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Analysis of Inter-Temporal Change in the Energy and CO_2 Emissions Efficiency of Economies: A Two Divisional Network DEA Approach

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Abstract: Measuring changes in energy consumption and carbon dioxide emissions of various large economies is fundamental for analyzing the impact and effectiveness of various policies in this direction. This study analyzes intertemporal changes in energy and CO_2 emissions efficiency of economies by applying a network data envelopment analysis approach that takes into consideration the internal structure of the analysis units. We have applied two divisional network data envelopment analysis models for analysis of the economic and distributive efficiency of economies from 2001 to 2011. The results are very useful in analyzing the situation; we found that none of the economies was efficient in both aspects in the sample period, implying that none of the countries in the analysis was efficient in the production and distribution of economic outputs simultaneously. Brazil, Canada, China and Germany showed improvement in economic efficiency but the distribution efficiency of the most of the economies is low because of the increase in population and high-income class. Most of the countries had an increase in the high-income class but China performed better in the second division because it has managed to improve its middle-income class in the recent past by moving more people from low-income class to middle income class. It is suggested that countries should emphasize on economic restructuring and expansion of the middle-income class to improve their performance in the production and distribution of economic outputs.

Keywords: energy efficiency; CO_2 emissions efficiency; data envelopment analysis; network DEA; SBM

1. Introduction

Despite a great deal of concern and efforts by all small and big contributors of carbon dioxide (CO_2) emissions the world has failed to slow down its increasing energy consumption and CO_2 emissions. Efforts of regulatory bodies at the national and international level have proved not as effective as they were expected to be. Evidence lies in the statistics published by various databases. It can be seen that the energy consumption was 12,982, 13,326, 13,569 and 13,514 million metric tons of oil equivalent (mMTOE) for the years 2010, 2011, 2012 and 2013 [1]. It can be noticed that the trend decreased over these years because the increase in 2010–2011 was 2.6% and in 2011–2012 it was 1.8% before turning into a fractional decrease in 2012–2013. The slight decrease in 2013 from 2012 was not consistent in upcoming years and data from various databases confirms this fact up to year 2016. Different countries have played their role in different ways. For example, the United States had a hike in energy use in the years 2010 and 2013 and in between it managed to reduce energy use [1], while on the other hand, China had a continuous expansion of energy use over the same period. CO_2 emissions measured in units of million metric tons of CO_2 ($mMtCO_2$) have continuously increased in quantity over the period from 2010–2016 [1]. If these trends are not be altered in the next few years the global environment may react by hitting hard with hazards that may amount to a deluge. Energy consumption and CO_2 emissions reduction present a dilemma for the present world because CO_2 emissions are an inevitable outcome of carbon-based fuel consumption for meeting the energy needs. If the proportion of renewable sources of the energy in the fuel mix remains low the problem may keep exacerbating over the next few decades.

In this regard measuring the economic efficiency of countries is a key step towards understanding and devising control measures for the excessive use of energy and excessive CO_2 emissions. Energy efficiency refers to a lesser use of energy in the production of economic outputs. On the other hand, CO_2 emissions efficiency is referred to as lesser emission of CO_2 in the production of economic outputs because CO_2 emissions are an undesirable output of economic activities. A number of studies can be found in literature studying energy and CO_2 emissions efficiency (ECEE). Many of them use data envelopment analysis (DEA) as a black box approach in their models. Very few studies use network DEA (NDEA) models to probe into the internal structure of economies to analyze ECEE issues at the problem centers. Among various ways to look into the internal structure of economies the one we prefer in this study is to look an economy as a composite structure of two divisions. One responsible for generating economic outputs and the other indulged in distributing those outputs [2]. We extend this analysis of two divisional network structure of economies to a dynamic analysis over the period of 2001 and 2011. An analysis of the intertemporal changes in ECEE of economies will help in analyzing trends in ECEE changes over the period under consideration. Therefore, this study is result of efforts to carve a way forward based on this background of research on ECEE of economies which matter more than others do because of their enormous sizes.

In this study, we have analyzed the intertemporal changes in ECEE of 19 major economies where ECEE is measured using the NDEA approach. The study contributes to the literature on ECEE, DEA and sustainable economic growth. It also probes the underlying causes for abnormal changes in energy consumption and CO_2 emissions. The results and analysis reinforce the suggestions made by previous studies for sustainable development at lowest cost of energy and environment. Moreover, new suggestions have been added to avoid rapid and detrimental changes in energy consumption and CO_2 emissions while keeping in view the welfare of all stakeholders in an economy altogether.

The rest of the paper leads readers from a literature review in Section 2 to the materials and methods in Section 3, to the results and an analysis of the intertemporal changes in ECEE in Section 4, to the conclusions of the whole study in Section 5.

2. Literature Review

In the last two decades, as the problems of environmental pollution, excessive energy consumption and CO_2 emission have aggravated, a large number of research studies have emerged intending to address these issues individually or combined with each other. Some studies (e.g., [3,4]) have studied energy issues individually. Another similar study that studied energy and CO_2 emissions individually and developed a relationship between CO_2 emissions and energy consumption was conducted by Song et al. [5]. Among the studies which considered analyzing the CO_2 emissions problem combined with energy efficiency issues those of Zhou and Ang [6]; Hadjiconstantinou and Bampatsou [7]; Camioto et al. [8]; Gómez-Calvet et al. [9]; and Woo et al. [10] may be cited. The literature also contains studies of either CO_2 emissions efficiency, or environmental efficiency combined with energy efficiency (e.g., [11–13]). Certainly, environmental efficiency studies, can be identified separately from CO_2 emission efficiency studies as they include other undesirable outputs in addition to CO_2 which is one of the greenhouse gases. Other undesirable outputs that may be included in environmental studies are oxides of carbon, oxides of sulfur, oxides of phosphorous and the various hydrocarbons that are emitted from traffic and industrial smokes [14].

Various set of economies have been studied by various research studies to analyze group ECEEs. The most widely researched group is that of the OECD as a number of papers can be found [6,12,15–18] pivoting their studies around these economies. Apart from these, EU-based studies [9,13,19], non-OECD-based studies [15], studies on APEC [19], G7 [8], BRICS [8,20], and ASEAN [19] can also be found. Moreover, there are few studies which base their sample of economies on the size of economy, energy consumption or CO_2 emissions [21–24]. Several studies focus on various administrative regions of large economies. For example, several studies use Chinese provinces and administrative regions as their units of analysis [25–28]. Goto et al. [29] used Japanese regions in their study as decision making units (DMUs). Similarly some authors have confined their study scope to the industrial level and used industries or sectors in an economy as decision making unit [30,31]. It can be found that there is no preferential way to select DMUs in the literature pertaining to ECEE analysis using non- parametric approaches. It all depends upon the criteria for selection as prescribed by various studies on DEA and the preferences of authors based on the objectives of the study.

Excessive energy consumption and CO_2 emissions have been studied in the context of economic activities which are linked with the production of economic outputs, e.g., gross domestic product (GDP), etc.; however, they have never been studied in the context of extravagant use of resources in the economy because of income disparity. Literature can be found on the relationship between income disparity and CO_2 emissions, for instance Jorgenson et al. [32] and Zhang and Zhao [33] establish that excessive energy consumption is linked to extra income and consequential excessive CO_2 emissions. Extravagance, as discussed for the first time by Walker and Large [34], can be identified as a cause of excessive energy consumption and CO_2 emission in the literature but there is a gap in literature on the empirical relationships between these variables. ECEE analysis while considering extravagance as an important element has never been conducted. As extravagance is not possible unless some people have more income than others, therefore it is definitely an outcome of poor distribution efficiency of an economic system which means it fails to distribute resources in a way that suits the masses. Therefore, it is necessary to find out the potential for ECEE efficiency improvement due to better economic efficiency and distribution efficiency of economies.

DEA is one of the most widely used linear programming techniques in energy and CO_2 emissions efficiency studies. The abovementioned literature supports this fact strongly and it can be verified by the literature review study conducted by Mardani et al. [35] on 144 studies published in ten years (2006–2015) using DEA for energy efficiency. This is because of various advantages it offers compared to other non-parametric studies. Its variety of models developed until now allows researchers to use it handily and investigate issues of interest easily. Initially, Charnes et al. [36] Charnes et al. advanced the work of Farrel [37] and developed the Charnes, Cooper and Rhodes (CCR) model [38]. Later on other variants of DEA were developed to overcome critical shortcomings of the CCR Model [39]. For example the Banker, Charnes, and Cooper (BCC) model was developed by Banker et al. [40] to overcome the inability of the CCR mode to deal with return to scale. Additive models-used slacks and later slack-based measures (SBM) of DEA were proposed to overcome shortcomings of previous models [39,41]. SBM presented by Tone [42] has been very effective in efficiency analysis studies. It is a radial measure which offers several advantages over non-radial measures of efficiencies [43], Furthermore its network structure models have also been developed to take into account intermediate products. After a first attempt by Färe and Grosskopf [44] to consider intermediate products they proposed a NDEA model in their paper in 2000 [45]. Once a new avenue for internal structure analysis of DMUs was opened by them, researchers developed NDEA for other variants of DEA. For instance Tone and Tsutsui [46] developed the NDEA of SBM developed by Tone [42]. Another development in this direction is the formulation of dynamic DEA models which can include carryovers of previous periods into the analysis [47]. Recently it has been proposed that NDEA and dynamic DEA model can be combined to form a comprehensive model which exhibits characteristics of both these models. There are a few studies which use NDEA for the analysis of ECEE. Bian et al. [48] have used parallel SBM to measure energy efficiency. A parallel network considers that a DMU consists of parallel divisions which means no division uses the output of a proceeding division as input. Ren et al. [49] have applied

NDEA for an overall and staged ecoefficiency analysis of regions in China while Huang et al. [50] used radial NDEA to analyze the efficiency of the environmental protection system in Taiwan. Feng et al. [51] have applied dynamic NDEA for developing the linkage between economic development, energy consumption and environmental and health sustainability in EU and non-EU countries. Similarly, other research studies using NDEA for analysis of energy and environment in different perspectives can be found. However, ECEE studies measuring ECEE of countries with NDEA are difficult to find. Despite so much variety emerging through evolution and modification of DEA it is a suitable approach for ECEE studies. A study by Gómez-Calvet et al. [9] used the SBM of Tone [42] and a directional distance function to analyze the differences between results. They found that both approaches are competitive and useful.

Another important aspect of ECEE studies that use DEA models is their treatment of undesirable outputs. Treatment of undesirable outputs can take many forms. Gómez-Calvet et al. [9] suggest that both SBM and the directional distance function can deal with undesirable outputs. Among others, Iftikhar et al. [11] have applied the SBM of Tone [42]. They preferred free disposability over the weak disposability assumption of undesirable outputs that had been being used in ECEE studies [52–54]. The weak disposability assumption can be effective for studies where pollution-generating sources of energy are inevitable and irreplaceable inputs of production system, for example, factories and machines, or sectors of economies which solely use fossil fuel in operation., whereas for systems where a mix of energy resources is used as input and the proportion of renewable sources of energy can be increased free disposability assumptions should be used [2]. Using undesirable outputs in network structure studies of ECEE makes the situation more complex and very little literature on this aspect is available. Song et al. [55] used two stage SBM model and treated undesirable outputs in second stage only. However, studies which use undesirable outputs in all stages of a network are rare [2].

Although the analyses in a number of studies span multiple periods [8,13,16–18,20,56], surely those are not dynamic studies as they perform analysis of ECEE at a point of time instead of analyzing changes in ECEE between the sample periods. There are only a few research studies which perform dynamic analyses of energy efficiency, CO_2 emissions efficiency and environmental efficiency. Woo et al. [10] analyzed the static and dynamic environmental efficiency of renewable energy in OECD countries. They used a Malmquist Index approach to conduct a dynamic analysis. Zhou et al. [21] have also used same technique to conduct a total factor carbon emissions performance study. Their study is a CO_2 emissions efficiency analysis. Another unique study which has taken a different approach for dynamic analysis is that of Guo et al. [57]. They have applied the dynamic DEA model of Tone and Tsutsui [58] to analyze the energy efficiency of OECD countries and China while considering carryovers. Iftikhar et al. [11] have conducted dynamic analysis of ECEE using another unique approach, which they called dashboard. This study has improved the dynamic analysis in comparison to the Malmquist Index and window analysis techniques. Despite being dynamic studies, these aforementioned studies do not account for the internal structure of the DMUs.

3. Materials and Methods

In this study, we have applied the NDEA model of Tone and Tsutsui [46] to measure the ECEE of selected economies for the years 2001 and 2011. We have used the set of 19 economies from Iftikhar et al. [11]. Following them, a network structure of economy is assumed and the free link case of NDEA model is applied with constant return to scale and free disposability of undesirable outputs. The specifications of model are given below in section 0. Finally a dashboard is developed following the method specified by Iftikhar et al. [11].

3.1. NDEA Model

The modified NDEA model of Tone and Tsutsui [46] with modifications for undesirable outputs in all divisions and constant return to scale is as follows. For a divisional economic structure with K divisions ($k = 1, \ldots, K$), each division k having m^k inputs, r^k desirable outputs, s^k undesirable outputs and t links between division k and division h denoted by (k,h) belonging to set of links L production possibility set is given in Equation (1) given that $X^k = \left[x_1^k, \ldots, x_n^k\right] \in R^{m_k \times n}$, $Y^k = \left[y_1^k, \ldots, y_n^k\right] \in R^{r_k \times n}$, $U^k = \left[u_1^k, \ldots, u_n^k\right] \in R^{s_k \times n}$ and $Z^{(k,h)} = [z_1^{(k,h)}, \ldots, z_n^{(k,h)}] \in R^{t_{(k,h)} \times n}$ are data matrices for inputs, outputs, undesirable outputs and links respectively:

$$\begin{aligned} &P(x) = \Big\{(x^k, y^k, u^k, z^{(k,h)})\Big| \\ &x^k \geq X^k\lambda^k, y^k \leq Y^k\lambda^k, u^k \geq U^k\lambda^k, z^{(k,h)} = Z^{(k,h)}\lambda^k, z^{(k,h)} = Z^{(k,h)}\lambda^h, \lambda^k \geq 0\Big\} \end{aligned} \tag{1}$$

where $\lambda^k \in R^n$ is vector of weights assigned to inputs, outputs, undesirable outputs and links for division k. Equation (2) gives NDEA model as indicated by Iftikhar et al. [11]:

$$\begin{aligned} &\rho_o^* = \min \frac{\sum\limits_{k=1}^{K} W^k [1 - \frac{1}{m^k} (\sum\limits_{i=1}^{m_k} \frac{s_i^{k-}}{x_{io}^k})]}{\sum\limits_{k=1}^{K} W^k [1 + (\frac{1}{r^k + s^k})(\sum\limits_{r=1}^{r_k} \frac{s_r^{kg}}{y_{ro}^k} + \sum\limits_{u=1}^{s_k} \frac{s_u^{kb}}{u_{uo}^k})]} \\ &s.t. \\ &x_o{}^k \geq X^k\lambda^k + s^{k-} \\ &y_o{}^k \leq Y^k\lambda^k - s^{kg} \\ &u_o{}^k \geq U^k\lambda^k + s^{kb} \\ &Z^{(k,h)}\lambda^h = Z^{(k,h)}\lambda^k \qquad\qquad (\forall(k,h)) \\ &\lambda^k \geq 0, s^{k-} \geq 0, s^{kg} \geq 0, s^{kb} \geq 0 \quad (\forall k) \end{aligned} \tag{2}$$

Note that s^{k-}, s^{kg} and s^{kb} represent the input slack vector, output slack vector and undesirable output slack vector, respectively. W^k is the weight assigned to division k based on its importance and in the case of a two division economic system, both divisions are taken as equally important, thus a weight of 0.5 is assigned to each so that $\sum_{k=1}^{K} W^k = 1$. ρ_o^* gives the efficiency scores of economies such that $0 \leq \rho_o^* \leq 1$. By finding s^{k-*}, s^{kg^*} and s^{kb^*} the optimal inputs, outputs, and undesirable outputs slacks for the Equation (2) divisional efficiency scores can be calculated from Equation (3):

$$\rho_k = \frac{1 - \frac{1}{m^k} (\sum\limits_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{io}^k})}{1 + (\frac{1}{r^k + s^k})(\sum\limits_{r=1}^{r_k} \frac{s_r^{kg*}}{y_{ro}^k} + \sum\limits_{u=1}^{s_k} \frac{s_u^{kb*}}{u_{uo}^k})} (k = 1, \ldots, K) \tag{3}$$

3.2. Dashboard for Analysis of Inter-Temporal Changes

The identification of key performance indicators is the first task at hand when building a dashboard. Following Iftikhar et al. [11] energy and carbon dioxide emissions efficiency (ECEE) is taken as the first KPI calculated from Equation (2), indicated by ρ_o^*. The second KPI is the change in technical efficiency (TE), also known as the catchup effect. The catchup effect represented by ratio of technical efficiencies in two years and is calculated as in Equation (4) below:

$$TE_{t+1} = \frac{\rho_{t+1}^*}{\rho_t^*} \tag{4}$$

A TE score of 1 would indicate a consistent technical efficiency in period t and $t + 1$ while a score above 1 or below 1 would indicate an increase and decrease in technical efficiency of an economy, respectively. The third and fourth KPIs are the change in energy efficiency (EE) and change in CO_2 emissions efficiency (CE). EE and CE are calculated using the formulae in Equation (5) and Equation (6) below:

$$\mathrm{EE} = \frac{x_o{}^{1E} - s_o{}^{1E-}}{x_o{}^{1E}} \tag{5}$$

The target for energy consumption in the numerator is calculated by subtracting the slack for energy consumption s_o^{1E-} from the actual energy consumption x_o^{1E}:

$$\mathrm{CE} = \frac{u_o{}^1 - s_o{}^{1b}}{u_o{}^1} \tag{6}$$

Similarly the target for CO_2 emissions is calculated by subtracting the slack for CO_2 emissions s_o^{1b} from the actual amount of CO_2 emissions u_o^1. Energy efficiency score and CO_2 emissions efficiency scores calculated using the above two equations may vary from 0 to 1. A score equal to 1 would indicate the achievement of a target and a score below 1 would indicate an inefficiency. The change in energy efficiency (EE) and change in CO_2 emissions efficiency (CE) is calculated from the ratio of EE and CE of 2011 to the EE and CE of 2001, respectively. Additionally, we used divisional ECEE scores calculated from Equation (3) to analyze changes in divisional efficiencies between 2001 and 2011 (see Table 3). The dashboard is calculated for year 2001 and 2011. For 2001, we applied NDEA model given in Equation (2) on 19 economies and for 2001–2011 we used $n + f$ formula [11] where n is 19, the total number of DMUs and f indicates economies which were at frontier in 2001. As we had no economy in frontier in 2001, therefore for 2001–2011 we used the same 19 economies or DMUs.

3.3. Data and Variables

This section is aimed at analyzing inter-temporal changes in energy and CO_2 emissions efficiency of the 19 largest economies following the selection of Iftikhar et al. [2] who actually aimed at analyzing the 30 major economies of Iftikhar et al. [11] but had to drop 11 economies because of the unavailability of data for a few variables or zero data points for others. The sets of all variable data are collected for the years 2001 and 2011 from The World Bank, Energy Information Administration (EIA) and the Pew Research Center. Data for total labor force, gross capital formation at market price (constant 2010 US$), GDP at market price (constant 2010 US$) and total population are collected from the World Bank. Data for primary energy consumption and CO_2 emissions is collected from EIA and data for income classes is taken from the Pew Research Center. Data for income classes is available as the percentage of total population calculated at purchasing power parity. We calculated the number of people from these percentages, also noting that the middle income class shows data combined for the upper middle income, middle income and lower middle income classes, indicated by MI, while the high income class is indicated by HI and poor as LI. Thus, people earning below $2 a day will be in LI, and people earning above $50 a will be in HI and people with daily incomes between $2 and $50 a day will be in MI. This categorization is consistent with that of the world development indicator (WDI). Total labor force, gross capital formation and total primary energy consumption are taken as inputs to the first stage and GDP is taken as the link between division 1 and division 2, while CO_2 emissions are taken as the only bad output for the first division. In the second division total population is taken as an additional input and MI is taken as a desirable output while HI and LI are taken as undesirable outputs. Descriptive statistics for the variables are given in Table 1 below.

Table 1. Descriptive statistics of variables for year 2001 and 2011.

Variable	Unit	Mean	S.D.	Range	Minimum	Maximum
Labor	million people	97.36	187.48	787.80	2.38	790.18
Capital	billion $	514.62	745.38	3132.76	40.67	3173.43
Energy	million MTOE	430.44	671.68	2788.87	45.37	2834.24
Carbon Dioxide	$mMtCO_2$	1077.92	1844.15	8911.30	39.86	8951.16
GDP	billion $	2148.30	3101.88	14,915.35	288.67	15,204.02
Population	million people	201.26	366.78	1339.62	4.51	1344.13
MI	million people	146.40	274.91	1175.01	1.10	1176.11
HI	million people	18.11	38.15	173.35	0.27	173.63
LI	million people	36.81	110.13	517.63	0.01	517.64

4. Results

In order to analyze changes in energy and CO_2 emissions efficiency caused by changes in production efficiency and distribution efficiency of GDP we have applied NDEA on data sets of 2001 and 2011. The results obtained are interesting and may help to understand the problem and suggest solutions. Table 2 shows the dashboard built after obtaining the results from Equations (2) and (4)–(6).

Table 2. Dynamic analysis of energy and CO_2 emissions efficiency (ECEE) for period 2001–2011.

Category	Country	ECEE 2001	Country	ECEE 2011	Change TE	Change EE	Change CE
Birds	Spain	0.9052	-	-	-	-	-
	Turkey	0.8446	-	-	-	-	-
	France	0.8369	-	-	-	-	-
	Poland	0.5577	Poland	0.5574	0.9996	1.3675	1.1311
Treaders	Russia	0.4725	Iran	0.4576	0.9859	0.6531	1.7820
	India	0.4717	Turkey	0.4543	0.5378	0.4278	0.3845
	Iran	0.4641	Mexico	0.4407	1.0458	0.7192	2.0480
	Mexico	0.4214	India	0.4393	0.9312	1.3245	0.8430
	Argentina	0.4098	Russia	0.4357	0.9223	1.5018	0.9786
	Venezuela	0.3839	Argentina	0.3946	0.9629	0.6374	1.6199
	Brazil	0.3452	China	0.3944	1.1790	2.3066	1.4777
	China	0.3345	Brazil	0.3765	1.0907	1.0577	1.1503
	-	-	Venezuela	0.3596	0.9367	0.7030	1.7820
Creepers	Italy	0.2893	Spain	0.2599	0.2872	0.1493	0.0642
	United Kingdom	0.2327	France	0.2397	0.2865	0.2113	0.1759
	Australia	0.2145	Italy	0.2287	0.7904	0.5167	0.5802
	Canada	0.1658	United Kingdom	0.2070	0.8896	0.4556	0.7475
	Germany	0.1506	Australia	0.1685	0.7858	0.9251	1.0428
	Norway	0.1377	Germany	0.1538	1.0214	1.4609	0.5645
	United States	0.1315	Canada	0.1468	0.8857	1.0963	1.2031
	-	-	United States	0.1396	1.0617	0.7071	0.7905
	-	-	Norway	0.0713	0.5176	0.3699	0.3699

The first column of the table shows the frontier categories. The economies with scores of 1 are be categorized as stars, the economies that had scores 1 in 2001 and now lost their position because of scores of less than one are categorized as falling stars and the ones that were below frontier but now in 2011 have obtained a position just below frontier are categorized as rising stars. In our current situation, we have no economy in all of these categories that is why our dashboard starts with birds. Economies with scores less than 1 but equal or above 0.5 are in the birds category, economies with scores below 0.5 up to 0.3 are in treaders and with scores less than 0.3 are in creepers. In 2001, no economy had a performance equal to 1. To be efficient with score equal to 1 with respect to overall ECEE a country has to be efficient in both divisions. Although many other countries have divisional performance scores of 1 in either of the two divisions, they cannot be considered efficient because of their less than 1 scores in the other division. As 2001 is the first year in the analysis so we do not expect economies in the rising stars or falling stars categories, thus all the remaining economies are present in the other three categories of the dashboard.

The ECEE 2001–2011 column in Table 2 shows the results obtained by running NDEA on $n + f$ economies. As there was no economy in frontier of 2001 so f is 0 and n is 19. We can see that in 2001–2011 also no country appears in the stars category. None of the countries is in the falling stars category either because there was no economy in 2001 with scores equal to 1. A disappointing fact is that none of the other economies has shown performance good enough to appear in the rising stars category. Thus, Table 2 is missing both the rising stars and falling stars categories as well.

Only Poland sustained its position, as all the rest of the countries shuffled their positions because of changes in efficiency in 2011 compared to their efficiency in 2001. Overall ECEE scores in 2011 are much lower than the scores in 2001 as it can be seen that all economies have performance below that of Poland (0.5574) in 2001–2011. Moreover, there are four economies in the birds group in 2001 and there is only one left in this section in 2001–2011. The highest score in 2001 is 0.9052 for Spain. Spain and France suffered a great loss of performance in the sample period as they have moved to the creeper category and Turkey which was also in the birds groups with them in 2001 shifted to the treaders in 2011. Only Poland managed to sustain its position in birds with a slight decrease in efficiency from 0.5577 to 0.5574. Russia moved down within the category below India, Iran and Mexico. On the other hand, Iran overtook India and Russia and China overtook Brazil and Venezuela within their category.

In the TE column of Table 2 showing the changes in technical efficiency it can be seen that Mexico, China, Brazil, Germany and United States have scores above 1, indicating an improvement in technical efficiency. Poland had an efficiency score near 1 because it experienced only a minor fall in technical efficiency, from 0.5577 to 0.5574. All the remaining economies suffered from a decrease in technical efficiency represented by scores below 1. France had the worst fall in technical efficiency as it was previously in the birds group with an efficiency score of 0.8369 but in 2011 it moved down to the creepers category with a score of 0.2397. The change in TE scores is 0.2865, which indicates that it only showed an efficiency of 28.65% as compared to the efficiency in 2001. Spain is following the same path and has the second worst performance after France. The EE and CE columns show the changes in the target to actual ratio in the case of energy consumption and CO_2 emissions, respectively, in the sample period. Scores above 1 indicate an improvement in EE and CE in the sample period, a score of 1 indicates no change and a score below 1 means a deterioration in performance. Looking at the EE scores, we find that highest improvement is observed for China and with respect to CE, the highest improvement is undergone by Mexico. On the other hand, in both EE and CE the lowest performance is that of Spain.

Divisional efficiency scores and change in divisional efficiency scores are tabulated in Table 3. Divisional efficiency scores are obtained by solving Equation (4). The divisional efficiency scores for 2001 show that only Spain had an efficiency score of 1 in the first division while the rest of the countries had scores below 1. France, India, Iran and Poland had efficiency scores of 1 in division 2. None of the economies had scores of 1 in both divisions. In 2011 the situation worsened because none of the countries in division 1had an efficiency score above 0.294, the score of Poland. Spain, which had score of 1 for division 1 in 2001 had a score of 0.067. The lowest score was 0.009 for Norway. However, the situation was still better with regard to the efficiency scores in division 2 in 2011. India, Iran and Poland still maintained efficiency scores of 1 in division 2, while France was unable to maintain its efficiency score of 1 in division 2 in 2011. Changes in divisional efficiency are shown in the last two columns of the table. An efficiency score of 1 shows that a country maintained its position between 2001 and 2011 and scores above 1 show improvement and below 1 show a deterioration in efficiency.

Table 3. Divisional ECEE scores and change in divisional ECEE in period 2001–2011.

Country	ECEE				Change in ECEE	
	2001		2011		2001–2011	
	Div 1	Div 2	Div 1	Div 2	Div 1	Div 2
Argentina	0.264	0.614	0.166	0.676	0.629	1.100
Australia	0.054	0.412	0.051	0.311	0.942	0.756
Brazil	0.163	0.568	0.201	0.577	1.231	1.015
Canada	0.036	0.330	0.043	0.274	1.171	0.829
China	0.048	0.839	0.083	0.962	1.717	1.148
France	0.703	1.000	0.099	0.408	0.141	0.408
Germany	0.050	0.277	0.062	0.271	1.252	0.979
India	0.174	1.000	0.129	1.000	0.744	1.000
Iran	0.183	1.000	0.162	1.000	0.885	1.000
Italy	0.100	0.513	0.061	0.457	0.606	0.891

Table 3. *Cont.*

Country	ECEE				Change in ECEE	
	2001		2011		2001–2011	
	Div 1	Div 2	Div 1	Div 2	Div 1	Div 2
Mexico	0.234	0.687	0.210	0.724	0.898	1.054
Norway	0.023	0.280	0.009	0.156	0.365	0.558
Poland	0.300	1.000	0.294	1.000	0.980	1.000
Russia	0.253	0.783	0.221	0.739	0.872	0.944
Spain	1.000	0.827	0.067	0.530	0.067	0.641
Turkey	0.714	0.998	0.201	0.800	0.282	0.801
United Kingdom	0.086	0.420	0.055	0.423	0.632	1.008
United States	0.029	0.256	0.026	0.288	0.878	1.127
Venezuela	0.164	0.701	0.120	0.661	0.729	0.944

Brazil, Canada, China and Germany had scores above 1, i.e., they improved their efficiency in division 1 in the sample period. This indicates that these four economies observed an improvement in their efficiency of production of economic output and obviously China had the highest improvement in efficiency of the first division. All the remaining economies have scores below 1 in division 1 and the biggest deterioration in efficiency of production was undergone by Spain. With respect to efficiency scores in division 2, which indicate efficiency of distribution of GDP, Argentina, Brazil, China, Mexico, United Kingdom and the United States had scores above 1, while India, Iran and Poland maintained their performance and had scores of 1. All the other countries had scores below 1. Furthermore, the lowest score was 0.408 for France. Here also the best improvement was maintained by China. It can be said that overall, in division 2 most of the economies had better performance than in division 1.

5. Discussion

During 2001–2011, the period under analysis, energy consumption and CO_2 emissions have been increasing gradually.

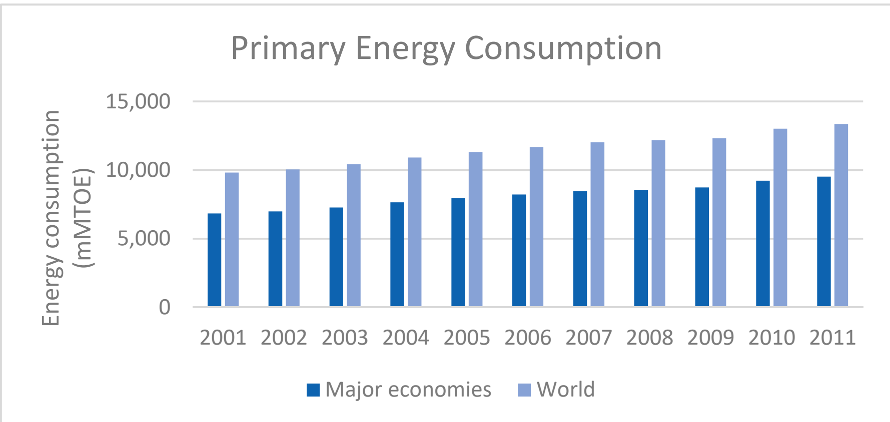

Figure 1. Primary energy consumption of major economies compared to the world energy consumption from 2001 and 2011.

Figures 1 and 2 show the growth trends in both energy consumption and CO_2 emissions, respectively, for the 19 larger economies compared to the world quantities for energy consumption and CO_2 emissions. The major economies in our analysis maintained an average share of approximately 70% and 71% in energy consumption and CO_2 emissions of the world, respectively.

The trend analysis conducted on the data of these economies and on the world data shows that on average these economies had a slightly higher rate of increase in energy consumption and

CO_2 emissions. The average increases in energy consumption were 3.38% and 3.14% for the major economies and the world, respectively, and the average increases in CO_2 emissions were 3.65% and 3.14%, respectively. This indicates that it is of utmost important for these economies to control their energy consumption and CO_2 emissions because they affect over 70% of the world energy consumption. They are having very high rates of increase, which indicate that if the average rate is below their average then the other 30% of the world is definitely having a growth rate less than that of these major economies, thus further adding to the importance of these economies as they should be analyzed and improvements of their policies suggested to improve to control their increasing trends of energy consumption and CO_2 emissions.

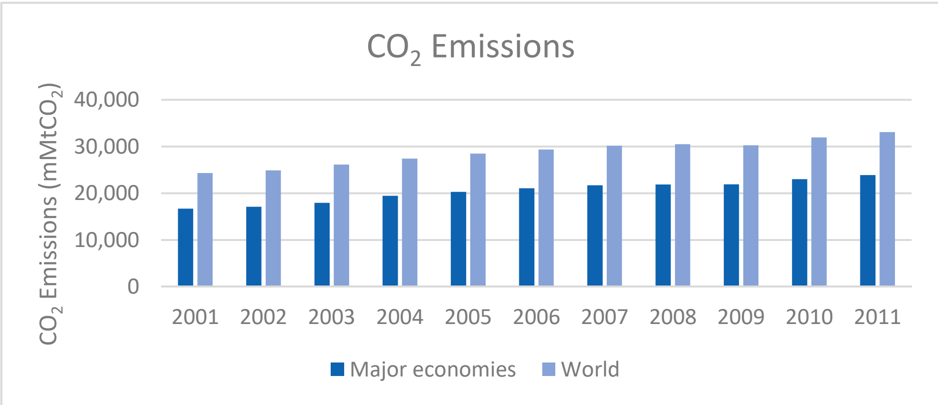

Figure 2. CO_2 emissions of the major economies compared with world CO_2 emissions from 2001–2011.

Our two divisional analysis shows that the energy consumption for most of the economies has been increasing from 2001 to 2011. In Figure 3 the length of bars shows the total energy consumption of the economies under analysis. It is evident that the bars for 2001 are shorter than the bars for 2011. Spain, Iran, Mexico and Venezuela are an exception to this as their energy consumption in 2011 is equal to or below their level of 2001. The blue parts of bars are indicators of energy consumption targets calculated using the formula in the numerator of Equation (5) and the parts in orange color are the indicator of excess energy consumption above target. It is obvious that the targets for most of the economies are much below the actual consumption and most of the economies have added huge amounts of excess to their energy consumption with the passage of time. The energy consumption of China increased more than twice in 2011 from the quantity in 2001. Although USA also has huge energy consumption, but it is consistently a high energy consuming country, while China just increased its energy consumption and now exceeds that of the USA.

Energy consumption and CO_2 emissions follow the same pattern of growth because both are linked, therefore, the CO_2 emissions total (length of bar), targets (blue parts of bars) and excess above target (orange parts of bars) shown in Figure 4 need no further explanation after we have already explained the energy consumption patterns in the previous paragraph.

As the efficiency scores of NDEA are carrying the effect of the efficiency of two divisions it would be better to analyze changes in both divisions' efficiency to gain a deeper understanding of the changes in overall efficiencies of the economies. The first division is an indicator of the efficiency of production of economic outputs that we call here economic efficiency and the second division indicates the efficiency of distribution of economic outputs, that we will call the distributive efficiency. Probing further the first division efficiency we can find that changes in economy size, structure, technological innovation, depreciation policies, carbon tax laws and rapid urbanization are some of the main factors which may be reponsible for the low efficiency of economies based on their particular situation. Only Brazil, Canada, China and Germany have managed to improve their ECEE scores in the first division (see Table 3) during the sample period.

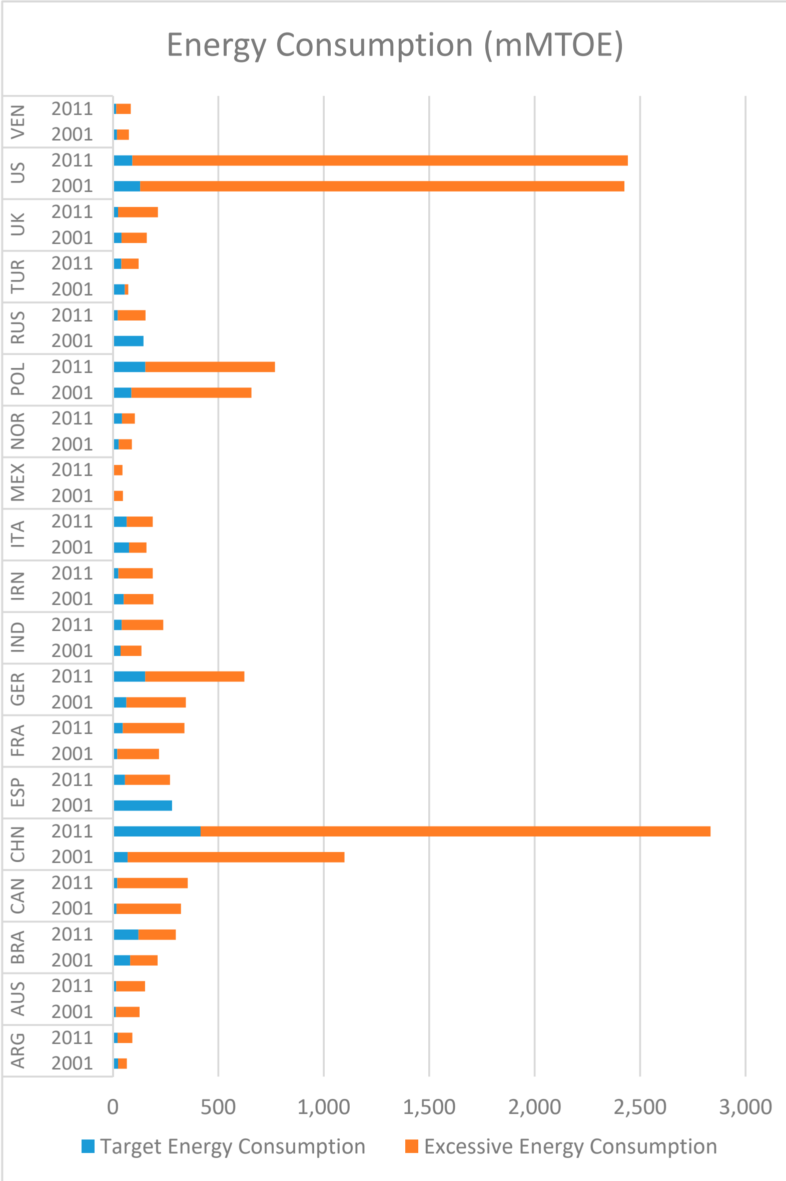

Figure 3. Energy consumption targets and excesses for years 2001 and 2011.

The improvement in economic efficiency is attributed to a lesser usage of energy inputs for an optimum amount of economic outputs, which is not possible unless an economy takes multiple measures to improve this ratio. Their keen attention to invest in better fuels and better and more efficient technologies is the main factor that drives this change, which may also be coupled with shifts in economic structure from manufacturing to focus on a service focused economy. Interestingly, even if China took most of the burden for production of economic outputs for the world on its shoulder it still has the greatest improvement in first division amounting to 71.7% of the ECEE in 2001. That is definitely because China has invested more in energy and environmentally-friendly technologies and renewable energy projects.

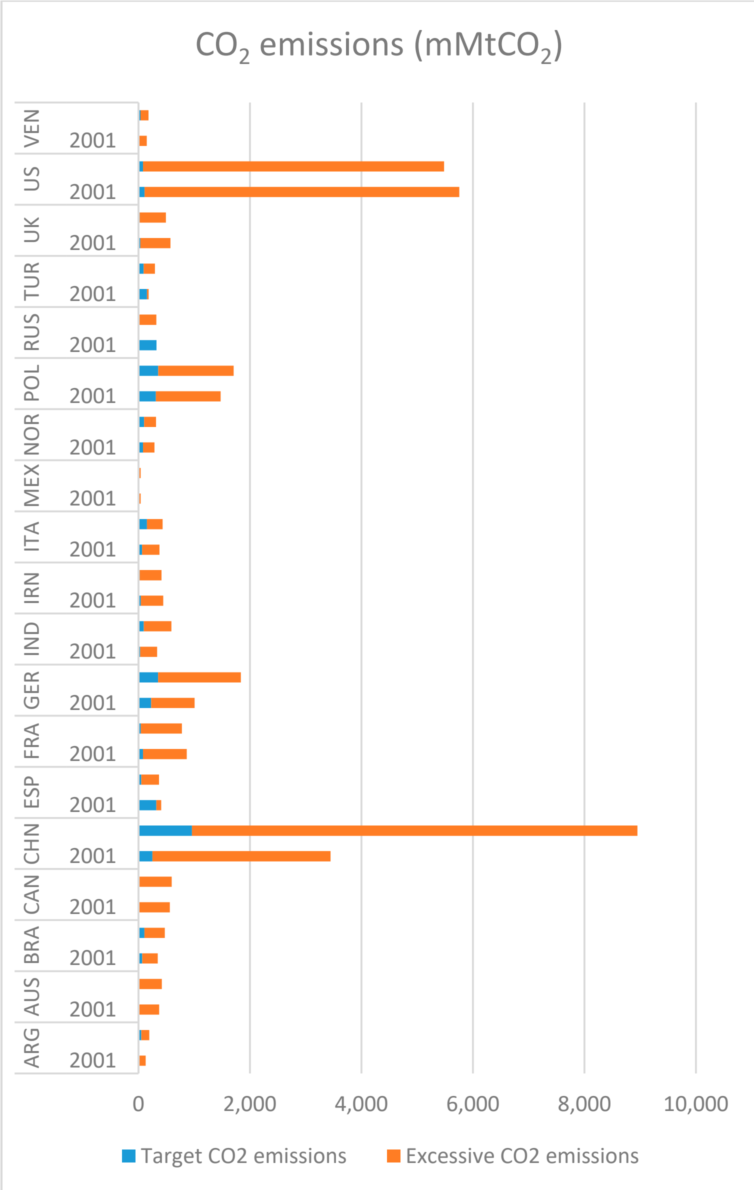

Figure 4. CO_2 emissions targets and excesses for years 2001 and 2011.

Furthermore, in the recent past the service industry in China has grown as well, but still China needs to improve its economic structure by improving the tertiary industry if it is to surpass the United States and other European economies. On the other hand Spain that was on frontier had the largest reduction in efficiency. Turkey had the second largest reduction in ECEE in first division after Spain. The very low performance of Spain, Turkey and Norway allows us to guess about their deteriorating economic balance with respect to structure and carelessness about their technological progress.

In order to further analyze intertemporal changes in the energy and CO_2 emissions efficiency of economies it would be better to first look into the changes in population, number of people in each income class and changes in the share of each income class in the total population. Table 4 shows us these statistcs. A score above 1 means an increase, a score of 1 means no change and one below 1 indicates a shrinkage. It can be noted that except for Germany, Poland and Russia, the rest of the economies in our analysis had an increase in population in the period 2001–2011. With respect to change in MI, China, India, Iran and United States managed to grow their MI while all the rest of the economies experienced a shrinking MI. Only Iran and the United States had scores below 1 for change in HI, while the rest of the countries had an expansion in HI. In LI, which is an indicator of the poor class the trend is mixed, that is many countries had an expansion in their poor class while others had a shrinkage. Canada has no change in LI, France, Germany, Italy, Norway, Spain, UK and USA had expansion in LI and the rest of the conntries observed a shrinkage in LI. Although looking into these changes in income classes and population is important, analysing changes in the percentage share of these income classes in the total population is more relevant and meaningful. Looking into this aspect we observe that curiously only China had an expansion in the share of MI in the total population and all the remaining larger economies have a shrinkage in their shares of MI in the total population between 2001–2011. On the contrary, all countries managed to decrease the share of LI in the total population, except for Germany, Poland and Russia. Australia, France, Germany, Italy, Norway, Poland and Russia have had an expansion in HI, while the rest of the economies have managed to shrink their HI. The expansion in the MI share of China in the total population explains well its highest performance in the second division. It has managed to improve its distribution of income. The increase in the share of HI and LI in the total population explains the deterioration in performance of Australia, France, Germany, Italy, Norway, Poland and Russia.

Table 4. The population statistics, change in scores of population, MI, HI, LI and change in scores of percentage share of income classes in the total population (2001–2011).

	Change in Scores (2001–2011)				Change in Scores of Percentage Share of Income Classes in Total Population (2001–2011)		
Country	**Population**	**MI**	**HI**	**LI**	**MI**	**HI**	**LI**
Argentina	1.112	0.992	1.033	0.818	0.893	0.929	0.736
Australia	1.151	0.928	1.162	0.997	0.807	1.010	0.866
Brazil	1.124	0.993	1.017	0.913	0.883	0.905	0.812
Canada	1.105	0.962	1.075	1.000	0.871	0.973	0.905
China	1.057	1.100	1.005	0.713	1.040	0.951	0.675
France	1.065	0.941	1.105	1.001	0.884	1.038	0.940
Germany	0.993	0.985	1.012	1.001	0.992	1.019	1.008
India	1.164	1.134	1.001	0.844	0.975	0.860	0.725
Iran	1.125	1.039	0.987	0.998	0.923	0.877	0.887
Italy	1.042	0.921	1.177	1.002	0.884	1.129	0.961
Mexico	1.155	0.999	1.008	0.906	0.865	0.873	0.785
Norway	1.097	0.810	1.208	1.003	0.738	1.101	0.914
Poland	0.995	0.987	1.012	0.999	0.991	1.017	1.004
Russian	0.979	0.971	1.070	0.984	0.992	1.093	1.005
Spain	1.147	0.943	1.089	1.010	0.822	0.950	0.881
Turkey	1.145	0.930	1.009	0.978	0.812	0.881	0.854
United Kingdom	1.070	0.965	1.053	1.008	0.901	0.984	0.942
United States	1.094	1.004	0.975	1.009	0.918	0.891	0.922
Venezuela	1.180	0.966	1.008	0.961	0.819	0.854	0.814

The overall performance in affected by both divisions together. Apart from the obvious factors analyzed above for individual divisions there may be factors which may help to explain the deterioration or improvement in overall performance. It is thought generally that HI is necessary to improve investment and they are drviers of all economic activites, innovation and tendencies to improve situation. In other words a larger HI may be taken as a sign of improvement in economic activities and technological innovation. However that is a very weak argument because investment is not determined by the pooling of huge funds in the hands of few people rather it is determined by the total wealth of an economy and the amount of spare wealth in the hands of people. For example it would not be important whether a thousand millionnaires invest a million of dollars each to create an investment of 1 billion or a million people from the middle class invest one thousand dollars each for the same goal, so it is clear that it does not matter how many parts we make of a amount rather important thing is presence of 1 billion spare money in economy that can be pooled. HI can not be given credit for investment for efficient and huge investment in economy, research and deevelopment. On the other hand, if we analyze it, it is obvious that HI can be a hurdle in efficient investment because the whole decision power lies in the hands of a few people and many projects which they don't think suitable would get no funding because of the absence of a huge MI which is more likely to easily divert small amounts of money to small and medium projects that may not be of interest to a majority but may prove pilot studies for huge projects. Hence if the power of making investment decisions goes into the hands of more people then better and more diverse investment decisions are more likely. This it would affect the performance of economies in both divisions and ultimately the overall performance will be improved.

6. Conclusions

By performing an analysis of inter-temporal changes in ECEE using the NDEA we found that none of the major economies was efficient in both divisions in the period from 2001 to 2011. Generally, it can be concluded that the performances of DMUs in the first division deteriorated in the sample period and performances in the second division showed a mixed trend where many had improvements, some had no change and others had a deterioration in performance. Although ratios are a good proxy for performance, when we look into the actual quantities, the overall situation appears worst regarding energy consumption and CO_2 emissions in the sample period. There are a few economies which have managed to shift population from HI and LI into MI. The larger the MI the better, as shown by the analysis performed in this paper. On the contrary, in reality we see an expansion in HI and LI, which is indicative of a greater class difference. Hence, it is obvious that energy usage cannot be optimum and this is true for CO_2 emissions as well.

There are a few suggestions for policy makers that can be put forth. First of all, it is obvious that economic restructuring is inevitable for sustainable growth characterized by better use of energy resources and preservation of the environment from the detrimental effects of economic growth. In this regard, expansion of the middle-income class is very necessary. Putting greater power of economic decision-making in the hands of the middle-income class is more likely to bring about a balance in energy consumption and wellbeing. Secondly, all economies should improve their performance in both the production and distribution of economic outputs. Mere fast economic growth resulting into larger economy size should not be the objective of economic policies but rather optimum growth should be pursued. In this regard, intertemporal changes should be measured regularly and policies should be fine-tuned to align growth with the strategic objectives of optimum growth. Thirdly, all economies should go for expansion in the tertiary industry and should shift their focus from huge production to better distribution so that services are paid in a more balanced way and the poor class is eliminated and the middle-income class expands. Finally, it should not be forgotten that efficient production with respect to energy consumption and CO_2 emission is also inevitable and should not be ignored when focusing on efficient distribution. In this regard new sources of energy like solar energy and electrical engines can contribute to the control of CO_2 emissions and new technologically advanced engines in cars and factories, respectively, can be a solution for better use of energy sources in production.

This study leaves room for further research in this area. On the one hand using NDEA in such studies is a challenge and further innovative ways to get deeper in analysis of ECEE in context of internal structure of economies are needed and on the other hand, inclusion of other pollutants can broaden the canvas of research. A limitation of our study is its use of a constant return to scale model which leaves room for the application of variable return to scale models in similar research. Last but not least, we have used a fixed link case for intermediate products in out NDEA model and the free link case could be used to further expand the analysis.

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