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ASSESSING ECO-EFFICIENCY OF COUNTRIES IN THE CONTEXT OF RENEWABLE AND NON-RENEWABLE ENERGY CONSUMPTION: A NON-PARAMETRIC PARTIAL FRONTIER PERSPECTIVE

Abstract. *There are numerous studies which asses the eco-efficiency of countries taking into consideration only the energy consumption as a total. However, results show the need to analyze the share of more eco-friendly energy sources. The current paper seeks to estimate the eco-efficiency at country level from a renewable and non-renewable energy consumption point of view. We employ nonparametric techniques in an input oriented setting using empirical data for 75 countries taking into account data for the year 2011. We built the FDH and the order α partial frontier in order to reveal the effect of extreme values on the efficiency estimates. Our study offers interesting insights regarding the relationship between economic development, renewable energy consumption and efficiency estimates. Results show that from the efficient countries the large economies employ in average a higher amount of energy consumption from eco-friendly resources than the small and medium size economies. This could lead to the conclusion that economic development can arise from more eco friendly energy sources.*

Keywords: *FDH, nonparametric efficiency estimators, partial frontiers, eco-efficiency;*

JEL Classification: C14, C28, I20, I23

Introduction

The matter of the scarcity of resources and their strategic utilization is one of the fundamental issues addressed by economists and policy makers. However, the limited aspect of resources is not put in relation with the ecological consequences of meeting

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human needs through industrialization until the early 1970 with the development of the formula that describes the impact of human activity on the environment (I=PAT by P. Ehlich and J. Holdren).The notion of eco-efficiency is first used several years later in 1978 by McIntyre and Thornton. Since then a very high number of papers addressed the issue of measuring the eco-efficiency of countries especially in terms of energy efficiency and CO_2 emissions. Most studies that stress over the influence of the energy supply and consumption from an environment sustainability approach offer a cross-country perspective. This kind of evaluations helps to assess the current position of a country relative to the ones from the empirical study. The papers are reveling in the sense of discovering the problems and identifying the countries that perform better. Furthermore, aside from offering a measurement of efficiency in terms of measurable inputs and outputs, important findings concerning the influence of policies and programs of the countries evaluated as best practice DMUs can be drown from the results. Various methods were adopted in order to assess the efficiency of countries. We can recall methods that range from simple measures as the ratio between GDP and the Total Energy Consumption to more complex techniques such as non-parametric efficiency techniques. In recent years the latter techniques seem to have achieved a lot of popularity among researchers due to the limited number of assumptions the production technology requires. Most of the studies that use non-parametric techniques in order to emphasize the importance of the ecological perspective combine economic indicators with undesirable outputs of the production process. The most commonly used indicator is the greenhouse gas emissions in the environment. As the latter is an effect of the energy industry, researchers frequently try to determine the relationship between energy consumption, CO_2emissions and economic indicators to provide a more in depth picture of the sustainability degree of a countries' economy. Some studies focus on considering the different sources of energy (oil, gas, coal) as inputs of the production process. Zhou and Ang's (2008) model takes into consideration the existence of undesirable outputs and revels the eco-efficiency from an energy source mix perspective. Others put an interest in evaluating eco-efficiency from a renewable and non-renewable energy consumption perspective. Apergis et al.(2008) offer an analysis of the OECD countries energy efficiency introducing the renewable energy consumption indicator. Their results show that EU countries perform better than NAFTA, G7 and Asian Tigers. Another important aspect of eco-efficiency studies is the choice of the DMUs from the sample. Various studies take into account only data availability when considering the illustrative group. Given the relative nature of the non-parametric estimators this could lead to misleading results. Daraio C. and L. Simar(2007, Chapter 2) explain that the influence of outliers in the data set could result in an efficient frontier made out of extreme points. Throughout this study we make use of various preliminary exploratory analysis methods which help us identify and

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eliminate extreme values presented in Empirical Data Overview section. We also employ the order α efficiency estimates which are more robust, hence less sensitive to the presence of outliers in the data set (Daraio C. and L. Simar(2007, Chapter 4)).

This paper is structured as follows: firstly we make a brief introduction of the current research trends of the eco-efficiency studies from the two different perspectives (the techniques employed and the most used indicators in recent studies), then we make a short presentation of the methodology in Section 1. The preliminary analysis of the original sample is shown in Section 2, and then we discuss the results of the Efficiency models for the production process from two perspectives: full and partial frontiers. We wrap up with the Conclusions section which makes a summary of the results of our study.

Section 1: Methodology

The methodology we apply on this data set is the nonparametric efficiency estimation technique. This deterministic approach lies on the probabilistic perspective that an attainable set of inputs and outputs is described as below by using the same notations as in Cazals, Florens and Simar(2002):

$\psi \equiv \{(x,y), wherexcanproducey\} \in R_+^{N+M}$where x is the input vector and $x \in R_+^N$ and y is the output vector and $y \in R_+^M$. (1)

The production process is defined by: $(X,Y) \in R_+^N \times R_+^M$ and the efficient frontier for the input oriented model is $C(y) = \{x \in R_+^N,\ \theta x \nexists C(y)\ \forall 0 < \theta < 1\}$, when $y \in \Psi$ and $C(y) = \{x \in R_+^N | (x,y) \epsilon\ \Psi\}$.

This means that any DMUs that are efficient lie on the frontier and the inefficient observations are the ones that are below the frontier. The measure of efficiency in an input oriented model for any observation (x_0, y_0) is:

$\theta(x_0,y_0) = \inf\{\theta | \theta x_0 \in C(y_0)\} = \inf\{\theta | (\theta x_0, y_0) \in \Psi\}$. (3)

In order to estimate the Ψ for a sample of observations nonparametric methods were developed that were firstly introduces by Deprinset. al (1984). The proposed estimators came to be known as the Free Disposable Hull estimators and they are based on the assumption of free disposability of inputs and outputs.

$\hat{\psi}_{FDH} = \{(x,y) \in R_+^{N+M} \big| y < Y_i,\ x < X_i\ , i = 1, \dots, n\}$ (4)

Where Y_i and X_i represent the input and output in a space of size N and M respectively. Under the free disposability of the production setΨ the Debreu-Farrell efficiency measures have the following representation for the input orientation:

$\theta(x_0,y_0) = \inf\{\theta | H(\theta x_0, y) > 0\}$ (5)

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As nonparametric methods are known for being sensitive to extreme values or the existence of outliers in the sample data set, statistical inference methods were developed in order to give the estimates a meaning. In order to find a more robust estimator with a diminished sensitivity to the sample dissimilarities partial frontiers estimates are developed in the work of Cazals, Florens and Simar (2002). These new estimators envelop only a portion of the sample data, thus minimizing the influence of extreme values in the observations set. Until now two types of well-known partial frontiers: the order m partial frontiers proposed by Cazals, Simar and Florens (2002) and the order α partial frontiers for the univariate case (Aragon, Daouia and Thomas-Agnan, 2005). The order α partial frontier estimator is used to identify the percentage of DMUs that are situated below the curve of the parameter α. The novelty of this new FDH estimator lies in the fact that it produces much more robust estimates and it has a convergence rate comparable with parametric methods. When employing order α partial frontier estimators the value of the parameter α must be defined to determine the percentage of input output combinations that are not part of the partial frontier. The value of the α efficiency estimate gives the relative efficiency of a decision unit in comparison with the percentage of the points from the sample set. The αquantile efficiency score is given by:
$\theta_{\propto}(x_0, y_0) = \inf\{\theta \big| F_{X|Y}(\theta x_0, y) > 1-\alpha\}$, where y is defined by $S_Y(y) > 0$ and $\alpha \in (0,1]$. (6)

For an efficiency score of 1, it is said that $\theta_{\propto}(x, y) = 1$ is input efficient at the $\alpha \times 100\%$ level and it is dominated by decision units that have an output greater than y with a probability of $1-\alpha$. The alpha quantile input efficiency is given by $\theta_{\propto}(x_0, y_0) = \phi_\alpha(y_0)/x_0$. The α quantile efficiency frontier is the efficient frontier at the level $\alpha \times 100\%$.
The efficient input can be defined as below:
$x_\alpha^\partial = \theta_\alpha(x, y)x$. (7)
The probability of this unit to be dominated is given by $H_{X|Y}\big(x_\alpha^\partial(y), y\big) = (1-\alpha)S_Y(y) \leq 1-\alpha$. For an $\alpha = 1$, $\theta_{\propto}(x, y)$ converges to the $\theta(x, y|P)$, where P is the full frontier and $\alpha \to 1$ and it is monotone and$\lim\limits_{\alpha \to 1} \searrow \theta_\alpha(x, y) = \theta(x, y|P)$. This also means that any (x, y)combination that is inside the full production frontier also belongs to anα quantile input efficient frontier.
Due to the fact that the α quartile efficiency estimate is a more robust one, we employ the partial efficiency technique on our data set in order to assess the ecological efficiency of countries from a renewable and non-renewable energy consumption perspective. The value of the parameter α was set to 5% which means that only 5% of

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the dominant countries from our empirical data set will be left out of the production frontier.

Section 2: Empirical data set overview

Following our work on determining eco-efficiency estimates taking into consideration only the energy consumption as a total, results show the need to analyze the share of more eco-friendly energy sources such as renewable energy (L. Beșir and A.Aldea 2018). The current paper seeks to estimate the eco-efficiency measures at country level from a renewable and non-renewable energy perspective taking into account data for the year 2011. Therefore, we introduce two new variables Renewable energy consumption per capita and Non-Renewable energy consumption per capita determined based on the Renewable energy share in the total energy consumption index from the World Bank and the Total Primary Energy Consumption from the International Energy Agency database. The other variables included in the model were previously used in L. Beșir and A. Aldea (2018).

Table 1. Inputs and Outputs description

Variable code	Input/Output	Variable description
RENEW_ECAP	Input	Renewable energy consumption per capita
NON_RENEW_ECAP	Input	Non-Renewable energy consumption per capita
CO2CAP	Input	Carbon Dioxide emissions per capita
GDPCAP	Output	GDP per capita (USD)

Summary statistics on the current data set are provided in Appendix 1. Comparison between the sample mean and the range of the variables for GDPCAP, RENEW_ECAP and NON_RENEW_ECAP show the need to separate the initial data set into groups in order to obtain more homogenous sets of data (Figure 2). This hypothesis is also sustained by the box plots generated in Appendix 3 which show the presence of outliers. Figure 1 from below shows the proportion of outliers for each variable. The lowest number of outliers were detected for GDPCAP(4.6%) and the highest proportion of outliers were found for CO2CAP (13.8%).

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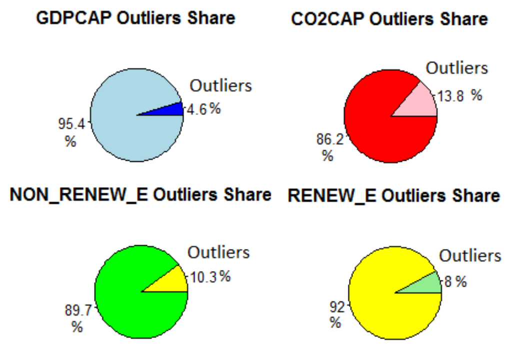

Figure 1.The Share of Outliers from the Total Sample of DMUs

As we plan to use nonparametric methods to estimate efficiency, the division of the initial data set into smaller groups with more similar DMUs, is the step to make as high discrepancy between observations can have impact on the efficiency frontier. We plotted the input variables against the GDP per capita in order to see whether we can determine the number of clusters we need to create in order to obtain more homogenous data sets (Figure 2). The relationship between the CO_2emissions per capita and the GDP per capita shows that the majority of the data from the sample is located in the left lower corner of the graphic. The high concentration on the lower left corner shows that CO_2emissions are highly correlated with GDP for small economies. This group could be named the small size economies group.Apart from this concentration, the other observations are spread on the graph. Following a visual analysis of Figure 2 we can divide the countries into 3 categories: highly polluted countries with high values for the CO_2emissions (lower part of the graph), large economies (left mid side of the graph) with high values for GDP per capita, but medium to low values for the CO_2emissions and large economies with high values for both indicators. The same spread and concentration can be also found for the graphical representation of the relationship between the non-renewable energy consumption per capita and GDP per capita. As far as for the dependency between the renewable energy consumption per capita and the GDP per capita, we can see that no matter the size of the economy, the observations are concentrated in the left side of the graph. Two DMUs located in the central and right side of the graph can be identified, Iceland and Norway which have higher values for renewable energy consumption.

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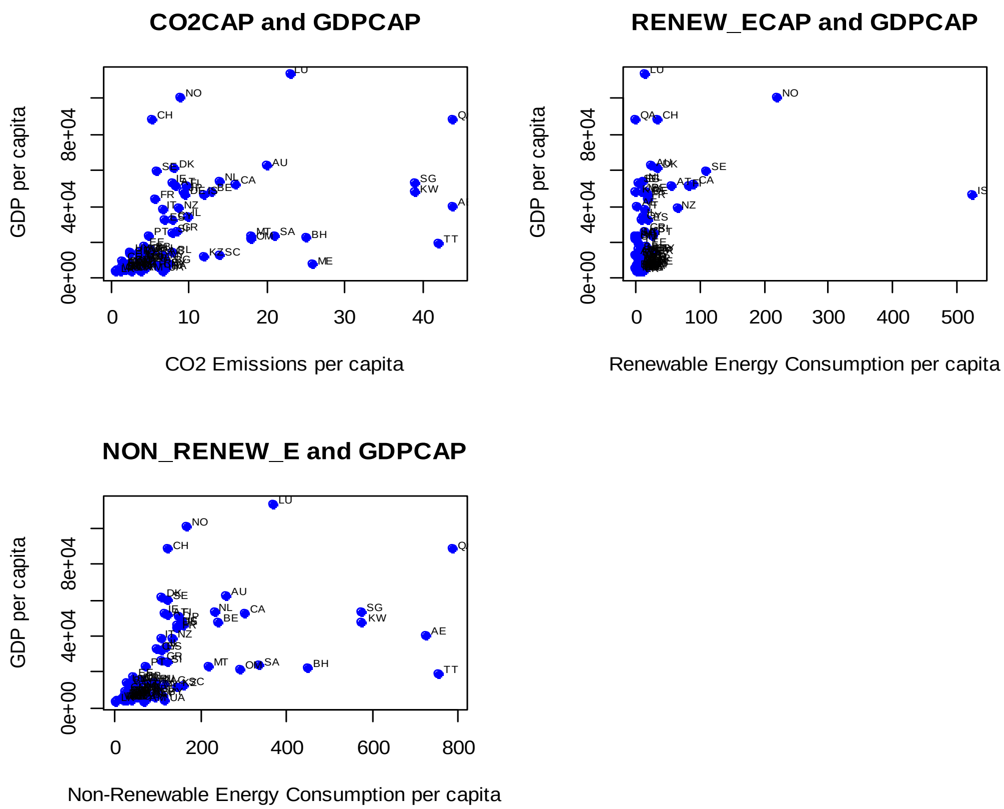

Figure 2. Preliminary Analysis of the Input-Output relationship

Although this could indicate the fact that Norway and Iceland are potential outliers, we will not eliminate them from the sample before further exploratory analysis is done. Other observations interesting to analyze are Switzerland, Qatar, Luxembourg which are located in the left high side of the graph, which denotes the fact that these large industrialized economies have low levels of renewable energy consumption. If we take into account only the case of Qatar, this could be due to the fact that this country is rich in natural gas resources. For Switzerland it is important to account the fact that most of the energy used is imported, but it is based on fossil fuels and nuclear power which are environmentally detrimental. By considering the data from the above, we

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could say that Luxembourg is the least green large economy in comparison with Switzerland and Qatar. Previous to efficiency estimation, data analysis methods are used in order to obtain a more homogeneous data set. Firstly, initial variables were divided to their standard deviation and we computed the correlation matrix between the inputs and the output.

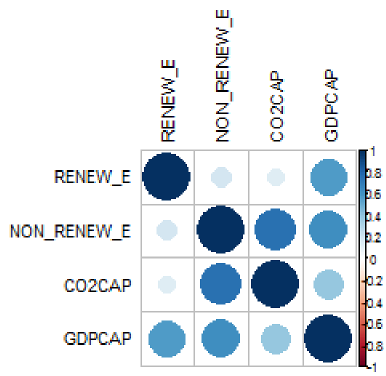

Figure 3. Correlations between Inputs and Outputs

As expected, high direct correlation is recorded between the non-renewable energy consumption and the CO_2 emissions (86%). Medium correlation can also be observed between GDP per capita and the non-renewable energy consumption and CO_2 emissions. This could be the first indicator of the fact that the current economic results of the countries taken into account in the sample is done at the expense of the environment. We also employ principal component analysis in order to reduce the space. This exploratory analysis will also be a good preliminary method to identify the number of clusters. Therefore we will obtain homogeneous sets of data that will lead to obtaining more robust efficiency estimates given the fact that the DMUs in the sets will be more similar to one another. The principal component analysis shows that 87% of the information is preserved by keeping the first two principal components. The space was reduced significantly with minor loss of information (13%). Below Figure 4 shows the two resulting clusters against the two principal components. The scatter plot depicts two groups: one concentrated in the left side of the graph and the other one spread on the right, around the first cluster.

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Figure 4. K-means Clusters

In order to obtain data sets with observations more similar to one another, we use the k-means clustering method on the standardized data set. As depicted by the preliminary analysis from above, two groups were formed, one with 12 countries and one with 75 countries. The smaller size group is formed of large economies with high non-renewable energy consumption and the outliers discussed in the previous section. Such examples are Iceland, Norway and Luxembourg that were placed in this group because of the high GDP per capita values, but differ in terms of renewable energy consumption. A simple comparison between the descriptive statistics indicators for the initial set against the two groups obtained after clustering shows proof of more homogenous data sets (Appendix 2). We could also see that the number of outliers for RENEW_E decreased from 7 to 4 (Appendix 4). If we take into account the GDP per capita, for example, we can see that the range decreased by 14% in comparison with the range of the homogenous cluster. Results also show that the standard deviation of renewable energy consumption per capita decreased by 29% for the second cluster in comparison with the initial data set. The preliminary analysis revealed that the initial data set consisting in 87 DMUs could be split into two groups. As the results of the clustering analysis shows that the group consisting in 75 DMUs was a more homogenous one, further on we will focus on this particular group. Eliminating the

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second group from the analysis relies also on the fact that the convergence rate for this group is very low, therefore we must focus on the consistent one. From now on results and interpretations will reflect only the analysis preformed on the homogenous group. As presented in the data description section of the paper, we will use three inputs and one output. Although the CO_2 emissions are considered to be an undesirable output in the production process, in order to minimize it, we will treat it as an input. The same method of treating undesirable outputs was also used in Reinhardt S. et al (2000). Also the choice of input variables is sustained by previous studies (Apergis et al., 2015).

Section 3: Efficiency models for the production process

Due to the fact that the work sample is composed out of 75 countries from the initial data set of 87 and the fact that we have multiple inputs in the model, the data may lie under the "curse of dimensionality". In order to reduce the space and avoid this problem, we use Mouchart and Simar(2002) dimensionality reduction method. The procedure is based on the aggregation of the input variables in this specific case. The basic principle was introduced by Mouchart and Simar (2002) and consists in finding an aggregate input / output that is a linear combination of the others inputs and thus to express as much as possible the information contained in all the other inputs. Since this factor represents a "proxy" for all other inputs, it should be positively correlated with all other inputs / outputs aggregated to be a linear combination of the other inputs and thus to express as much as possible the information contained in all other inputs. After exploring the data, we use the statistical input / output aggregation methodology used by Daraio and Simar (2007) in order to obtain a single aggregate input / output. We calculate the aggregated factor by using the eigenvector that corresponds to the highest eigenvalue (0.79;0.16;0.72). This is a linear combination of all inputs / outputs in the model.

$$F = \sum_{i=1}^{n} w_i \times F' \quad (12)$$

$F'$is the standardized input matrix obtained by dividing the initial variables by their standard deviation. The weights w_i are obtained by computing the eigenvector for the highest eigenvalue of the Input matrix.

Estimating the eco-efficiency of countries from a renewable and non-renewable energy consumption perspective

As we want to assess the ecological and energy efficiency of countries, the input orientation is intuitive to apply in the context of minimizing the negative effect on the environment. Firstly, we build the FDH efficiency frontier and then the order α partial frontier for, α=0.95 for the input orientation using the FEAR package with the R

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software created by Wilson P. (2008). Our purpose is to assess the efficiency of countries in relation with the renewable and non-renewable energy consumption. Thus, we aim to find which are the characteristics of efficient countries in terms of economic development and renewable energy consumption.

Efficiency estimates (Full and Order α partial frontier) – Input Orientation

Firstly we construct the full and partial order α frontier by choosing the input orientation. The reasoning behind the input reduction option is to reveal those DMUs that are most efficient in protecting their environment. If we look at the results of the FDH input oriented model, 11 of the DMUs are found efficient, from these 11, only 3 (Switzerland, Portugal and Italy) of them are shown as efficient at the 95% level. This also implies that only the former three countries are found to be dominated by firms producing more output (GDP per capita) with a probability of 5%.

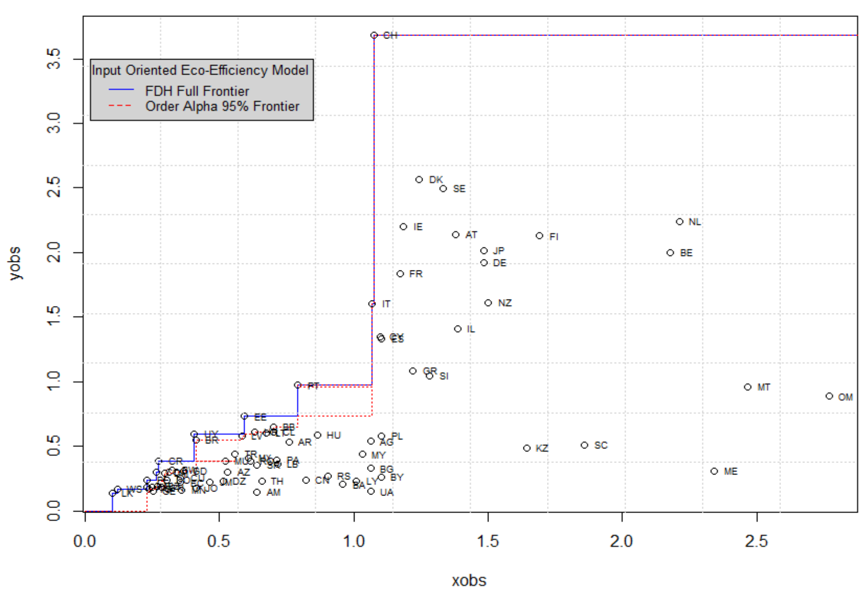

Figure 5. Full and partial frontiers for the Input Oriented Model

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By looking at the values for GDP per capita for the efficient countries in the full frontier model we could identify these countries have a consumption of non-renewable energy close to the average of the 75 countries. 27% out of the efficient DMUs are large economies, which can lead to the conclusion that eco-efficiency can also be achieved in less developed economic environments (Estonia, Uruguay and Costa Rica). As expected, we found that the share in the non-renewable energy consumption was higher than the share of renewable energy consumption. However, if we make a comparison with the average renewable energy consumption of the sample, we found that only Switzerland and Portugal had a share of renewable energy consumption two times higher (in the case of Switzerland) and almost 180% higher (for Portugal) than the average renewable energy consumption. Given this evidence one could argue that in definite only these are the countries that are eco-efficient for α=0.95 level. In the case of Switzerland we could also see that the non-renewable energy consumption is 50% higher than the average of the sample for this indicator. This shows Switzerland tries to compensate for the non-renewable energy consumption, by using a large share of more eco-friendly energy sources.

Also, we choose to compare DMUs that are regarded as “super-efficient” by the partial frontier approach and compare the partial estimate with the full FDH estimate. We use the “super-efficient” term as described by Daraio C. and L. Simar, (2007, Charper 4) in the context of order α quantile frontier. In this case we chose 25% as a threshold for the maximum possible increase in input a country can perform and still reach the 95% partial efficiency frontier.

We found that ~19% of the countries can be regarded as super-efficient and show a possible 25% increase in input in order to reach the 95% frontier. Summary statistics for these DMUs are presented in Appendix 6. We can split the 14 countries into two groups: large economies (Sweden, France, Denmark, Spain and Ireland) and small and medium to small size economies (Slovenia, Greece, Cyprus, Lithuania, Ecuador, Cuba, Georgia, Dominican Republic and Tunisia).

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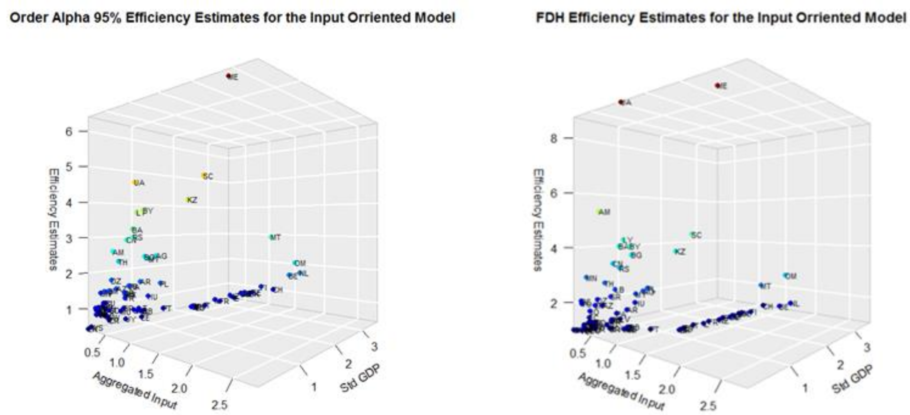

Figure 6. 3D representation of the Efficiency Estimates

All the super-efficient large economies have a renewable energy consumption share over the average of the sample. We could see that the large economies from this group have renewable energy consumption 211% higher than the average of the data set. This could lead to the conclusion that developed countries are more preoccupied in finding more eco-friendly ways to satisfy their energy consumption. On the other hand if we look at the partial efficiency estimates for countries that need to reduce their input in order to reach the 95% input efficient frontier, we can see that only small size economies are part of this category(Uruguay, Costa Rica, Peru, Columbia, Albania are some of them).

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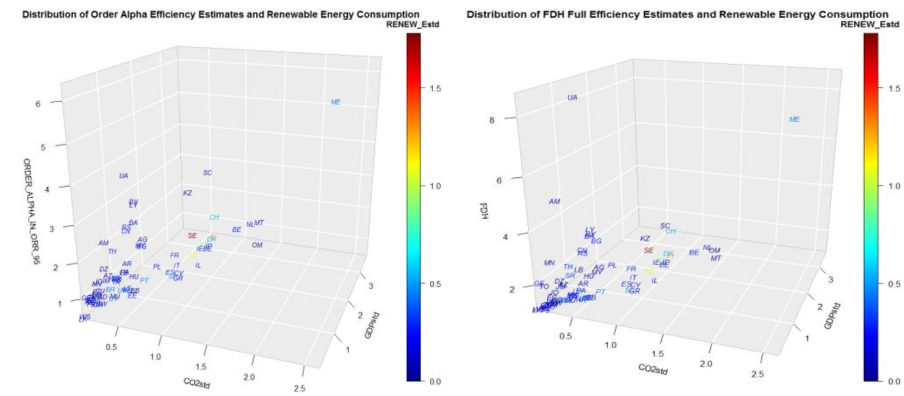

Figure 7. Distribution of Efficiency Estimates and Renewable Energy Consumption

As the purpose of the paper is take closer look on the renewable energy consumption and the overall eco-efficiency of the countries, Figure 7 shows the distribution of efficiency estimates and the $CO_2$and renewable energy consumption. The full frontier model shows that least inefficient DMUs have CO_2emissionslower than the average (Sweden, France, Slovenia, Denmark, Spain, Ireland, Italy and Austria).Out of these countries only large economies (Finland, New Zealand, Sweden and Austria) have renewable energy consumption over the average level of the sample. This might lead to the conclusion that these countries are more preoccupied with balancing environmental goals with economic progress aspirations. Given the fact that the CO_2 emissions can represent a "proxy" for a healthy environment, we could say that these are in fact the greenest countries. Other interesting DMUs are Sweden, Finland and New Zealand. Although these were not found efficient in the full frontier or the partial frontier model, we found that the partial estimates which are more robust show that Finland could increase its inputs by 57% to reach the full frontier and New Zealand needs an input increase of 40% to reach the full frontier. The latter countries have the highest renewable energy consumption from our 75 countries sample.

Conclusions

This study shows that nonparametric techniques applied to eco-efficiency problems reveal interesting facts regarding the constant strive of the economies of the world to balance environment preservation hand in hand with economic development. Although the initial set was made out of 82 countries, the preliminary analysis showed the need

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to keep only the cluster with homogenous DMUs(75 countries).We built the input oriented model and employ full and partial order α frontiers in order to get insight with regards of the eco-efficiency of countries. Switzerland, Portugal and Italy were found efficient in both full and partial models. From these 3 countries we could argue that Switzerland and Italy are indeed the greenest ones because they gave renewable energy consumption levels almost double than the sample average. It was interesting to see that from these two counties Switzerland has non-renewable energy consumption over the average, but at the same time the eco-friendly energy sources are two times over the average. We could also see that 73% of the efficient counties from the full frontier model had a GDP per capita lower than the average which supports the idea that eco-efficiency can be achieved in less developed economies. From a partial frontier perspective we could see that we could divide the countries that can increase their output in order to reach the 100% frontier into two different groups: large economies and small and medium to small size economies. From the two groups we could see that the large economies employ in average a higher amount of energy consumption from eco-friendly resources than the small and medium size economies. This could lead to the conclusion that economic development can arise from more eco friendly sources as well. A brother perspective on the countries effort to preserve the environment could be achieved by introducing in the analysis variables such as the government expenditure on promoting eco-friendly energy sources which can be split into grants and research and development funds. Further analysis could also try to assess the trade-off between economic development and environment preservation by employing hyperbolic measures.

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Appendix

Appendix 1. Summary statistics for the initial data set

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
CO2CAP	8.88	5.70	9.82	0.70	44.00
GDPCAP	23,092.12	12,817.84	23,869.58	3,221.15	113,239.56
RENEW_E	23.10	9.96	61.76	0.00	526.18
NON_RENEW_E	133.13	79.09	162.07	5.30	790.00

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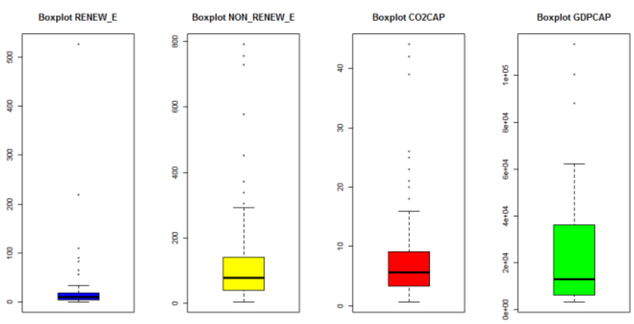
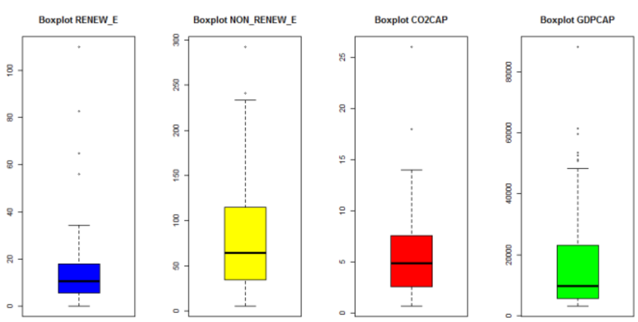
Appendix 2. Summary statistics for the homogenous data set

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
CO2CAP	5.85	4.90	4.41	0.70	26.00
GDPCAP	17,893.17	9,730.28	17,982.37	3,221.15	88,002.61
RENEW_E	15.07	10.59	17.90	0.00	109.86
NON_RENEW_E	81.35	63.93	57.59	5.30	292.00

Appendix 3. Boxplots for the initial data set



Appendix 4. Boxplots for the homogenous data set



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Appendix 5. Summary statistics of the outliers of the initial set

Variable	Mean	Median	Standard Deviation	Minimum	Maximum	% of Outliers from the Total Sample
CO2CAP	21.705	19	13.3002	5.3	44	8.54
GDPCAP	50320.1	49169.47	28838.74	7319.149	113239.6	10.98
RENEW_E	62.89327	19.20325	121.9694	0	526.1824	14.63
NON_RENEW_E	334.5567	275.515	234.423	35.2222	790	4.88

Appendix 6. Summary statistics of the "super-efficient" DMUs

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
CO2CAP	5.186667	5.7	2.643014	1.3	8.6
GDPCAP	25751.69	24983.69	20600.7	3725.063	61304.06
RENEW_E	21.02532	13.5298	26.1846	4.1323	109.858
NON_RENEW_E	80.70801	99.0606	43.99932	26.0148	148.0056

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