 doi:10.20944/preprints202101.0467.v1

Article

Energy Efficiency in OECD Countries: A DEA Approach

Filip Fidanoski [1,*], Kiril Simeonovski [2] and Violeta Cvetkoska [3]

[1] UNSW Business School, University of New South Wales, Sydney, Australia; f.fidanoski@unsw.edu.au
[2] Faculty of Economics – Skopje, Ss. Cyril and Methodius University in Skopje, Skopje, Republic of Macedonia; kiril.simeonovski@gmail.com
[3] Faculty of Economics – Skopje, Ss. Cyril and Methodius University in Skopje, Skopje, Republic of Macedonia
* Correspondence: f.fidanoski@unsw.edu.au; Tel.: +61466337561

Abstract: This paper is about energy as viewed through an integrated model that links energy with environment, technology and urbanisation as related areas. Our goal is to empirically investigate the (in)efficient energy use across 30 developed OECD member states during the period from 2001 to 2018. For that purpose, we set up an output-oriented BCC data envelopment analysis that employs a set of input variables with non-negative values to calculate the efficiency scores on minimising energy use and losses as well as environmental emissions. We develop a couple of baseline models for primary energy and secondary energy (electricity) in which we find that countries have mean inefficiency margins of 16.1 per cent for primary energy and from 10.8 to 13.5 per cent for electricity. Then, we extend the baseline models by adding environment as an important closely related concept and confirm the consistency of the baseline findings. In the context of this analysis, however, the inefficiency scores, on the one hand, point out to a mismatch in the utilisation of the inputs to produce efficiency but, on the other hand, they uncover a hidden potential to increasy efficiency through re-allocation under constant inputs.

Keywords: energy efficiency; primary energy; electricity; DEA analysis

JEL Classification: C6, P18, Q4

---

1. Introduction

Energy and environment are essential for sustainable development. The efficient energy use with minimal emissions with the policy impact of the existing frameworks enjoy an increasing interest in the economic circles, although there is a lack of economic literature dealing with these issues in a quantitative fashion compared to those that treat it descriptively. Therefore, we find it challenging to contribute to the existing literature by providing a quantitative assessment of energy efficiency and its implications on the decisions relating the energy management.

The goal of this paper is to examine how efficiently do the developed countries use energy and are there possibilities to increase efficiency through re-allocation. For that purpose, we construct a sample of OECD

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

member states and choose the period 2001–2018. We divide the broad concept of energy into primary energy and secondary energy (electricity), and subsequebtly define a set of energy-related variables alongside a few other indicators as proxies for related and important areas such as technology, urbanisation and environment in order to develop an integrated framework. Furthermore, we set our objective to minimise energy intensity and energy loss in view of the levels of other energy indicators as input variables. Based on our extensive review of other papers studying efficiency, we opt-in for the data envelopment analysis (DEA) framework and construct an output-oriented model to yield (in)efficiency scores on energy use. The advantage of this method is that it is agnostic regarding the functional assumptions for performance assessment and its conclusions are thereby reliable. In that context, we explain why the DEA framework is a useful method applicable to examining energy efficiency and argue why scholars should seriously consider it for similar empirical analyses.

Our paper contributes to the existing literature in the following ways. Firstly, it sheds light on the quantitive side of the energy efficiency analysis with the aim of providing evidence for drawing coherent conclusions. Secondly, it makes the use of derived variables that were specifically defined to capture the essence of energy use. Thirdly, this paper further extends the area of applicability of the DEA framework and its formulation can be used a starting point for future research. Fourthly, the multi-country approach allows for cross-country discussion of the results and opens up other possibilities for linking the concept of energy efficiency with other relevant areas such as economic development. All in all, our research conveys the importance of DEA on energy efficiency and the results we arrive at are beneficial from both theoretical and empirical perspectives.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 discusses the construction of the sample, lists the data sources and defines the variables included in the empirical analysis. Section 4 unfolds the main trends throughout the analysed period. The DEA methodology is set up in Section 5, while the results from the optimisation are presented and discussed in Section 6. The paper concludes with final remakrs given in Section 7.

2. Literature review

In this section, we review the literature related to the application of the DEA framework to energy and environmental economics. To that end, we divide the existing literature into two strands — the first focussing on other literature reviews about the frequency of matching the DEA methodology with energy economics, and the second reviewing literature with empirical application of the DEA models to yield concrete results regarding energy efficiency.

Of the first strand of literature, [1] make a literature review on DEA in energy and environmental economics. They analyze 145 articles from two online databases: Scopus and Web of Science in the period 2000–2018. They provide an extensive analysis of the implemented DEA model in a tabular format. Besides this, they show the distribution of DEA papers in the analysed areas of the 45 journals and they find that the Journal of Cleaner

Production has the highest number of publications (17), followed by Sustainability (16) and Energy (14). Also, based on the distribution of papers per year, they provide a line chart and appropriate analysis by which it can be concluded that the interest of researchers in these areas have dramatically increased. In 2015, there were only 12, while in 2017 there were 14 papers. In addition, they use the papers from Web of Science to visualise the co-occurrence of the keywords. On the co-occurrent keywords figure, it can be seen that the word 'efficiency' has the strongest link with the other keywords. The keywords are clustered in 3 clusters of their co-occurrence. In the green cluster, the keywords are efficiency, DEA, input, output and DEA model; in the red cluster, there are China, region, energy, energy efficiency, emission, etc.; while in the blue cluster there are productivity, economy, sustainability, eco-efficiency, environmental performance, sustainable development and sustainability.

[2] make a literature survey on the application of data envelopment analysis in sustainability. They focus on articles in the Web of Science database and, after excluding papers that are not related with DEA in sustainability, their sample consists of 320 papers published in the period 1996 to March 2016. The distribution of papers in the period 1996–2015 is presented in a visual form, which incdicates that the interest of DEA in this area has significantly increased in the last five years. The first DEA paper in sustainability is by [3]. The authors visualise the distribution of papers in journals, and they point out that, in 20 journals, approximately 48% of the papers get published. The journal Energy Economics is on the first place, followed by the Journal of Cleaner Production and Energy Policy. In this paper, the authors focus on citation analysis by applying three citation methods: the citation chronological graph, main path analysis and Kamada-Kawai algorithms. They find that the current key route of data envelopment analysis application in sustainability is focused on measuring eco-efficiency.

Likewise, [4] conducted a literature review on evaluation of energy efficiency using DEA. They focus on recent publications, i.e. the period from 2011 to 2019 and analyse 281 papers from the Web of Science database. According to the distribution of papers per year, the visualised data in a bar chart demonstrate that there is a gradual increase over years and the highest number of papers (61) was in 2019. They present a tree map with the number of publications across journals, with Energy Economics assuming the leading role with 26 papers, followed by Sustainability (25 papers) and Energy (22 papers). In order to visualise the keywords and their context evolution in the analysed period, they use Citespace. Accordingly, they present a figure by which it can be seen that DEA models are enriched in order to enable a better evaluation of energy efficiency and, besides the theory enrichment, there are several DEA applications. Models that are used in the analysed papers range from traditional as CCR and BCC to SBM models, from using one output to inclusion of output that is undesirable, and from a static to a network structure. The data refer to countries, regions, industries and companies, and most of the studies as DMUs use regions. When data envelopment analysis is used to measure the total factor energy efficiency (TFEE), energy, capital and labor are taken as inputs, while GDP is expected output, while the undesirable output is carbon emissions.

Another systematic review on studies that assess the performance of renewable energy using the DEA framework was done by [5]. They search studies in Science Direct, SCOPUS and Google Scholar, and implement the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. By analysing 72 scholarly articles, they provide visual presentation of the distribution of these studies, from which it can be noted that the first study was published in 2001 (Ramanathan, 2001) and the peak (14 studies) was achieved in 2017. The studies are categorised according to seven technologies: renewable energy, solar energy, wind energy, municipal solid waste, biomass, hydropower and other renewable energies (biogas, biofuel, and geothermal). Based on the chart of the distribution of studies in the identified areas, the renewable energy has the highest percentage (43.06%), followed by solar energy (15.28%), and wind energy and municipal solid waste (both with 13.89%). They provide tabular representation of DEA studies for each of the identified renewable energy technologies with focus on authors and year, scope, duration, methodology and references. In addition, they present a distribution of the studies according to the used DEA method based on which it can be noted that a two-stage DEA model is applied in 28 studies, a traditional DEA model is applied in 18 studies, a three-stage DEA model in 8 studies, a DEA with special data in 5 studies, an extended DEA model in 4 studies, and a Slack-based model and a Malmquist model are applied in 3 studies.

The DEA class of methods is particularly recommended for in-depth analysis of energy efficiency. [6] provide a comprehensive literature review on DEA models applied to energy efficiency. They use the PRISMA statement in order to identify and select the proper papers. They identify 144 papers in the period from 2006 to 2015, published in 45 journals and indexed in the Web of Science database. In the first year of the analysed period, only one paper was identified but the interest of researchers in energy efficiency has grown over the years and, from 2013 to 2014, the number of papers has increased from 20 to 42. In the journal Energy Policy, 17.36% of the articles get published, followed by the journals Renewable and Sustainable Energy Review and Energy with 19 and 13 papers, respectively. According to expert opinions, all papers are classified in 9 areas so that energy efficiency issues is the area with highest number of papers (35), followed by the other application areas (25 papers), and environmental efficiency as well as renewable and sustainable energy (each with 23 papers), while the water efficiency is an areas that has the least number of papers (4). The authors provide detailed tabular format for the distribution of the papers in each of the areas that consists of author(s) and year, scope, duration, application, purpose of the study, and results and outcome. In addition, they provide distribution of papers regarding the nationality of the authors in a tabular format. They have identified 29 nationalities and countries, with China on the top in terms of the number of published papers on energy efficiency (44 papers), followed by Iran (18 papers), USA (9 papers), Taiwan, Spain and Korea (each with 8 papers).

Of the second strand of literature, [7] conduct a study that focuses on the energy trend in the world and consequently describe how the DEA as a non-parametric approach for measuring efficiency can be applied to the energy industries. The energy is categorised as primary and secondary. The primary energy consists of fossil-fuel energy (oil, natural gas and coal) and non-fossil energy (renewable and nuclear), while the secondary energy refers to electricity. The authors use charts to present the energy trends in the world for the main categories of energy and their sub-categories. They present formulations for using DEA for the fossil and non-fossil energy.

Furthermore, [8] evaluate the efficiency of energy consumption in the main industry in China, manufacturing on panel data in the period 2004-2014 by applying the non-parametric methodology DEA. The DEA model is constructed by using piecewise linear utility function. In the DEA model, one output indicator (energy consumption intensity) and five input indicators (competition within industries, technological Progress, energy consumption structure, opening up, environmental regulations and energy efficiency policy) are used. The energy efficiency policy is an environmental indicator and is considered as quantitative but as well as qualitative indicator, and accordingly two DEA models are created. One model considers only the quantitative environmental regulations, while in the other, the quantitative and qualitative environmental regulations are integrated. Based on the comparison of the obtained results (with and without energy policy) it was found that the low energy policy encourages the development of high energy-consumption industries, while its impact on the development of low or moderate energy-consumptions industries is low.

[9] evaluate the environmental performance of Danish product and household types by using the DEA methodology. Based on the overall score for environmental performance, they find that middle-income families living in houses, which represent a large proportion of all Danish families, are characterised by the least environmentally friendly consumer basket. In contrast, those families that live in urban flats are characterised by the most environmentally friendly consumer basket.

An interesting approach for environmental assessment with focus on corporate sustainability by employing DEA is proposed by [10]. They use 153 observations on S&P 500 corporations in 2012 and 2013. Considered data is from 7 US industries (consumer discretionary, consumer staples, energy, healthcare, industrials, information technology and materials). The following variables are taken into account: estimated annual CO_2 saving and return on assets as desirable outputs; direct and indirect CO_2 emissions as undesirable outputs; and number of employees, working capital and total assets as inputs. Their approach provides an answer of the question which technology innovation should be selected to reduce the undesirable output (CO_2 emissions). They find that, amongst the seven industries, the energy sector is the best one to invest in technology in order to achieve corporate sustainability.

Lastly, [11] propose a new approach that deals with the difficulties — theoretical and empirical — of the DEA framework for environmental assessment. The DEA environmental assessment can be applied to measure the performance of decision-making units (DMUs) that use inputs and produce desirable but also undesirable outputs. For example, desirable output is electricity, while undesirable output is the amount of CO_2 emissions. The authors propose solution to four difficulties arising from the application of the DEA environmental assessment. They are: disposability

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

concepts, disposability unification, undesirable and desirable congestion and values that are zero or negative.

3. Data and variables

Our sample consists of 30 OECD member states1 for which we collect annual data for the period 2001–2018. Countries were selected on the basis of their OECD membership throughout the entire analysed period. Data were collected from multiple sources, including US Energy Information Administration (EIA) database, World Bank's World Development Indicators (WDI) database and the OECD database. Since the raw data collected are in different metric units, we apply conversion to make them suitable for the empirical analysis.

Considering that energy is a broad concept that may appear in different forms, we opt for primary energy and secondary energy (electricity) as proxies to study energy efficiency. In that regard, we define energy-related specific variables that are relevant for studying these two forms of energy and we also add a few other variables as measures of areas that are closely related to and important for energy efficiency.

The variables that we use in the efficiency analysis are the following:

- **Primary energy intensity.** Energy intensity is an indicator of the energy efficiency in an economy and thus primary energy intensity shows how efficient are countries in terms of primary energy. This variable tells how much output does the use of energy generate or, in other words, what is the price of converting energy into output. We calculate this variable using the formula

$$\textbf{Primary energy intensity} = \frac{\textbf{Primary energy consumption}}{\textbf{GDP}}, \qquad (1)$$

  where primary energy consumption is measured in billion kWh and GDP in international US$ using current prices. Therefore, primary energy intensity essentially points out to the primary energy use per unit of GDP. Normally, the higher value of the measure signifies more energy use needed to produce a unit of GDP and that is higher energy inefficiency.

- **Primary energy trade dependence.** The mismatch of production and consumption of primary energy reveals country's trade orientation. It stands to reason to assume that a country producing more energy than it can consume will export the excess and a country needing more energy than it can produce will import to mouth its needs. Otherwise, the mismatch will lead to distribution losses or energy deficiency. For the sake of measuring how much a country is oriented towards trading primary energy, we define an indicator calculated as the ratio

$$\begin{matrix}\textbf{Primary energy}\\ \textbf{trade dependence}\end{matrix} = \frac{|\textbf{Primary energy balance}|}{\textbf{Primary energy production}}, \qquad (2)$$

[1] The countries included in the sample with their ISO 3166-1 alpha-3 codes in parentheses are the following: Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Czech Republic (CZE), Denmark (DNK), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Iceland (ISL), Ireland (IRL), Italy (ITA), Japan (JPN), Luxembourg (LUX), Mexico (MEX), Netherlands (NLD), New Zealand (NZL), Norway (NOR), Poland (POL), Portugal (PRT), Slovakia (SVK), South Korea (KOR), Spain (ESP), Sweden (SWE), Switzerland (CHE), Turkey (TUR), United Kingdom (GBR) and United States (USA).

where primary energy balance is the difference between the consumed and produced primary energy. As our goal is to measure trade dependence without making difference between import- and export-orientation, we take the absolute value of the primary energy balance.

- **Primary energy from renewables.** Sustainable energy is one of the cornerstones of energy efficiency and the production of energy of low cost from naturally replenishing sources is a major efficiency goal. In order to proxy for sustainable energy in the efficiency analysis, we take the share of primary energy that is produced from renewable sources.
- **Electricity intensity.** In a similar way as the primary efficiency intensity, this variable aims to tell how efficient countries in consuming electricity are to produce output. The formula for calculating the electricity is

$$\textbf{Electricity intensity} = \frac{\textbf{Electricity consumption}}{\textbf{GDP}}, \qquad (3)$$

where electricity net consumption is measured in billion kWh. Again, the higher value of the measure points out to more electricity needed to produce a unit of GDP and that denotes higher electricity inefficiency.

- **Electricity loss ratio.** Electricity losses are the units of electricity that remain unused. In light of this definition, our variable to measure the electricity losses is defined as

$$\textbf{Electricity loss ratio} = \frac{\textbf{Electricity loss}}{\textbf{Electricity production}}, \qquad (4)$$

where electricity loss is the unused electricity yielded after the traded electricity is added to the electricity balance, that is

$$\textbf{Electricity loss} = \underbrace{\begin{matrix}\textbf{Electricity}\\ \textbf{production}\end{matrix} - \begin{matrix}\textbf{Electricity}\\ \textbf{consumption}\end{matrix}}_{\textbf{Electricity balance}} + \textbf{Electricity net import}. \ (5)$$

- **Electricity capacity.** The installed electricity capacity is an indicator of how efficiently electricity is generated and it refers to the amount of electricity that can be produced from electricity generators under given conditions. In order to better suit in our analysis, we calculate the ratio of the electricity installed capacity to the electricity production. The higher value of this measure points out to higher efficiency in electricity generation.
- **Electricity from renewables.** As for primary energy, we use the share of electricity produced from renewable sources as a measure of sustainable electricity.
- **Renewable electricity capacity.** In a similar way as the electricity capacity ratio, this variable measures the efficiency of electricity generation from renewable sources.
- **R&D expenditure.** Technological progress can lead to energy production at lower cost and more efficient consumption. We proxy for technology through the R&D expenditure of GDP.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

- **CO_2 emissions.** Energy efficiency does not only mean producing at minimum cost and consuming to generate maximum output. We find it convenient to take care about the environmental issues coming out of the energetic sector and we therefore calculate the level of carbon dioxide (CO_2) emissions in metric kg relative to GDP as a proxy for environment.
- **Urbanisation rate.** Since the demand for and consumption of electricity are significantly higher in the urban compared to the rural areas, the level of urbanisation can be properly considered a useful variable in the analysis of electricity efficiency. We calculate the urbanisation rate as urban population relative to total population.

The intensity variables and the CO_2 emissions are the only used as output variables, while the rest are included as input variables in the empirical analysis.

4. Main trends

4.1. Descriptive statistics

Descriptive statistics are reported in Table 1. Given that the values of the energy-related variables differ significantly from one to another country and yield outlying results, we calculate weighted means as well as weighted standard deviations for these indicators.

Table 1. Descriptive statistics

Variable	*Obs.*	*Mean*	*Min.*	*Max.*	*St. Dev.*
Input variables					
Primary energy trade dependence	540	0.405	0.009	104.322	1.187
Primary energy from renewables	540	0.139	0.007	1.000	0.131
Electricity capacity	540	0.257	0.149	7.323	0.046
Electricity from renewables	540	0.201	0.008	1.000	0.188
Renewable electricity capacity	540	0.303	0.093	0.894	0.097
R&D expenditure rate	502	0.018	0.003	0.045	0.009
Urbanisation rate	540	0.774	0.537	0.980	0.106
Output variables					
Primary energy intensity	540	1.643	0.496	8.026	0.613
Electricity intensity	540	0.222	0.071	1.231	0.078
Electricity loss ratio	540	0.064	0.014	0.677	0.024
CO_2 emissions	540	0.342	0.056	1.812	0.232

Notes: The sample consists of 30 countries with data for 18 time periods.

The mean value for primary energy intensity is 1.643, meaning that 1.643 kWh are needed to generate an output of 1 US$. Czech Republic, Slovakia, Iceland, Poland and Canada are countries with the highest intensities, in all above 3, while Switzerland, Ireland and Denmark record the lowest intensities, in all below 1 on average. The general trend is that the inefficiency measured through this variable is steadily decreasing over time — namely, from 3.331 in 2001 to 1.421 in 2018. The mean electricity intensity is several times lower and equals 0.222. All countries have average intensities below 0.5, except for Iceland which stands out with 0.866 and is the only country that has attained intensity above 1 in some years. Again,

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

the inefficiency measured through this variable follows a downward trend and it went down from 0.433 in 2001 to 0.215 in 2018. In regard to the electricity loss ratio,the quantity of energy that remains unused is around 6.4 per cent on average across countries. Only Turkey, Mexico, Luxembourg and Hungary have mean amount of unused energy above 10 per cent. Unlike, the previous two measures of inefficiency, this one has remained fairly constant around 7 per cent on average throughout the entire period.

Trade dependence has a moderate weighted mean index value of 0.405, indicating that countries need to trade primary energy of about 40.5 per cent of the produced amount in order to fill the production-consumption gap. Countries that are the most independent of trading primary energy are Denmark (18.2 per cent), Mexico (20.4 per cent) and United States (27.3 per cent), while countries that depend the most on the trade are Luxembourg and Ireland whose traded amounts of primary energy are 62 and 10 times the quantity they produce, respectively. The evidence is conclusive that the trade dependence across countries reduces over time, being more than two times lower in 2018 than the peak achieved in 2003.

Primary energy produced from renewable sources accounts for 13.9 per cent on average across countries with a standard deviation of 13.1 per cent. Iceland, Luxembourg and Portugal are countries with full production from renewables, while Australia, Mexico and Poland generate less than 5 per cent of their primary energy from these sources. Likewise, the share of electricity generated from renewables amounts to 20.1 per cent with higher standard deviation of 18.8 per cent. The only country that fully produces electricity from renewables throughout the entire period is Iceland and Norway follows closely with about 98.8 per cent. However, it is worth noting that Luxembourg has had full electricity generation from renewables since 2016 but, because of the lower share in the previous years, its average share is only 32.4 per cent. The shares of both primary energy and electricity produced from renewable sources tend to move upwards as time goes by and have ramped up from less than 30 per cent in the early 2000s to more than 40 per cent in the 2010s.

The installed electricity capacity averages around 25.7 per cent of the total electricity production, ranging from 16.5 per cent in Iceland to 170.4 per cent in Luxembourg. Yet this large difference between the two countries, most countries have fairly equal installed capacity in the interval from 20 to 30 per cent, which can be further confirmed by the standard deviation of only 4.6 per cent. With respect to the installed capacity for generating electricity from renewables, it averages around 30.3 per cent and is highest in Greece with 56.3 per cent and South Korea with 48.4 per cent. Both capacity measures follow upward movements from year to year.

Of the variables proxying for the related areas, it is worth noting that countries spend about 1.8 per cent of GDP on research and development on average, being slightly higher in the end years compared to the start years of the analysed period. The share ranges from 0.7 per cent in Greece, Slovakia and Turkey to 3.3 per cent in Finland, South Korea and Sweden. Next, the mean carbon dioxide emissions amount to 0.342 Mkg per 1US$, with lowest average emissions of 0.088 Mkg/US$ in Switzerland and highest of 0.837 Mkg/US$ in Poland. CO2 emissions had a downward-sloping curve in the 2000s but it eventually flattened out in the 2010s. Finally, the average

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

level of urbanisation across the sampled countries equals 0.774, indicating that 77.4 of the total population inhabits urban areas, and it tends to go slightly up over time.

4.2. Energy use and economic development

In this section we study energy use across countries as measured through the energy output variables with respect to their economic development as proxied by the nominal GDP per capita (see Appendix A).

The correlation coefficients for all three output variables — primary energy intensity, electricity intensity and electricity loss ratio — with the nominal GDP per capita are negative, which indicates that, in general, countries with higher economic development tend to use energy in a more efficient manner.

Primary energy intensity has a moderate to strong negative correlation coefficient of -0.53. Most countries with average GDP per capita between 20,000 to 50,000 US$ are clustered with intensity values between 1.0 and 2.0, while the intensity of all six countries with GDP per capita lower than 20,000 US$ exceeds 2.0. Countries that stand out and, at the same time, record high GDP per capita and high intensity above 3.0 are Iceland and Canada.

Electricity intensity and nominal GDP per capita have weak negative correlation coefficient of -0.27. Almost all countries are scattered in a cluster with intensity values between 0.1 and 0.4. Countries standing out of the cluster and hinting to a negative direction are Luxembourg, Norway, Switzerland and Iceland. The last one, albeit with a very high GDP per capita, has electricity intensity that is more than two times that of the next country.

Electricity loss ratio has very weak negative correlation coefficient of -0.10. Countries are scattered with no visible direction and similar loss ratios in the interval from about 3 to 9 per cent are associated with different levels of GDP per capita. Hungary, Turkey and Mexico point out to a negative direction with loss ratios above 10 per cent but this tendency is well off-set by Luxembourg as a country with the highest GDP per capita and second highest loss ratio.

At first glance, these findingsseem to somewhat contradict the popular view that countries with higher energy intensity are economically more developed with high-intensity industrial production, while those with lower energy intensity are developing countries with labour-intensive economies. Nonetheless, it has to be to noted that, even though countries differ significantly in terms of economic development, OECD consists of relatively well-developed economies where countries with the least GDP per capita have still much more advanced economies than the developing world. Thence, it can properly be concluded that the negative direction does not imply that the industrialised economies attain more efficient energy use than the labour-intensive ones but that, amongst the industrialised ones, those with higher GDP per capita usually perform better.

5. Methodology

The main goal of our empirical analysis is to get efficiency scores with regards to the energy efficiency indicators for each country over the

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

analysed period. Since we aim to employ energy-related indicators as both output and input variables, and enrich the analysis with other variables capturing technology and urbanisation as input variables, we find it convenient to follow the efficiency literature (see [12]) and implement the data envelopment analysis (DEA) using DMUs. DEA is a non-parametric technique that, through linear programming, approximates the true but unknown technology without imposing any restriction on the sample distribution. In fact, DEA is a complex benchmarking technique that yields production possibilities where efficient multi-criteria DMUs positioned on this surface shape the frontier (see [13]).

Specifically, we use the most popular methodology which, compared to parametric approaches, has several important advantages (see [14]): i) it is not necessary to find out the concrete form of production function and is with less restrictions; ii) it is easier to deal with the case with multiple inputs and multiple outputs; iii) the technological efficiency analysis enables the enterprises to find out which input is not efficiently utilised and to look for the best way to improve efficiency in addition to knowing the input efficiency of the evaluated structure in question compared to the most outstanding enterprises; and iv) the non-parameter approach allows not only to arrive at a conclusion about the technological efficiency but also to calculate the economic efficiency, allocation efficiency and pure technology efficiency, which makes it possible to conduct an inclusive evaluation and should be regarded as a comprehensive assessment index of achievements.

There are several assumptions that we find it necessary to establish before moving on to the optimisation problem that we are going to solve. They are presented in turn.

Assumption 1 (Linearity): *The objective function in the optimisation using DEA is linear.*

This assumption implies that the optimisation is done using a linear programming technique. However, this may be problematic in practice because the objective function and the constraints are expressed as fractions and they are thus non-linear, which requires the optimisation problem to be formulated in a linear form.

Assumption 2 (Non-negativity): *The values of the inputs $\boldsymbol{x_{i,n}}$ and outputs $\boldsymbol{y_{i,m}}$ as well as the weights $\boldsymbol{\lambda_i}$ are non-negative, i.e. $\boldsymbol{x_{i,n}}, \boldsymbol{y_{i,m}}, \boldsymbol{\lambda_i} \geq \mathbf{0}$.*

Non-negativity means that the selected variables as inputs and outputs cannot take any negative values or, alternatively, need to undergo a procedure that will allow them to be included in the analysis with non-negative values.

Assumption 3 (Convexity constraint): *The weights $\boldsymbol{\lambda_i}$ sum up to 1, i.e. $\sum_{i=1}^{C} \boldsymbol{\lambda_i} = \mathbf{1}$.*

The convexity constraint is the main feature that distinguishes the BCC DEA from the CCR DEA and assumes that the model accounts for variable returns to scale (VRS) instead of constant returns to scale (CRS).

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

As lower values of the energy indicators that we use as outputs indicate efficiency, we set up a minimisation output-oriented model with an objective function

$$f(x, y) = \min \theta_i \quad (1)$$

$$\text{s. t. } \sum_{i=1}^{C} \lambda_i y_{i,m} \geq \theta_i y_{i,m}, \quad m \quad (2)$$

$$\sum_{i=1}^{C} \lambda_i x_{i,n} \leq x_{i,n}, \quad n = 1, \dots, N \quad (3)$$

$$\sum_{i=1}^{C} \lambda_i = 1 \quad (4)$$

$$x_{i,n}, y_{i,m} \geq 0 \quad (5)$$

$$\lambda_i \geq 0 \quad (6)$$

where $x = (x_1, \dots, x_n) \in R_+^N$ is the set of N inputs, $y = (y_1, \dots, y_n) \in R_+^M$ is the set of M outputs, λ_i are the intensity weights for the linear combination of the sampled countries and $\theta_i = \sum_{i=1}^{C} \lambda_i y_{i,m} / \sum_{i=1}^{C} \lambda_i x_{i,n}$ denotes the efficiency score. The constraint in (4) results directly from Assumption 3, while the constraints in (5) and (6) illustrate Assumption 2.

At the end, we consult [14] and introduce two definitions as necessary pre-conditions to achieve relative DEA-efficiency.

Definition 1: *If the optimal program satisfies* $\boldsymbol{f}(\mathbf{x}, \mathbf{y}) = \mathbf{min}\boldsymbol{\theta_i}$, *then* $\boldsymbol{DMU_i}$ *is weakly DEA-efficient.*

This definition tells that the $\theta_i = 1$ is the efficient score that can be obtained from the optimisation. In other words, this means that a weakly DEA-efficient DMU_i when $\theta_i = 1$ lies on the DEA frontier. In case $\theta_i < 1$, then the $1 - \theta_i$ is an inefficiency margin, which reveals by how much the output level should be improved at the given inputs to reach efficiency.

Definition 2: *If the optimal program satisfies Definition 1 and Assumption 2 holds, then* $\boldsymbol{DMU_i}$ *is relatively DEA-efficient.*

The importance of Definition 2 is that it gives conditions that should be satisfied in order to reach a stronger form of DEA-efficiency.

6. Results and discussion

This section reports and discuss the results obtained in the empirical analysis.

6.1. Baseline models

We develop separate models for primary energy and secondary energy (electricity) as the two forms of energy that are subject to examination in our empirical analysis. In the baseline DEA model for primary energy, we employ primary energy trade dependence, primary energy from renewables, R&D expenditure and urbanisation rate as input variables and primary energy intensity as the only output variable. In the case for electricity, our baseline DEA model includes electricity from renewables, electricity installed capacity ratio, R&D expenditure and urbanisation rate as input variables and electricity intensity as well as electricity loss ratio as output variables. We run two versions of this model — the first one with the electricity installed capacity ratio and the second one with the renewable

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

electricity installed capacity ratio. Given the discrepancies in the values of the variables from year to year as well as the missing values for R&D expenditure, we calibrate the model with the country averages over the entire period. The inefficiency margins from the baseline models are presented in Columns 1, 3 and 5 of Table 2.

The average inefficiency margin minimising primary energy intensity is 16.1 per cent, indicating that there is room for further reduction while keeping all inputs unchanged. Seven of the sampled countries, namely Australia, Canada, Czech Republic, Denmark, Mexico, Poland and Slovakia, are relatively DEA-efficient with DMUs on the frontier, whereas Belgium, Japan, Luxembourg, Finland and Spain are farthest from the frontier with inefficiency scores above 30 per cent. It is tempting to conclude that the first group of countries performs better than the second group where a mismatch of the inputs to produce optimal output has been established but the results unfold an opportunity for the countries from the second group to make new decisions with little effort to yield better output. Literally speaking, being on the DEA frontier means that all possibilities to use the current inputs to produce better output have been exploited and the only way to make an improvement is to better the input levels.

In the model where the objective is to minimise electricity intensity and electricity capacity is used as an input, the average inefficiency score is lower and equals to 10.8 per cent. This finding reveals that countries make more efficient decisions regarding electricity use, which can be explained through the fact that primary energy is a complex groupping of various forms of energy that is much more difficult to deal with than electricity. A total of eight countries lie on the frontier in this set-up, whereas Denmark and Luxembourg score the highest inefficiency margins, both above 30 per cent. Though Mexico, Poland and Slovakia are again on the DEA frontier, it is worth noting that there are significant differences across countries compared to the case with primary energy, which further supports the notion that managing primary energy is very diferent from managing electricity. For instance, Belgium, which had an inefficiency of 39.8 per cent, now scores an inefficiency of 12.2 per cent and South Korea, whose inefficiency margin was 22.3 per cent, is on the frontier in this set-up. However, there are also examples with change in the opposite direction. United States scored an inefficiency of 7.6 per cent while optimising primary energy intensity and its inefficiency with respect to the electricity intensity has almost doubled to 14.2 per cent.

The results obtained from the model for electricity intensity and renewable electricity capacity as an input are only partially consistent with the model using electricity capacity. Countries have a slightly higher mean inefficiency of 13.5 per cent and, although Austria and Switzerland bring the number of countries on the DEA frontier up to ten, there is a general trend of increased inefficiency compared to the other version of this model. A more thorough examination of the differences reveals that the inefficiency margins go up for countries whose renewable electricity capacity is greater than the electricity capacity.

6.2. Extended models

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

We extend the baseline models by adding the environment component proxied by the CO_2 emissions as an output variable in each of them. The inefficiency margins from the extended models are reported in Columns 2, 4 and 6 of Table 2.

The inefficiency scores yielded in the extended models for optimising primary energy intensity and electricity intensity when electricity capacity is included are fully consistent with those in the baseline models. The steady scores amidst the addition of CO_2 emissions means that countries face a split-off of the improvement across the output variables that they could achieve with a better match of the inputs at its current levels. Slight differences are noticeable in the extended model for electricity with renewable electricity capacity as an input and all of them point to a decreased inefficiency. As a result, the mean inefficiency margin amounts to 12.6 per cent, which is 0.9 percentage points lower to that in the baseline model. Czech Republic is the country with most significant change from an inefficiency of 12.0 per cent in the baseline model to DEA efficiency on the frontier in the extended model.

Table 2. Inefficiency margins across countries calculated in the DEA models

Country	*Specification*					
	Primary energy		Electricity			
			With electricity capacity		With renewable electricity capacity	
	Baseline model (1)	Including emissions (2)	Baseline model (3)	Including emissions (4)	Baseline model (5)	Including emissions (6)
Australia	0.000	0.000	0.151	0.151	0.286	0.286
Austria	0.042	0.042	0.036	0.036	0.000	0.000
Belgium	0.398	0.398	0.122	0.122	0.339	0.339
Canada	0.000	0.000	0.057	0.057	0.115	0.114
Czech Republic	0.000	0.000	0.083	0.083	0.120	0.000
Denmark	0.000	0.000	0.334	0.334	0.320	0.320
Finland	0.308	0.308	0.109	0.109	0.105	0.088
France	0.241	0.241	0.081	0.081	0.240	0.240
Germany	0.250	0.250	0.173	0.173	0.256	0.256
Greece	0.195	0.194	0.151	0.151	0.161	0.161
Hungary	0.121	0.121	0.000	0.000	0.000	0.000
Iceland	0.150	0.150	0.000	0.000	0.000	0.000
Ireland	0.107	0.107	0.023	0.023	0.023	0.019
Italy	0.200	0.200	0.169	0.169	0.160	0.142
Japan	0.380	0.380	0.217	0.217	0.165	0.165
Luxembourg	0.378	0.378	0.302	0.302	0.302	0.235
Mexico	0.000	0.000	0.000	0.000	0.000	0.000
Netherlands	0.258	0.258	0.183	0.183	0.294	0.294
New Zealand	0.134	0.134	0.049	0.049	0.022	0.022
Norway	0.238	0.238	0.111	0.111	0.138	0.138
Poland	0.000	0.000	0.000	0.000	0.000	0.000
Portugal	0.090	0.090	0.000	0.000	0.000	0.000
Slovakia	0.000	0.000	0.000	0.000	0.000	0.000
South Korea	0.223	0.223	0.000	0.000	0.000	0.000
Spain	0.300	0.300	0.248	0.248	0.255	0.213
Sweden	0.245	0.245	0.145	0.145	0.257	0.257
Switzerland	0.193	0.193	0.184	0.184	0.000	0.000
Turkey	0.160	0.160	0.000	0.000	0.000	0.000
United Kingdom	0.155	0.155	0.158	0.158	0.253	0.250
United States	0.076	0.076	0.142	0.142	0.243	0.243

7. Conclusion

Our study of energy use and economic development reveals that OECD member states with higher nominal GDP per capita, in general, use primary energy and secondary energy (electricity) more efficiently. The findings that we arrive at in the empirical analysis show that OECD member states could reduce the inefficiency stemming from primary energy intensity by around 16.1 per cent under constant inputs, whereas the level of electricity intensity could be decreased by around 10.8 to 13.5 per cent. These results are consistent when adding the environment component as an output variable, although countries face a split-off of the improvement across the increased number of output variables. We also note that the (in)efficiency scores for primary energy and electricity drastically differ across countries, which hints that the managing of efficient energy use of these two forms is essentially different.

The approach we develop to study energy efficiency primarily using energy-related variables with several other indicators that proxy for other related and important concepts is not ideal, though, and it has some limitations that need to be addressed in future research papers on the topic. Firstly, the right choice of variables as inputs is oftentimes difficult and may lead to omission of important concepts. In first place, this applies to the geographic and climate factors that can impact the way a country manages its energy resources. Secondly, another related problem is the lack of data for specific variables that could calibrate the model in a proper way. Thirdly, the DEA framework assumes linearity and employs techniques of linear programming, which may not always be true and can produce results that lead up to conclusions that do not reflect reality. Fourthly, although the approach is sound to study efficiency and it can very well support important decisions regarding energy use, it does not explicitly tell what should be done to make a re-allocation that will bring closer to the frontier or how should the inputs be changed to free some room for improvement.

We acknowledge that any future research on this topic should start off from the possibility to solve the foregoing limitations and produce a more coherent and all-embracing empirical analysis. A major next step to consider is expanding the sample size by bringing in more countries with varying levels of economic development.

Appendix A. Charts on energy use and nominal GDP per capita

The charts below plot the average values of the energy-related output variables and nominal GDP per capita over the analysed period for all countries in the sample.

Figure 1. Primary energy intensity and nominal GDP per capita

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 January 2021 doi:10.20944/preprints202101.0467.v1

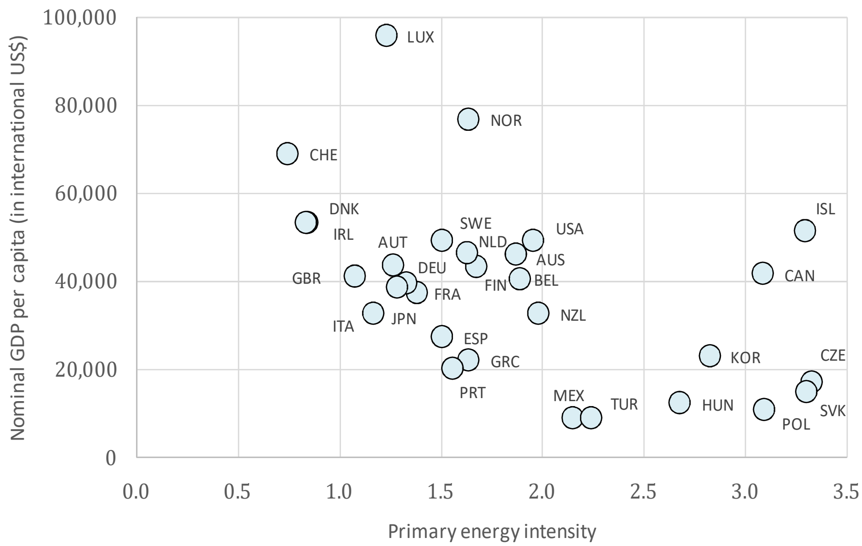


Figure 2. Electricity intensity and nominal GDP per capita

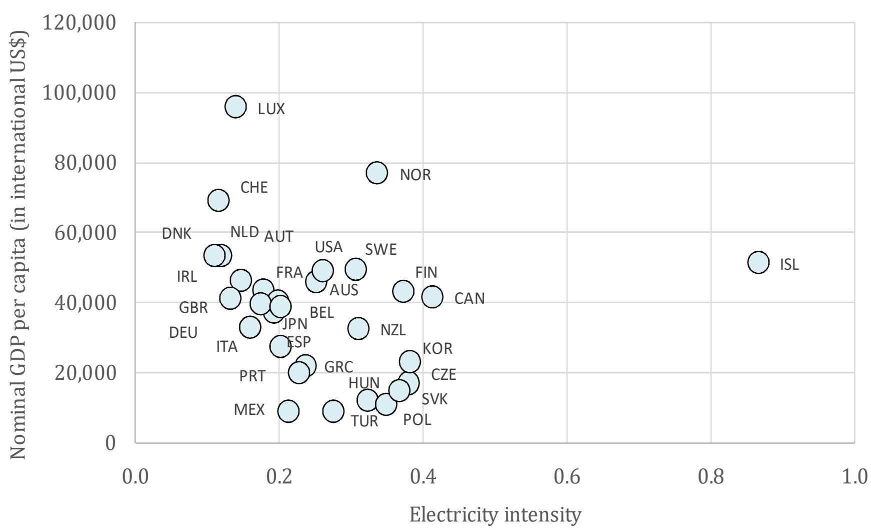
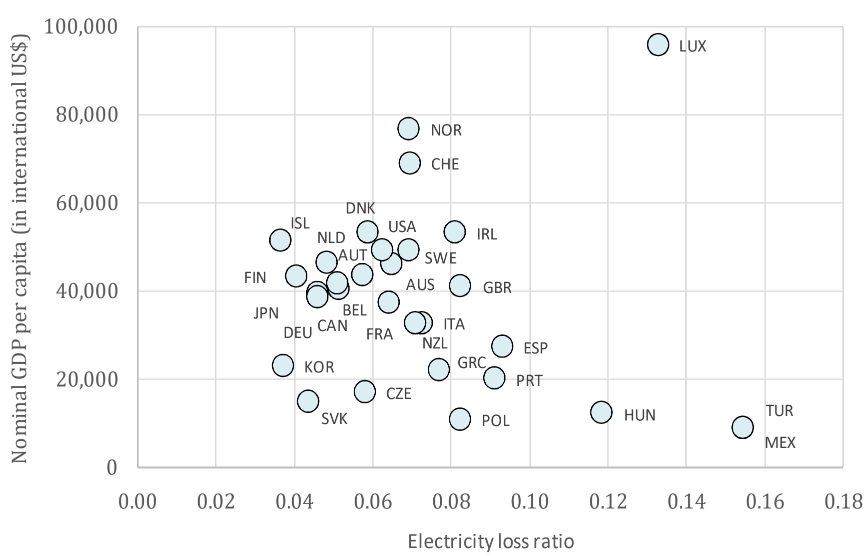


Figure 3. Electricity loss ratio and nominal GDP per capita



 doi:10.20944/preprints202101.0467.v1

Author Contributions: Conceptualization, F.F. and K.S. and V.C.; methodology, F.F and K.S. and V.C.; software, K.S.; validation, K.S., F.F. and V.C.; formal analysis, K.S. and F.F.; investigation, K.S.; resources, K.S.; data curation, K.S. and F.F; writing—original draft preparation, F,F., K.S. and V.C.; writing—review and editing, F.F., K.S. and V.C.; visualization, K.S.; supervision, F.F. and V.C.; project administration, F.F. Authorship must be limited to those who have contributed substantially to the work reported.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.
Data Availability Statement: The data used for the sake of the empirical analysis can be found at the following links:

- https://databank.worldbank.org/source/world-development-indicators
- https://data.oecd.org/
- https://www.eia.gov/totalenergy/data/browser/

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Mardani, A.; Streimikiene, D.; Balezentis, T.; Saman, M. Z. M.; Nor, K. M.; Khoshnava, S. M. Data envelopment analysis in energy and environmental economics: An overview of the state-of-the-art and recent development trends. *Energies* **2018**, *Volume 11 Number 3*, page range: 1-21.
2. Zhou, H.; Yang, Y.; Chen, Y.; Zhu, J. Data envelopment analysis application in sustainability: The origins, development and future directions. *European Journal of Operational Research* **2018**, *Volume 264 Number 1*, page range: 1-16.
3. Färe, R.; Grosskopf, S.; Tyteca, D. An activity analysis model of the environmental performance of firms—Application to fossil-fuel-fired electric utilities. *Ecological Economics* **1996**, *Volume 18 Number 2*, page range: 161-175.
4. Xu, T.; You, J.; Li, H.; Shao, L. Energy efficiency evaluation based on data envelopment analysis: A literature review. *Energies* **2020**, *Volume 13 Number 4*, page range: 1-20.
5. Chachuli, F. S. M.; Ludin, N. A.; Mat, S.; Sopian, K. Renewable energy performance evaluation studies using the data envelopment analysis (DEA): A systematic review. *Journal of Renewable and Sustainable Energy* **2020**, *Volume 12 Number 6*, 062701.
6. Mardani, A.; Zavadskas, E. K.; Streimikiene, D.; Jusoh, A.; Khoshnoudi, M.; Khoshnava, S. M. A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renewable and Sustainable Energy Reviews* **2017**, *Volume 70 Number 1*, page range: 1298-1322.
7. Sueyoshi, T.; Goto, M. World trend in energy: An extension to DEA applied to energy and environment. *Journal of Economic Structures* **2017**, *Volume 6 Number 1*, page range: 13-36.
8. Chen, X.; Gong, Z. DEA efficiency of energy consumption in china's manufacturing sectors with environmental regulation policy constraints. *Sustainability* **2017**, *Volume 9 Number 2*, page range: 210-233.
9. Wier, M.; Christoffersen, L. B.; Jensen, T. S.; Pedersen, O. G; Keiding, H.; Munksgaard, J. Evaluating sustainability of household consumption—Using DEA to assess environmental performance. *Economic Systems Research* **2005**, *Volume 17 Number 4*, page range: 425-447.
10. Wang, D.; Li, S.; Sueyoshi, T. DEA environmental assessment on U.S. Industrial sectors: Investment for improvement in operational and environmental performance to attain corporate sustainability. *Energy Economics* **2014**, *Volume 45 Number 1*, page range: 254-267.
11. Sueyoshi, T.; Goto, M. Difficulties and remedies on DEA environmental assessment. *Journal of Economic Structures* **2018**, *Volume 7 Number 1*, page range: 7-37.
12. Cooper, W. W.; Seiford, L. M.; Zhu, J. *Handbook on data envelopment analysis* (2nd ed.). New York: Springer. **2011**.
13. Lafuente, E.; Szerb, L.; Acs, Z. J. Country level efficiency and national systems of entrepreneurship: A data envelopment analysis approach. *Journal of Technology Transfer*, **2016**, *Volume 41 Number 6*, pange range: 1260-1283.
14. Deng, C. G.; Liu, T.; Wu, J. Efficiency analysis of China's commercial banks based on DEA: Negative output investigation. *China-USA Business Review*, **2007**, *Volume 6 Number 2*, page range: 50:56.