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EFICIENCIA MEDIOAMBIENTAL Y DISPONIBILIDAD O DISPOSICIÓN TECNOLÓGICA. UNA EVIDENCIA DE LA UE.

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RESUMEN

En la actualidad, el concepto de desarrollo sostenible es un pilar fundamental y un importante reto para el crecimiento y el progreso en los países desarrollados. Este concepto puede definirse como el tipo de desarrollo que cubre las necesidades del presente sin comprometer las necesidades de las generaciones futuras. Por otra parte, para el World Business Council for Sustainable Development (WBCSD), la eficiencia medioambiental vendría determinada por un conjunto de actividades que satisfacen las necesidades humanas y que otorgan calidad de vida al mismo tiempo que consiguen minimizar el impacto medioambiental progresivamente. Por tanto, con estas dos definiciones, está claro que la eficiencia medioambiental es una variable clave para el desarrollo sostenible, pero ¿hay alguna variable que esté influyendo directamente en este tipo de eficiencia? Con este trabajo se ha descubierto que la disponibilidad o disposición tecnológica se trata de un factor influyente en la eficiencia medioambiental. Para la UE, la eficiencia medioambiental está relacionada con la disposición tecnológica de manera que la disponibilidad tecnológica explica parte de la eficiencia medioambiental pero no se trata de un factor determinante. En otras palabras, un alto índice de disposición tecnológica implica un score de eficiencia alto, pero no viceversa. Se usará la metodología Data Envelopment Analysis (DEA) para obtener los scores de eficiencia, y para el índice de disponibilidad tecnológica se usará el desarrollado por The World Economic Forum. Una vez los datos sobre eficiencia medioambiental hayan sido obtenidos, se aplica un modelo de regresión para profundizar en el estudio esta relación, eficiencia medioambiental y disponibilidad o disposición tecnológica.

Palabras clave: desarrollo sostenible, eficiencia medioambiental, disponibilidad o disposición tecnológica, UE.

ENVIRONMENTAL EFFICIENCY AND TECHNOLOGICAL READINESS. AN EVIDENCE FROM EU-28.

ABSTRACT

Nowadays, the concept of sustainable development is a fundamental pillar and an important challenge for growth and progress for developed countries. For the World Business Council for Sustainable Development (WBCSD), the environmental efficiency can be determined as the set of activities that satisfies the human requirements and that provides quality of life at the same time the environmental impacts are minimized progressively. It is clear that the environmental efficiency is a key variable for the sustainable development, but there is any variable influencing directly this efficiency? In this work it has been found that the technological readiness is an important factor influencing the environmental efficiency. For EU, the environmental efficiency is related to technology so that the technological readiness explains part of environmental efficiency but it is not a determinant factor. This means, a high technological readiness index implies a high efficiency scores but not viceversa. It will be used the Data Envelopment Analysis methodology to obtain the efficiency scores, and the technological readiness index developed by The World Economic Forum. Once the data are obtained, a regression model is applied to further study the relation between both.

Key Words: sustainable development, environmental efficiency, technological readiness, EU.

Clasificación JEL: E5

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1. INTRODUCTION

The 2020 European strategy emphasizes smart, sustainable and inclusive growth as a way to overcome the structural weaknesses in Europe's economy, improve its competitiveness and productivity and underpin a sustainable social market economy. The principal goals of this strategy are to increment the efficiency of energy use, decrease the CO2 emissions and increase the use of renewable energy.

According to the report Agora Energiewende and Sandbag (2018) published by Agora Energiewende and Sandbag, in 2017 wind, solar and biomass energy generated a total of 679 terawatts per hour exceeding for the first time in the history of the European Union the 669 terawatt-hours generated by coal. However, greenhouse gas emissions have remained unchanged, due to the increase in demand and the fall of hydroelectric and nuclear power plants. The authors of the report consider that this fact "raises doubts about the progress in energy efficiency".

Fearing an economic slowdown, the most of the countries are still reticent to diminish CO2 emissions. Several countries are in a discussion phase-out (Germany, Denmark, Malta, Ireland, Croatia, Slovak Republic) but others have not even open discussion (Greece, Spain, Slovenia, Hungary, Poland, Bulgaria, Czech Republic). In this scenario is important to know the factors that influence the CO2 emissions but also to improve the efficiency of the resources utilization.

From a methodological perspective, the efficiency measurement has attracted increasing interest to provide relevant information to design appropriate policies in different nations. The aggregated measurement of environmental performance, which is often in the form of Environmental Performance Index (EPI), is an important upstream issue for decision making in energy and environmental (E&E) systems Zhou et al. (2006). From the point of view of operations research, the existing techniques for constructing aggregated EPIs can be divided into two big categories, namely the indirect and the direct approach Zhou et al. (2008b). The first one, identifies the principal factors susceptible to take in account in the study and then they are normalized and integrated into an overall index by some weighting and aggregating techniques (see the environmental sustainability index). In the second group, where the theory of productive efficiency plays an important role, an aggregated EPI is directly obtained from the observed quantities of the inputs and outputs using a non-parametric approach called Data Envelopment Analysis (DEA).

This methodology, proposed by Charnes et al. (1978) is a well-established non-parametric frontier approach for evaluating the relative efficiency of a set of comparable entities (called Decision Making Units or DMUs) featured with multiple factors grouped into two groups: inputs and outputs. Classical DEA models rely on the assumption that inputs have to be minimized and outputs have to be maximized, Vencheh et al. (2005). Thus, in the standard DEA model, decreases in outputs are not allowed and only inputs are allowed to decrease (similarly, increases in inputs are not allowed and only outputs are allowed to increase), Seiford and Zhu (2002), but the production process could generate also undesirable outputs (pollutants) and it also could be inputs susceptible to be maximizing (i.e. the recycling process).

There are several approaches for incorporating undesirable outputs in DEA model. These models can also be classified into two groups: the ones that take an indirect perspective and the ones that take a direct approach. As Scheel (2001) said, indirect approaches transform the values of the undesirable outputs by a monotone decreasing function such that the transformed data can be included as desirable outputs in the technology set; and direct approaches use the original output data bu modify the assumptions about the structure of the technology set in order to treat the undesirable outputs appropriately. Some indirect approaches are the additive inverse [ADD], suggested by Koopmans (1951), or the translation invariance [TRβ], suggested by Ali and Seiford (1990) or the multiplicative inverse [MLT], suggested by Golany and Roll (1989). The first of these three methods incorporates the undesirable outputs U as desirable outputs with values $f(U) = -U$; the second transform the output set values as $fki(U) = -uki + \beta i$, where i represents the output i, k denotes the DMU under evaluation and β is a scalar. Finally, the [MLT] approach the undesirable outputs are transformed by $fki(U) = 1/uki$. As Scheel (2001) remarks, the indirect approaches assume that the transformed data have their own meaning, for example if we transform the undesirable output mortality rate, then we can study the desirable output survival rate. In contrast, the direct approach uses the original output set, but it changes the assumptions taken. The direct approach suggested by Färe et al. (1989) replaces strong disposability of outputs by the assumption that outputs are weakly disposable while only the subvector of desirable outputs is strongly disposable. The direct approach is recommended as it uses the original data and is not necessary to reinterpret the results obtained in terms of “new” variables (e.g. mortality rate and survival rate).

In the pioneering work of Chung et al. (1997), the effect of undesirable output on environmental efficiency was evaluated using the directional distance function (DDF). “The directional distance function is applied on the basis of quantitative data without requiring any input/output price data and it does not need to impose any assumptions of functional form on production function”. However, Chiu et al. (2012) highlighted that DDF methodology does not consider the possible technology heterogeneity among different groups assuming that the DMUs of different group are equipped with similar levels of technology. For this reason, before the application of this methodology is required to wonder if this condition is verified. Oh (2010) concluded that European countries are good at innovating and take the lead in the world frontier technology. This conclusion may be supported by the fact that the technological readiness metric of the European Union (UE-28) for the year 2014 varies from 4.37 to 6.36 (measured on a 1 to 7 scale) being all countries above the world average at 3.96. This indicator captures the availability of latest technologies, firm-level technology absorption, foreign direct investment (FDI) and tech transfer, individuals using the Internet, fixed broadband Internet subscriptions, international Internet bandwidth, and mobile broadband subscriptions, (World Economic Forum, 2014).

Based on this information, the goal of this paper is to calculate the environmental efficient scores of different European countries in 2014 considering that they present similar technological levels. In addition, some interesting conclusions are obtained from the analysis of the efficiency of each country as a function of the technological readiness metric. The structure of the work is as follows: Section 2 reviews the related scientific literature, Section 3 presents in detail the applied methodology, Section 4 obtains the efficiency for the different countries and relates it with the technological readiness metric. Finally, Section 5 presents the main contributions of this paper.

2. LITERATURE REVIEW

Zhou et al. (2008a) reviewed a large set of studies using DEA in the broad area of energy and environmental analysis. Only three out of the hundred works reviewed by these authors analysed a set of European countries: with a radial efficiency measure and focused on electricity distribution utilities Edvardsen and Førsund (2003) presented a theoretical and applied work for five European countries while Jamasb and Pollitt (2003) presented an applied work related to six European countries. On the other hand, Korhonen and Luptacik (2004) presented a general study for Europe based in a constant returns to scale radial methodology focused on environmental performance measurement. None of the papers reviewed by Zhou et al. (2008a) applied the directional distance function (DDF) to European countries.

Zhang and Choi (2014) reviewed 70 papers with application of the DDF methodology in energy and environmental studies but only two works are focused on Europe. Mahlberg et al. (2011) analysed country-level data of 2011 addressing the eco-productivity growth while Krautzberger and Wetzel (2012) analysed the transportation industry for 2012 addressing the environmentally sensitive productivity growth. Both works applied a radial methodology with output orientation.

On the other hand, Chiu et al. (2012) combined the DDF and a meta-frontier analysis to measure the environmental efficiency in 90 countries worldwide for the 2003-2007 period. He concluded that the average environmental efficiency of high competitiveness countries is greater than that of lower-middle, low and upper-middle competitiveness countries. However, he also concluded that due to the excessive labour force and carbon dioxide emissions the upper-middle competitiveness countries perform worse that the lower middle an low competitiveness countries.

3. METHODOLOGY

As we have previously said, DEA evaluates the relative efficiency of a set of DMUs. Mathematically, we can express the efficiency as:

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs}$$

Suppose the set of DMUs consists of DMUk, $k = 1, 2, \ldots, K$; $x_{nk} = (x_{1k}, x_{2k}, \ldots, x_{Nk})$, and $y_{mk} = (y_{1k}, y_{2k}, \ldots, y_{Mk})$ are the vectors of inputs and outputs, respectively. The efficiency of DMU1 can be obtained by solving the following problem:

$$\max E_1$$
$$s.t.$$
$$\frac{\sum_{m=1}^{M} \beta_{mk} y_{mk}}{\sum_{n=1}^{N} \alpha_{nk} x_{nk}} \leq 1$$
$$n = 1, \ldots, N$$
$$m = 1, \ldots, M$$
$$\alpha_{nk}, \beta_{mk} \geq 0\ , k = 1, 2, \ldots, K$$

If we transform this problem into a linear one:

$$\max \sum_{m=1}^{M} \beta_{m1} y_{m1}$$
$$s.t.$$
$$\sum_{n=1}^{N} \alpha_{n1} x_{n1} = 1$$
$$\sum_{m=1}^{M} \beta_{mk} y_{mk} - \sum_{n=1}^{N} \alpha_{nk} x_{nk} \leq 0$$
$$n = 1, \ldots, N$$
$$m = 1, \ldots, M$$
$$\alpha_{nk}, \beta_{mk} \geq 0\ , k = 1, 2, \ldots, K$$

where α_{nk} and β_{mk} are the weighted vectors.

In the practice, the calculation of the efficiency scores is simpler by using the dual problem that can be specified from an input-oriented or an output-oriented perspective:

INPUT ORIENTED:

$$\min \theta_1$$
$$s.t.$$
$$\sum_{k=1}^{K} z_k x_{nk} \leq \theta_1 x_{n1}$$
$$\sum_{k=1}^{K} z_k y_{mk} \geq y_{m1}$$
$$n = 1, \dots, N$$
$$m = 1, \dots, M$$
$$z_k \geq 0 \,, k = 1, 2, \dots, K$$

OUTPUT ORIENTED:

$$\max \theta_1$$
$$s.t.$$
$$\sum_{k=1}^{K} z_k x_{nk} \leq x_{n1}$$
$$\sum_{k=1}^{K} z_k y_{mk} \geq \theta_1 y_{m1}$$
$$n = 1, \dots, N$$
$$m = 1, \dots, M$$
$$z_k \geq 0 \,, k = 1, 2, \dots, K$$

Let suppose two different types of outputs: desirable (y_{mk}) and undesirable outputs $u_{jk} = (u_{1k}, u_{2k}, \dots, u_{Jk})$. Then, the direct approach introduces the undesirable outputs using the original output set, but changing the initial assumptions. It replaces strong disposability of outputs by the assumption that outputs are weakly disposable while only the subvector of desirable outputs is strongly disposable. That is:

Outputs are weakly disposable, i.e. $if\ (x, y, u) \in T$and $0 \leq \theta \leq 1$, then $(x, \theta y, \theta u) \in T$. It means that the proportional reduction in desirable and undesirable outputs is possible.

Desirable outputs and undesirable outputs are null-joint, i.e. $(x, y, u) \in T$ and $u = 0$ imply that $y = 0$. It means that the only way to eliminate all undesirable outputs is to end production process.

With this, the production technology for DMUk, following Färe et al. (1989), can be characterized as:

$$T = \{(x, y, u):$$
$$\sum_{k=1}^{K} z_k x_{nk} \leq x_n \,;\ n = 1, \dots, N$$
$$\sum_{k=1}^{K} z_k y_{mk} \geq y_m \,;\ m = 1, \dots, M$$
$$\sum_{k=1}^{K} z_k u_{jk} = u_j \,;\ j = 1, \dots, J$$
$$z_k \geq 0 \,, k = 1, 2, \dots, K\}$$

As Färe and Grosskopf (2004) said, since T is formulated in the DEA framework, it could be termed as the environmental DEA technology. And then, if DMU1 wants to diminish as much as it were possible its undesirable outputs (relatively), the linear problem to solve is the following:

$$\min \theta_1$$
$$s.t.$$

$$\sum_{k=1}^{K} z_k x_{nk} \leq x_{n1} \; ; \; n = 1, \dots, N$$
$$\sum_{k=1}^{K} z_k y_{mk} \geq y_{m1} \; ; \; m = 1, \dots, M$$
$$\sum_{k=1}^{K} z_k u_{jk} = \theta_1 \, u_{j1} \; ; \; j = 1, \dots, J$$
$$z_k \geq 0 \, , k = 1, 2, \dots, K \tag{1}$$

This problem pursues a new perspective: undesirable output orientation (Tyteca (1996, 1997)). The inequalities for inputs and desirable outputs in (1) makes them freely disposable; undesirable outputs are modelled with equalities which makes them not freely disposable; the non-negativity constraints on z_k allow the model to exhibit Constant Returns to Scale (CRS) (Chung et al. (1997)). Once the problem (1) was solved, values of θ_k (environmental efficiency scores for each DMU) would have been obtained, and if $\theta_k = 1$, DMUk will be (relatively) efficient; if $\theta_k < 1$, DMUk may improve its practices to be more environmentally efficient.

At this point, it is important to say that for a country is not only important to be environmentally friendly but also to be productively efficient, so the different efficiency scores would be better to ensure not only the reduction of undesirable outputs like pollution but also the increase the desirable outputs like GDP. Chiu et al. (2012) said the following: "Conceptually, environmental efficiency measurement is based on the fundamental concept of the environmental efficiency index constructed from the distance function […]".

Following Chung et al. (1997), the efficiency scores in this paper will be determined by model (2).

$$\max \theta_1$$
$$s.t.$$
$$\sum_{k=1}^{K} z_k x_{nk} \leq (1 - \theta_1) \, x_{n1} \; ; \; n = 1, \dots, N$$
$$\sum_{k=1}^{K} z_k y_{mk} \geq (1 + \theta_1) \, y_{m1} \; ; \; m = 1, \dots, M$$
$$\sum_{k=1}^{K} z_k u_{jk} = (1 - \theta_1) \; u_{j1} \; ; \; j = 1, \dots, J$$
$$z_k \geq 0 \, , k = 1, 2, \dots, \tag{2}$$

If the value of θ_k is 1, the DMU under examination (the country under examination) will be efficient (environmentally and productively). If it is less than 1, the country may improve its practices. In this case, θ_k represents the efficiency score, while $(1 - \theta_k)$ will represent the inefficiency score. The DMU under examination will be relative efficient if the efficiency score has the value 1 and the inefficiency score has the value 0.

To obtain the concerning results, we are going to use R-project, specifically the package "non-paraeff" (non-parametric methods for measuring efficiency and productivity). In this library, there is implemented the function "direc.dea", that solve the DDF with undesirable outputs under the CRS assumption. The result is a vector of which is inefficiency score $(1 - \theta_k)$.

4. DATA AND EFFICIENCY RESULTS

The data set covers the 28 countries of the European Union in 2014 for the following variables (data set from World Bank official website: https://data.worldbank.org):

- Desirable output (YG): GDP (US$ - current prices)

- Undesirable output (YB): CO2 emissions (kt).
- Inputs (Xn): population, energy use (kg of oil equivalent per capita), Foreign Direct Investment, FDI (net; current US$) and value added of manufacturing (current US$).

Table 1 shows a descriptive analysis of the data set.

Table 1

The data. Source: Own elaboration from the dataset.

Statistic	Desirable output	Undesirable output	Inputs			
	GDP (Y_G)	CO_2 emissions (Y_B)	Population (X_1)	Energy use (X_2)	FDI (X_3)	Manufacturing (X_4)
Min.	1.119e+10	2347	427364	1592	-1.910e+11	9.528e+08
1st Qu.	5.699e+10	18850	3911884	2280	-3.620e+09	8.185e+09
Median	2.330e+11	44237	9118842	2771	-7.849e+08	4.057e+10
Mean	6.640e+11	115780	18148473	3188	-1.878e+09	9.268e+10
3rd Qu.	5.522e+11	114182	17626001	3813	3.995e+09	8.544e+10
Max.	3.880e+12	719883	80982500	6861	9.660e+10	8.020e+11

The minimum values for both desirable and undesirable outputs are from Malta, while the maximum values correspond to Germany in the case of desirable output and United Kingdom if we pay attention to undesirable output. United Kingdom has also the minimum value for FDI, and Malta is the smallest country in terms of population (France is the largest). Manufacturing industry has its most importance in Italy, while in Cyprus its value added is the minimum. Finally, the use of energy in Luxembourg is the most intense (as the FDI), and in Romania we have the minimum value for this variable, energy use.

Once the variables are presented, the methodology is applied to obtain the different values of θk. Table 2 shows these values for the 28 European countries. Note that the efficient countries are those which inefficiency scores values are 0 and efficiency scores are 1: Germany, Cyprus, Denmark, France, Greece, Luxembourg, Malta, Netherlands, United Kingdom and Sweden. It is important to highlight that values for relative efficiency high or even equal to 1 do not mean that respective countries are efficient, but they are the most efficient regarding the rest of DMUs analysed, Guccio et al. (2012); Cavalieri et al. (2017).

The second group with efficiency scores between 0.8 and 1 includes the following countries: Finland (0.933), Italy (0.927), Ireland (0.887), Austria (0.861) and Belgium (0.824). Countries with efficiency scores between 0.5 and 0.8 are included in the third group: Spain (0.787), Portugal (0.761) Latvia (0.761), Croatia (0.628), Lithuania (0.531) and Slovenia (0.503). Finally, the last group with efficiency score values are lesser than 0.5 represents the most inefficient countries: Hungary (0.464), Slovak Republic (0.452), Romania (0.442), Poland (0.358), Bulgaria (0.348), Estonia (0.327), Czech Republic (0.301). Any country has a efficiency score value of 0 (inefficiency score value of 1), so there are any totally inefficient country.

In Figure 1 the efficiency score is represented joint to the technological readiness metric from the global competitiveness indicator published by the World Economic Forum (2014). Note that all the countries with a technological readiness index higher than 5.5 present an efficiency index higher than 0.8. However, it is possible to find countries with efficiency index up to 0.8 with readiness index varying from 4.56 (Cyprus) to 6.36 (Luxembourg). This indicates that a high technological readiness index implies a high efficiency scores but not viceversa. This implies that a country can present high efficiency with a low level of technology. Indeed, the technology readiness index only explains the 42,4% of the efficiency using the following estimated regression $Efficiency = -0.687 + 0.271\, Technological\ readiness$ implying that other variables may explain this significative differences.

Table 2

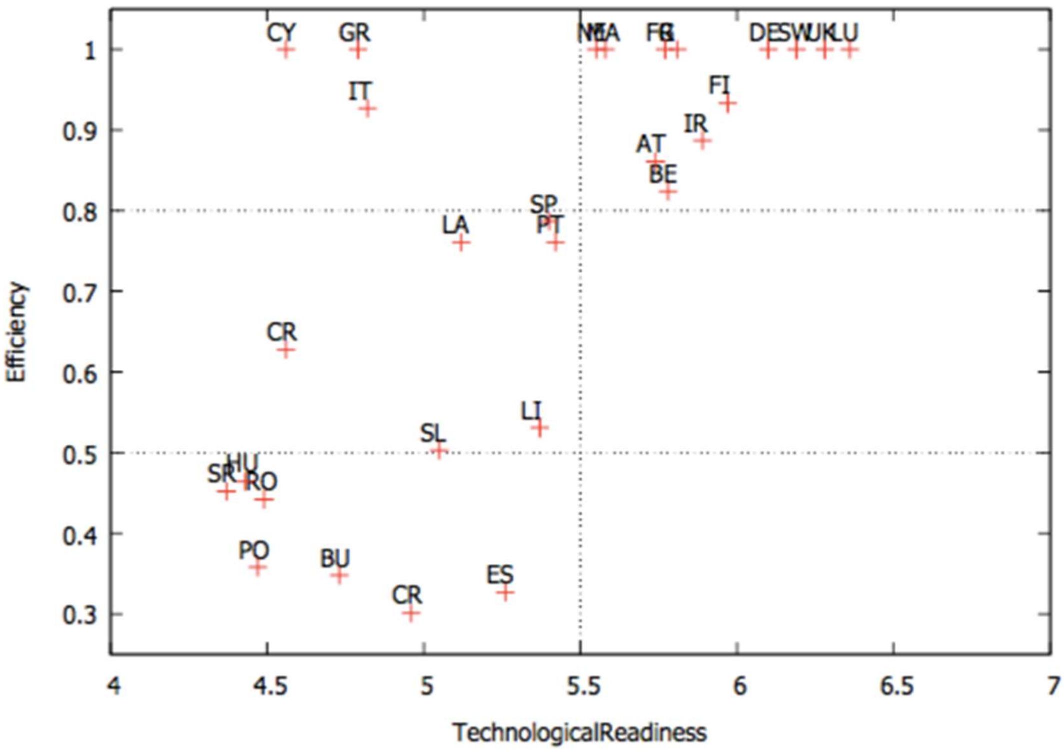
Inefficiency and efficiency scores for UE-28. Source: Own elaboration from the dataset.

Country	Inefficiency score	Efficiency score
Germany	0	1
Austria	0.139	0.861
Belgium	0.176	0.824
Bulgaria	0.652	0.348
Cyprus	0	1
Croatia	0.372	0.628
Denmark	0	1
Slovenia	0.497	0.503
Spain	0.213	0.787
Estonia	0.673	0.327
Finland	0.067	0.933
France	0	1
Greece	0	1
Hungary	0.536	0.464
Ireland	0.113	0.887
Italy	0.073	0.927
Latvia	0.239	0.761
Lithuania	0.469	0.531
Luxembourg	0	1
Malta	0	1
Netherlands	0	1
Poland	0.642	0.358
Portugal	0.239	0.761
United Kingdom	0	1
Czech Republic	0.699	0.301
Slovak Republic	0.548	0.452
Romania	0.558	0.442
Sweden	0	1

Table 3
Technological readiness indicator for European countries in 2014. Source: The global competitiveness report 2014-2015, World Economic Forum (2014).

Country	Technological readiness indicator
Germany (G)	5.81
Austria (AT)	5.74
Belgium (BE)	5.78
Bulgaria (BU)	4.73
Cyprus (CY)	4.56
Croatia (CR)	4.56
Denmark (DE)	6.10
Slovenia (SL)	5.05
Spain (SP)	5.40
Estonia (ES)	5.26
Finland (FI)	5.97
France (FR)	5.77
Greece (GR)	4.79
Hungary (HU)	4.43
Ireland (IR)	5.89
Italy (IT)	4.82
Latvia (LA)	5.12
Lithuania (LI)	5.37
Luxembourg (LU)	6.36
Malta (MA)	5.58
Netherlands (NE)	5.55
Poland (PO)	4.47
Portugal (PT)	5.42
United Kingdom (UK)	6.28
Czech Republic (CR)	4.96
Solvak Republic (SR)	4.37
Romania (RO)	4.49
Sweden (SW)	6.19
Minimum	4.37
Maximum	6.36
Average	5.315
Worldwide average	3.96
Worldwide Variation Coefficient	0.3

Figure 1
Efficiency scores and technological readiness



Source: Own elaboration.

5. CONCLUSION

In order to implement appropriate policies against climate change is necessary to take into account that a country needs not only be environmentally friendly but also to be productively efficient. For this reason, is important not only to reduce GHG emissions but also to increase the gross domestic production. With the application of the Directional distance function, this paper has obtained the different efficiency scores ensuring the reduction of undesirable outputs and the increase of desirable outputs. Thus, it is said that a country is relative efficient if it is environmentally and productively efficient. For the application of this methodology is important that all DMUs present similar technological level and for this reason the data set include only European countries for the year 2014.

After the application of the methodology, the study concludes that Germany, Cyprus, Denmark, France, Greece, Luxembourg, Malta, Netherlands, United Kingdom and Sweden are the most efficient countries. Note that it means that these countries are efficient with regard to the rest of countries analysed and not “absolutely” efficient.

We present the regression of the efficiency as a function of the readiness technological index showing great heterogeneity for countries with efficiency index higher than 0.8. However, all countries with an efficiency index lower than 0.8 present a readiness technological indicator lower than 5.5. In other words, all countries with a technological readiness index above 5.5 present levels of efficiency above 0.8. Italy, Greece and Cyprus are interesting cases since they present a high efficiency with a low level of technology. Future research line may cover more variables and also a longer period of study including the evolution of the countries since Europe 2020 strategy was implanted.

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