at 6.75% and Turkey also had the highest growth rate in terms of CO_2 emission at 7.76%. The highest energy consumption is observed in the United States at 2231 (Mtoe). The highest growth rate was measured in India with respect to GDP at 7.33% during the period studied; India also had the second highest growth rate recorded for CO_2 emissions at 4.98%. Japan showed negative

CO_2 growth rates of 1.97% and also negative growth rate (−1.40%) in terms of energy consumption. However, compared with 2013, in 2017 the overall growth rates of GDP, CO_2 emission and energy consumption increased.

Table 1. Descriptive statistics of the variables (2013–2017).

	Energy Consumption		CO_2		GDP		Population		GDP per Capita	Openness
	Mean	Growth Rate (%)	Mean	Growth Rate (%)	Mean	Growth Rate (%)	Mean	Growth Rate (%)		
Iran	25.67	3.50%	284.44	2.40%	1423.03	2.78%	46.52	−0.02	27879	45.18
Australia	136.98	0.90%	402.38	0.86%	1313.87	2.42%	23.86	1.87	58115	43.08
Brazil	296.52	2.50%	485.4	−1.05%	2341.93	−1.38%	205.90	0.16	10290	25.23
Canada	334	0.70%	540	1.44%	1806.79	2.08%	35.88	1.99	46791	64.29
China	3013.94	4.10%	9184.02	0.07%	8934.85	6.94%	1371.86	0.165	7954	41.35
France	242	−0.70%	317.24	−1.17%	2779.62	1.25%	66.33	0.42	39512	61.15
Germany	326.9	0.21%	765.44	−0.95%	3716.02	1.95%	81.168	0.62	44519	85.08
India	690.66	5.30%	2151.4	4.98%	2302.06	7.33%	1308.65	1.16	1658	45.12
Indonesia	170.32	4.10%	496.68	−0.46%	991.17	4.99%	258.65	1.16	3572	36.65
Italy	153.82	0.10%	339.92	−0.40%	2068.02	0.85%	60.65	0.13	32713	56.72
Japan	457.72	−1.40%	1212.08	−1.97%	6003.19	1.09%	127.86	−0.12	38106	34.69
South Korea	285.8	1.30%	658.26	1.26%	1269.89	3.03%	50.48	0.51	27631	88.05
Mexico	187.5	1.10%	471.04	0.04%	1220.73	2.76%	125.85	1.32	9528	70.62
Russia	687.64	2.56%	1517.8	0.02%	1678.59	−0.19%	144.22	0.17	11796	47.27
Saudi Arabia	255.22	4.50%	575.46	2.74%	666.77	2.14%	31.45	2.41	22214	72.29
Poland	96.4	0.90%	39.12	−2.51%	632.19	1.53%	8.51	1.14	82757	97.02
Turkey	137.36	6.75%	353.34	7.76%	1083.34	5.46%	78.36	1.59	11412	50.4
United Kingdom	194.72	−0.50%	439.48	−5.38%	2695.58	2.28%	65.63	0.73	42789	45.12
United States	2231.44	0.74%	5220.16	−1.05%	16581.96	2.29%	321.46	0.74	56208	28.25
South Africa	122.8	0.20%	207.6	−0.15%	874.13	2.26%	16.49	0.48	48467	61.78

3.1. Energy Consumption Efficiency

The energy consumption score of the top 20 industrial countries are first calculated with Model 3. The results obtained are presented in Table 2. It can be seen that throughout the study period, among the 20 countries, Australia, China, Japan, Saudi Arabia, and Poland are the best performing countries with an efficiency score of 1. On the other hand, Mexico, Indonesia, Russia, and Brazil are identified as the least efficient among all 20 countries from 2013 to 2017. The relative rankings of Germany, the United Kingdom, South Korea, France, Turkey, and Mexico remain almost the same every year from 2013 to 2017, whereas Canada, Iran, and South Africa show significant improvement during the five-year period. The United States and Italy show a gradual decline during the study period. In the case of India, the country is ranked 16th in 2013, whereas in the succeeding years, it performs best with an efficiency score of 1. The energy intensity of all developed countries and large developing countries is declining, mainly due to changes in technology, energy mix, economic structure, and the way capital is invested and the labor used.

Table 2. Primary energy consumption efficiency of the top 20 industrial countries from 2013–2017.

	2013		2014		2015		2016		2017	
DMU	**Score**	**Rank**	**Score**	**Rank**	**Score**	**DMU**	**Score**	**Rank**	**Score**	**Rank**
Iran	0.635	13	0.641	14	0.659	13	0.657	14	0.676	13
Australia	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Brazil	0.425	20	0.424	20	0.411	20	0.391	20	0.389	20
Canada	0.725	11	0.729	12	0.724	12	0.725	11	0.736	11
China	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
France	0.634	14	0.623	15	0.618	15	0.625	15	0.626	15
Germany	0.826	8	0.824	9	0.816	9	0.818	9	0.811	9
India	0.521	16	1.000	1	1.000	1	1.000	1	1.000	1
Indonesia	0.461	18	0.466	18	0.481	18	0.485	18	0.507	18
Italy	0.734	10	0.731	11	0.731	11	0.725	12	0.721	12
Japan	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
South Korea	0.655	12	0.653	13	0.657	14	0.662	13	0.674	14
Mexico	0.507	17	0.499	17	0.507	17	0.507	17	0.508	17
Russia	0.461	19	0.459	19	0.445	19	0.441	19	0.439	19
Saudi Arabia	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Poland	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Turkey	0.544	15	0.575	16	0.553	16	0.559	16	0.579	16
United Kingdom	0.812	9	0.814	10	0.793	10	0.779	10	0.767	10
United States	0.884	6	0.884	7	0.871	8	0.865	8	0.865	8
South Africa	0.869	7	0.873	8	0.887	7	0.891	7	0.891	7

Table 3 presents the average primary energy consumption efficiency and the energy intensity of the top 20 industrial countries from 2013–2017. Energy intensity (EI) measures how much a bit of energy benefits the economy. This value is calculated by taking the ratio of total primary energy consumption (including all types of the fuels and flows that a country uses to get energy) to GDP. Notice that Australia, China, Japan, Saudi Arabia, and Poland are efficient countries with a score of 1, while Turkey, Mexico, Indonesia, Russia, and Brazil are the least efficient countries with an efficiency score of 0.563, 0.506, 0.481, 0.449, and 0.408, respectively. The second column indicates the energy intensity of the top 20 industrial countries. Russia has a maximum score of 0.409 while Poland has a minimum score of 0.044. By comparing primary energy consumption and energy intensity, India was ranked fourth on the energy intensity score, but its score in primary energy consumption is 0.904, making it ranked sixth amongst all 20 countries. Similarly, Russia was first with the highest energy intensity, though its primary energy consumption efficiency score was 0.449, ranked 19th. However, these findings indicate that to investigate the energy efficiency of countries, the use of energy intensity may not be appropriate.

We illustrate our approach and address economic development for the top 20 industrial countries for the period of 2013–2017. As of 2017, the top 20 industrial countries collectively accounted for 52.2% of global nominal gross domestic product (GDP) and 42.8% of global GDP at purchasing power parity. The energy demand globally increased by 2.2% in 2017, above its 10-year average of 1.7%. This growth trend was driven by the industrial countries, particularly Asian and EU countries. Moreover, due to increases in energy demand, the global power production also increased by 2.8% in 2017, close to its 10-year average. Most of the growth in energy demand came from developing countries making them an important group of countries to which we should pay close attention. However, several factors make the industrial countries important for this study. Almost all these countries belong to Annex I parties under the Kyoto protocol with legally binding targets for carbon emission reduction. These countries have also signed a Paris agreement on the carbon emission reduction and climate change. Investigating the main drivers of the changes in energy intensity and the impact of these drivers on carbon emissions will be informative for energy policy-makers who aim to improve environmental performance of energy consumption.

Table 3. Average total energy consumption efficiency and energy intensity of the top 20 industrial countries.

Energy Consumption Efficiency			Energy Intensity		
DMU	**Mean**	**Rank**	**DMU**	**Mean**	**Rank**
Australia	1.000	1	Russia	0.409	1
China	1.000	1	Saudi Arabia	0.384	2
Japan	1.000	1	China	0.337	3
Saudi Arabia	1.000	1	India	0.312	4
Poland	1.000	1	South Korea	0.224	5
India	0.904	6	Canada	0.187	6
South Africa	0.882	7	Indonesia	0.173	7
United States	0.874	8	Mexico	0.152	8
Germany	0.819	9	United States	0.134	9
United Kingdom	0.793	10	Turkey	0.127	10
Italy	0.728	11	Brazil	0.127	11
Canada	0.728	12	Australia	0.104	12
South Korea	0.66	13	Netherlands	0.097	13
Iran	0.654	14	Iran	0.095	14
France	0.626	15	Germany	0.088	15
Turkey	0.563	16	France	0.087	16
Mexico	0.506	17	Japan	0.076	17
Indonesia	0.481	18	Italy	0.074	18
Russia	0.449	19	United Kingdom	0.072	19
Brazil	0.408	20	Poland	0.044	20

The potential energy saving (PES) of inefficient countries is calculated with model 5. It can be seen from Figure 2 that the countries with the highest PES savings value (in Mtoe) were the United States (437), Russia (365), Brazil (175), and South Korea (97). On the other hand, Italy, United Kingdom, and South Africa have the lowest PES value of 41.8, 40.2, and 9.99, respectively. The overall energy consumption of the United Sates is higher among all top 20 industrial countries, even though its primary energy consumption efficiency score is 0.874. Therefore, for countries that utilize a lot of energy, even by slightly improving their energy use efficiency, large amounts of energy can be saved. Although energy efficiency analysis in the case of energy consumption identifies the potential for saving natural energy resources and developing renewable energy, it also reduces CO_2 emissions from the use of fossil fuels. The world's greenhouse gas emissions from fossil fuels account for 64% and 84% of CO_2 emissions, respectively [46]. The increase in atmospheric carbon dioxide concentration is attributed to industrialization and excessive use of natural resources [47]. Excessive use of energy increases greenhouse gas emissions has a negative impact on ecosystems and human life. However, the quality of life in these countries has reached a saturation point and it is necessary to reduce consumption and production levels to maintain a sustainable world. Also, these countries have great potential for reducing carbon dioxide emissions and saving energy consumption.

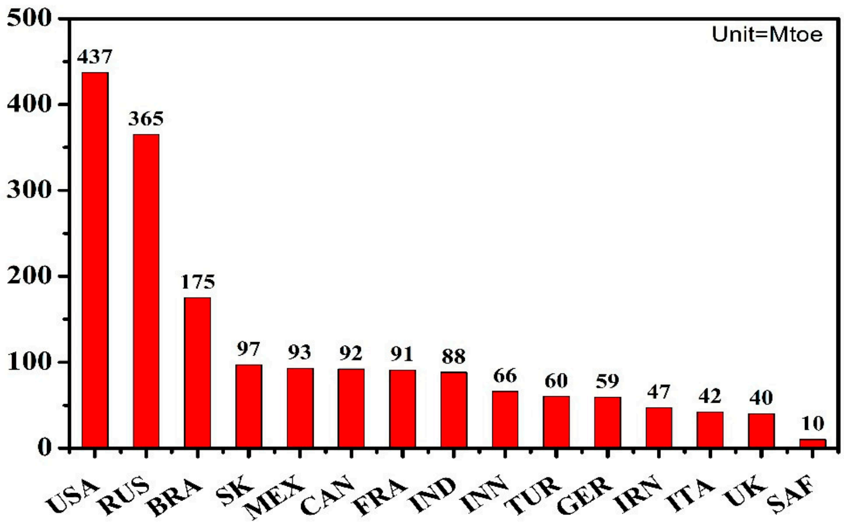

Figure 2. Potential primary energy saving of top 20 industrial countries from 2017.

3.2. Carbon Dioxide (CO_2) Efficiency

The overall CO_2 emission efficiency score of all top 20 industrial countries from 2013 to 2017 are represented in Table 4. It can be seen from Table 4 that of the 20 economies, Brazil, France, and Saudi Arabia are "efficient for five" consecutive years from 2013 to 2017, whereas the United States and China are the least efficient countries. Also, among all economies, the efficiency of Turkey, Iran, Italy, South Korea, Indonesia, and the United Kingdom remain unstable for the five consecutive years. Poland was efficient in the first year of the study, but in 2014 and 2015 its efficiency slightly declined, yet became efficient again in the last two years of the study. According to the relative ranking, the efficiency of the United Kingdom, South Korea, and Mexico significantly improved.

Table 4. CO_2 emission efficiency of top 20 industrial countries over the period of 2013–2017.

	2013		2014		2015		2016		2017	
DMU	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Iran	0.563	11	0.571	10	0.523	11	0.492	11	0.517	11
Australia	0.783	5	0.715	7	0.681	8	0.639	8	0.65	9
Brazil	1	1	1	1	1	1	1	1	1	1
Canada	0.697	7	0.726	6	0.684	6	0.629	9	0.698	7
China	0.198	20	0.21	20	0.214	20	0.229	20	0.222	20
France	1	1	1	1	1	1	1	1	1	1
Germany	0.348	16	0.378	16	0.379	16	0.383	16	0.37	16
India	0.76	6	0.787	5	0.767	5	0.78	5	0.787	5
Indonesia	0.471	13	0.477	14	0.432	15	0.442	15	0.451	15
Italy	0.479	12	0.512	12	0.491	12	0.486	13	0.482	13
Japan	0.296	18	0.316	18	0.326	17	0.34	17	0.331	17
South Korea	0.447	14	0.481	13	0.49	13	0.488	12	0.499	12
Mexico	0.648	9	0.689	9	0.682	7	0.689	7	0.684	8
Russia	0.663	8	0.696	8	0.676	9	0.748	6	0.703	6
Saudi Arabia	1	1	1	1	1	1	1	1	1	1
Poland	1	1	0.972	1	0.987	1	1	1	1	1
Turkey	0.59	10	0.552	11	0.599	10	0.568	10	0.594	10
United Kingdom	0.381	15	0.417	15	0.442	14	0.473	14	0.456	14
United States	0.283	19	0.297	19	0.302	19	0.313	19	0.303	19
South Africa	0.307	17	0.325	17	0.308	18	0.316	18	0.305	18

Average CO_2 emission efficiency and CO_2 intensity of all the top 20 industrial countries from the period 2013–2017 is presented in Table 5. Carbon emission intensity is defined as the emission rate of a given pollutant relative to the intensity of an industrial process or a particular activity. We calculate CO_2 emission intensity as the ratio of CO_2 emissions produced to the GDP of each country. It can be seen from the first column that Brazil, France, and Saudi Arabia are efficient economies with an efficiency score of 1. Among all top 20 industrial countries, the least efficient countries are Japan, South Africa, United States, and China with efficiency scores of 0.321, 0.312, 0.299, and 0.214 respectively. The second column presents the CO_2 emission intensity of all top 20 industrial countries. The value of CO_2 emission intensity ranges from 0.637 to 0.0619, in which India has the maximum and Poland has the minimum CO_2 emission intensity score among all top 20 industrial countries.

Further, by comparing the carbon emission efficiency and carbon emission intensity, Poland has the second highest efficiency score, ranked fourth, but in CO_2 emission intensity it has the lowest score and is ranked 20th. CO_2 emission efficiency scores and CO_2 intensity are extremely comparable with each other. Therefore, the transition economies such as India and Russia tend to have the highest carbon intensity.

Table 5. Overall average CO_2 emission efficiency and CO_2 emission intensity.

CO_2 Emission Efficiency			CO_2 Emission Intensity		
DMU	**Mean**	**Rank**	**DMU**	**Mean**	**Rank**
Brazil	1	1	India	0.637	1
France	1	1	Russia	0.604	2
Saudi Arabia	1	1	Saudi Arabia	0.462	3
Poland	0.991	4	China	0.445	4
India	0.776	5	South Korea	0.418	5
Russia	0.697	6	Indonesia	0.403	6
Australia	0.693	7	Mexico	0.386	7
Canada	0.686	8	Turkey	0.325	8
Mexico	0.678	9	United States	0.315	9
Turkey	0.580	10	Australia	0.306	10
Iran	0.533	11	Canada	0.298	11
Italy	0.489	12	South Africa	0.237	12
South Korea	0.480	13	Brazil	0.207	13
Indonesia	0.454	14	Germany	0.206	14
UK	0.433	15	Japan	0.202	15
Germany	0.371	16	Iran	0.199	16
Japan	0.321	17	Italy	0.164	17
South Africa	0.312	18	UK	0.163	18
United States	0.299	19	France	0.114	19
China	0.214	20	Poland	0.061	20

CO_2 emission reduction is a common indicator used to track the success of climate mitigation efforts. Countries seek to calculate emission reductions to evaluate the performance of climate change mitigation goals and the success of energy policies. Figure 3 presents the potential CO_2 emission reduction of inefficient countries in 2017; potential CO_2 emission reduction is calculated using model 6. United States, China, Japan, and Iran are the major countries with potential CO_2 emission reduction, whereas the minimum potential CO_2 emission reduction countries are South Africa, Australia, and Poland, as presented in Figure 3. United States is the major emitter of CO_2 emission among all top 20 industrial countries in 2017. Any enhancement in CO_2 emission efficiency may lead to a considerable amount of CO_2 reduction. From the time when the "Paris Agreement" entered into force in 2016 there has been a greater incentive to estimate emission reductions. In reducing greenhouse gas emissions, numerous countries have computed their contribution in the efforts of global climate change mitigation, more formally known as the United Nations Framework Convention on Climate Change [48,49].

Carbon dioxide emissions from energy consumption account for a large portion of total greenhouse gas emissions. Improvements in energy systems can change carbon dioxide emissions levels and lead to emissions reductions. Simply improving energy efficiency will not be enough to reduce emissions, and countries must adopt deep de-carbonization pathways, including switching to clean energy and more use of energy in end use sectors. Excessive changes in energy systems (particularly in power generation) help to rapidly adopt clean energy such as nuclear power and renewable energy (wind energy, solar energy, hydroelectric, and biomass energy). Separating the impact of different changes on energy systems, such as improving energy efficiency and shifting to cleaner energy, provides governments with more information on drivers of emissions change.

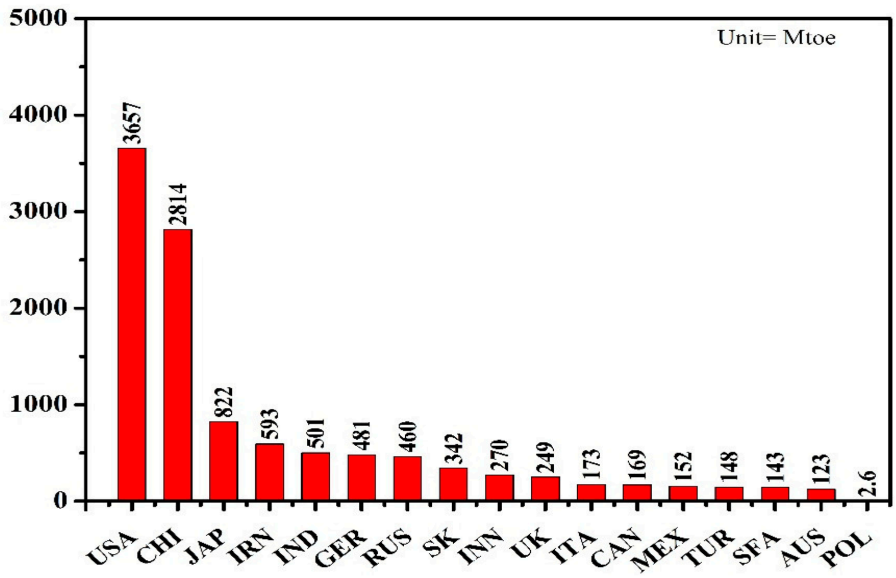

Figure 3. Potential carbon emission reduction of top 20 industrial countries from 2017.

3.3. Economic-Environmental Efficiency

Table 6 shows the economic environmental efficiency scores of the top 20 industrial countries from 2013 to 2017. Model 7 was used to measure the environmental efficiency, whereas model 8 was used to generate the economic efficiency score. In addition, we defined economic environmental efficiency (EEE) by the sum of the two efficiency values measured from Models 7 and 8. The economic-environmental efficiency (EEE) score of the top 20 industrial countries from 2013 to 2017 are presented in Table 6. When comparing economic and environmental efficiency, the economic efficiency score of most countries is higher than the environmental efficiency score. According to the results presented in Table 6, Poland has an EEE score of 2, indicating the country is economically and environmentally efficient, whereas Iran, France, Russia, Turkey, Mexico, Indonesia, India, and Brazil are the least efficient countries with EEE scores of less than 1. In economic-environmental efficiency results, Poland, Australia, United States, South Africa, and Japan are the top performers, whereas Turkey, Russia, Mexico, India, and Brazil are the five bottom performers over the study period. Figures 4 and 5, respectively, show the economic-environmental values for the top and bottom five performers as of 2017.

Table 6. Economic environmental efficiency (EEE) of the top 20 industrial countries from 2013 to 2017.

	2013		2014		2015		2016		2017	
Economies	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Russia	0.83	15	0.825	17	0.809	17	0.812	17	0.82	17
China	1.104	10	1.105	10	1.109	10	1.111	10	1.114	10
Brazil	0.634	20	0.624	20	0.601	20	0.571	20	0.568	20
Australia	1.59	2	1.576	2	1.572	2	1.569	2	1.565	2
India	0.679	19	1.084	11	1.086	11	1.085	11	1.084	11
Germany	1.259	6	1.232	6	1.218	6	1.22	6	1.211	6
France	0.921	14	0.883	15	0.88	15	0.889	15	0.898	15
Iran	0.956	13	0.95	14	0.978	14	0.969	14	1.002	14
S. Korea	1.038	12	1.025	13	1.028	13	1.037	13	1.057	12
Italy	1.092	11	1.064	12	1.066	12	1.056	12	1.053	13
Japan	1.369	4	1.344	4	1.328	5	1.321	5	1.315	5
Turkey	0.828	16	0.86	16	0.825	16	0.828	16	0.854	16
Mexico	0.762	17	0.741	18	0.747	18	0.745	18	0.743	18
Canada	1.171	9	1.168	9	1.155	9	1.163	8	1.182	8
Saudi Arabia	1.206	8	1.199	7	1.199	7	1.195	7	1.187	7
Poland	2	1	2	1	2	1	2	1	2	1
USA	1.407	3	1.398	3	1.379	3	1.369	3	1.368	3
UK	1.219	7	1.195	8	1.158	8	1.131	9	1.116	9
Indonesia	0.71	18	0.696	19	0.711	19	0.71	19	0.73	19
South Africa	1.348	5	1.329	5	1.35	4	1.355	4	1.353	4

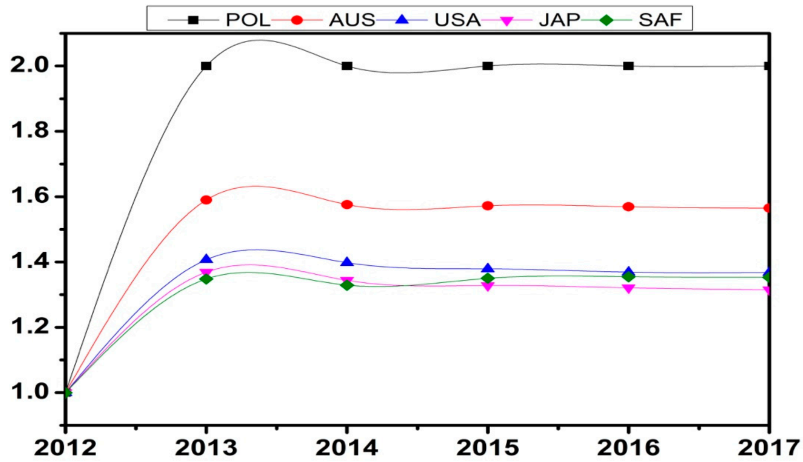

Figure 4. Economic-environmental efficiency trends for five top performers over the period.

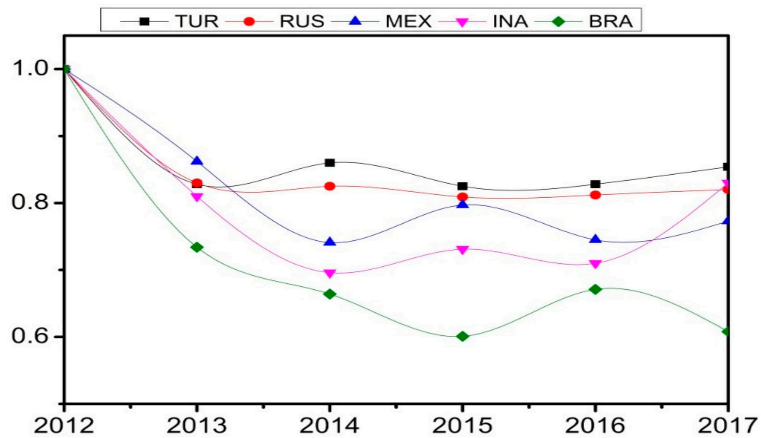

Figure 5. Economic-environmental efficiency trends for five bottom performers over period.

3.4. Regression Results

The regression analysis in this study shows that the error term is independent of the cross-country dummy variable, which provides further reasons for using cross-country regression analysis. The results of the cross country multiple linear regression model are presented in Table 7. It can be seen from Table 7 that all the determinant factors of variables are statistically significant. The values of the coefficient of determination represented by R^2 (0.652) and adjusted R^2 (0.596) indicate that the regression model fits the data reasonably. The GDP per capita coefficient is positive and statistically significant. The results of energy intensity and CO_2 emission intensity have a negative relationship with environmental economic efficiency. Also, we found that the openness index of a country has a positive relationship with environmental economic efficiency. Further, when evaluating the coefficients for the dummy variables COUNTRY, Poland is considered as the base country due to having the top performing EEE among 20 countries. The coefficients for the top performing countries in environmental economic efficiency are not significantly different from zero. The top performing countries have positive coefficients and *p*-values while the worst performing countries usually have negative coefficients with small *p*-values. This indicates they are worse than Poland in terms of environmental economic performance.

Table 7. The results of the multiple linear regression model.

Variable	Coefficient	*p*-Value
CONSTANT	0.597	0.021
GDPPC	0.412	0.012
EI	−3.585	0.000
CI	−0.432	0.001
OPENI	0.064	0.003
United States	0.321	0.167
Australia	0.256	0.231
Brazil	0.493	0.132
Germany	0.262	0.118
Canada	0.229	0.006
Italy	−0.261	0.016
Iran	0.282	0.358
Turkey	0.526	0.089
China	−0.591	0.107
France	0.384	0.431
India	0.495	0.000
Indonesia	−0.572	0.127
Russia	0.815	0.201
Japan	−0.0030	0.753
Saudi Arabia	0.814	0.211
Mexico	0.525	0.000
South Korea	0.318	0.026
United Kingdom	−0.368	0.619
South Africa	−0.205	0.009

3.5. Discussion

This research paper provides an in-depth analysis of energy efficiency, CO_2 emission efficiency, and environmental economic efficiency of the top 20 industrial countries worldwide. The energy efficiency and CO_2 emission efficiency score represents an effective policy tool toward future decision-making and to monitor progress towards the sustainable future of energy consumption and the environment. Most countries showed improvement in their energy consumption efficiency, e.g., Australia, China, Japan, Saudi Arabia, and Poland remain efficient countries with a score of 1 during the period in question. Also, when comparing energy efficiency and energy intensity, India was ranked fourth in energy intensity score, but its score in primary energy consumption is high (0.904) and was ranked sixth amongst all 20 countries. Similarly, Russia was first with the highest energy intensity and its energy efficiency score was 0.449. However, the findings indicate that to measure the energy efficiency of countries, the use of energy intensity may not be appropriate. In the case of potential energy saving, the share of United States is 36% among all inefficient countries. Therefore, for countries that consume a lot of energy, even if their energy efficiency is slightly improved, they can save a lot of energy.

Brazil, France, and Saudi Arabia are efficient countries in CO_2 emission efficiency. Interestingly, Japan and China were found efficient in energy efficiency but in CO_2 emission they are least efficient. When comparing CO_2 emission efficiency and CO_2 emission intensity, Poland has the second highest score in CO_2 emission efficiency but is least efficient in CO_2 emission intensity. It can be concluded that CO_2 emission efficiency scores and CO_2 intensity are highly coincident with each other. Transition economies such as India and Russia tend to have the highest carbon intensity. The intensity of carbon dioxide emissions in developing countries tends to be slightly higher than in industrialized countries, mainly because the GDP of developing countries usually comes from energy-intensive activities. However, industrialized countries have a more significant economic share contributed by low carbon service sectors. In the case of economic-environmental efficiency, the economic efficiency score of most countries is higher than the environmental efficiency score. Based on the results generated in this study, it is clear that more case studies of economic-environmental efficiency are required, including dynamic shifts in national environmental sustainability trajectory analysis models.

4. Concluding Remarks and Policy Recommendation

Most modern techniques of energy production and energy use create environmental problems locally, regionally, and globally. To solve these problems caused by global climate change, we need to better understand the energy consumption efficiency, CO_2 emission efficiency, and economic environment performance model. In this study, we used the DEA approach to evaluate the energy consumption efficiency, CO_2 emission efficiency, and environmental economic efficiency of the top 20 industrial countries worldwide. It is found that for energy efficiency of Australia, China, Japan, Saudi Arabia, and Poland are the best performing countries with an efficiency score of 1, whereas Mexico, Indonesia, Russia, and Brazil are identified as the least efficient among all 20 countries from 2013 to 2017. In addition, the relative rankings of Germany, the United Kingdom, South Korea, France, Turkey, and Mexico remain almost the same throughout the study period. In case of energy intensity, Russia has the maximum score of 0.409 and Poland has the minimum score of 0.044. In the comparison of energy efficiency and energy intensity, the use of energy intensity in order to measure the energy efficiency of countries may not be appropriate. In the case of CO_2 emission efficiency, out of 20 countries, Brazil, France, and Saudi Arabia are efficient, whereas the score of nine countries was less than 0.5. Also, as compared to CO_2 emission efficiency, most of the selected economies had higher scores in energy use efficiency. When evaluating environmental economic efficiency, most countries show higher economic efficiency as compared to environmental efficiency. The cross-country regression analysis results show that the openness index and GDP per capita have a positive effect, while energy intensity and CO_2 emission intensity have negative effect on economic-environmental efficiency.

With the intention of meritoriously increasing energy efficiency based on the outcomes, we put forward the following policy suggestions.

1. The government should reconcile the reform of state-owned organizations to entice private investment to low carbon energy reforms.
2. The government should promote energy price reforms to ensure that energy prices contribution towards renewable energy and discourage the fossil fuel, which will truly achieve marketization of energy demand and supply in the region.
3. The private entities and government should invest in research and development to improve energy efficiency and ensure advance progress in production facilities.
4. The regions decision-makers should regularly monitor the production to stay away from cheap material production.

5. There is a dire need to introduce foreign capital and having advance technology and experienced management increase energy efficiency and ecological environment of the region.
6. The government should introduce low taxes renewable energy policies to increase energy self-sufficiency and environmental efficiency.
7. Energy consumption is at the heart of global warming and the core of solutions. The developing countries should promote low-carbon development and transformation concepts, such as detecting and controlling air pollution sources for industrial energy utilization, regulating petroleum fuel supplies, and encouraging automakers to implement clean fuels technologies that can replace petroleum products.
8. Policies to address energy use not only reduce carbon dioxide emissions, but also reduce sulfur dioxide (SO_2) emissions and other pollutants that directly affect human health; however, this impact relates to future policies of air pollution. Certain mitigation policies may also have adverse side effects by promoting energy supply technologies that increase some form of air pollution.
9. Developing countries should take steps to make room for green energy development, such as reducing the share of fossil fuel energy or increasing the share of renewable energy. These are important measures to reduce energy-related carbon dioxide emissions and promote a green economy. In addition, controlling fossil fuel growth ensures there is sufficient room for the development of low-carbon energy. At the same time, the improvements in energy efficiency and reducing carbon emissions are considered to be the most effective ways to reduce the environmental impact of energy production.
10. Developing countries should initiate commercial services that provide energy solutions, including energy efficiency, retrofits, outsourcing of energy infrastructure, risk management, energy supply, power generation, and implementation of energy efficiency projects.

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