Resource Efficiency And Energy Productivity. Is There A Definite Direction?

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The present dissertation entitled

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I would like to dedicate my dissertation to my family!

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Summary

Energy is vital to our daily lives. Without energy, people and businesses can not function. Turning on our computers or starting our cars are actions we take for granted, but they represent the final stage of a complex process. First of all, energy resources must be extracted from our environment. Primary energy sources are converted into energy products available for consumption. For example, crude oil is converted to motor gasoline, while mineral, nuclear, and renewable energy are converted into electricity. The role of environmental efficiency (EE) is an important and critical issue on the policy agenda and it is therefore vital to have an accurate assessment of environmental performance. In order to assess the impact of carbon dioxide emissions in the country, we use both the Data Envelopment Analysis method and the Directional Distance Function (DDF) function to assess technical, energy and environmental efficiency. This dissertation will attempt to estimate these indicators using a sample of 27 European countries for the period 2000-2017, i.e. for 18 years. All this will be done in the light of the heterogeneity of technology that exists between states. The aim of the present study is to investigate whether countries that appear to be technically efficient are in fact, whether they are energy efficient and of course how environmentally efficient.

Keywords: Productive Performance, Energy efficiency, Environmental efficiency, Data envelopment analysis, Directional distance function, Panel Data Heterogeneous technologies, Metafrontier, Competitiveness, Spillover effects

Περίληψη

Η ενέργεια είναι ζωτικής σημασίας για την καθημερινή μας ζωή. Χωρίς ενέργεια, οι άνθρωποι και οι επιχειρήσεις δεν μπορούν να λειτουργήσουν. Η ενεργοποίηση των υπολογιστών μας ή η εκκίνηση των αυτοκινήτων μας είναι ενέργειες που θεωρούμε δεδομένες, αλλά αντιπροσωπεύουν το τελικό στάδιο μιας σύνθετης διαδικασίας. Πρώτα απ΄όλα, οι ενεργειακοί πόροι πρέπει να εξάγονται από το περιβάλλον μας. Οι πρωτογενείς πηγές ενέργειας μετατρέπονται σε ενεργειακά προϊόντα διαθέσιμα για κατανάλωση. Για παράδειγμα, το αργό πετρέλαιο μετατρέπεται σε βενζίνη με κινητήρα, ενώ το ορυκτό, η πυρηνική και η ανανεώσιμη ενέργεια μετατρέπονται σε ηλεκτρική ενέργεια. Ο ρόλος της περιβαλλοντικής αποδοτικότητας (ΕΕ) είναι ένα σημαντικό και κρίσιμο ζήτημα στην ατζέντα πολιτικής και ως εκ τούτου είναι ζωτικής σημασίας να υπάρχει ακριβής εκτίμηση των περιβαλλοντικών επιδόσεων. Προκειμένου να εκτιμηθεί ο αντίκτυπος των εκπομπών διοξειδίου του άνθρακα στη χώρα, χρησιμοποιούμε τόσο την μέθοδο της Ανάλυσης Περιβάλλουσας Δεδομένων όσο και την λειτουργία Λειτουργία κατεύθυνσης απόστασης για την εκτίμηση της τεχνικής, ενεργειακής και περιβαλλοντικής απόδοσης. Η παρούσα διπλωματική θα προσπαθήσει να εκτιμήσει αυτούς τους δείκτες χρησιμοποιώντας ένα δείγμα 27 Ευρωπαικών χωρών για το χρονικό διάστημα 2000- 2017. δηλαδή για 18 έτη. Όλα αυτά θα γίνουν υπο το πρίσμα ότι λαμβάνουμε υπόψιν την ετερογένεια της τεχνολογίας που υπάρχει μεταξύ των κρατών. Στόχος είναι να δούμε αν οι χώρες που φαίνεται να είναι τεχνικά αποτελεσματικές, το κατά πόσο είναι ενεργειακά αποδοτικές και φυσικά ποσο περιβαντολλογικά αποδοτικές.

Λέξεις κλειδιά: Παραγωγική απόδοση, Ενεργειακή απόδοση, Περιβαλλοντική απόδοση, Ανάλυσης Περιβάλλουσας Δεδομένων, Λειτουργία κατεύθυνσης απόστασης, Πάνελ Δεδομένα, Τεχνολογική Ετερογένεια, Μέτα-Ανάλυση, Ανταγωνιστικότητα, Επίδραση

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Environmental performance and climate change are two concepts that have played an important role in our daily lives over the last decades. As a result, more and more policies are turning to the environmental footprint of a country's economy, because it plays a key role in influencing the quality of life and prosperity. In this light, several environmental restrictions have been created since 1992, although they have been in place since 2005. The best known is Kyoto's Protocol, which set guidelines for environmental protection and awareness. Therefore, countries began to think about how to become more environmentally friendly by upgrading the quality of life of both the current and future generations. Some other guidelines that have been followed are Copenhagen and Cancun, 2010, Durban and Doha, 2011, Warsaw, 2013, Paris agreement, 2015, Katowice summit, 2018, Bonn Conference, 2019. All of this has resulted in the creation of specialized reports on the environmental impact that a production process can have both at the national and industrial levels.

According to Eurostat in 2018 [1], energy consumption came from various sources. More specifically, starting our analysis from the source with the lowest participation rate, we see that Crude Oil supplied only 3.9%. Natural Gas then held a stake of 9.3%. In addition, Solid Fuels covered 21.6% of energy consumption. Of course,

[1] Site:`https://ec.europa.eu/eurostat/web/products-digital-publications/-/KS-02-20-278?inheritRedirect=true&redirect=%2Feurostat%2Fweb%2Fenergy%2Fpublications`

Nuclear Energy could not be missing as it was the second-largest energy supplier with a percentage of 30.9 %. Finally, we observe that the use of Renewable Energy Sources has entered our lives for good, as it is the largest supplier with a rate of 34.3 %.

Focusing on the European Union, it is clear that one of the first issues on the political agenda is industrial activities that endanger the quality of the environment. Of course, it should be noted that the European industries have realized the huge potential benefits that will result from the adoption of environmentally friendly technologies. Of course, this can be achieved by improving environmental efficiency, improving production efficiency, and increasing competitiveness. For this reason, the European Council has proposed guidelines (e.g. European Directive 2009 / 28-33) with the aim of promoting various policies for industries through information, economic, legislative and tax measures, and market-based tools (e.g. EU Trade Fair).

In this regard, some specialized guidelines are the Thematic Strategy for Sustainable Use of Natural Resources (2005) and the Flagship Resource Performance Initiative (2011) as one of the seven initiatives under the "Europe 2020" strategy. The roadmap for a Europe that makes efficient use of resources (COM, 2011 571) is an important pillar of the emblematic initiative that provides a framework for both planning and implementing long-term actions. Of course, the goal is to improve the use of natural resources, but at the same time reduce carbon dependence through a more effective action plan that will result in a prosperous and sustainable Europe.

In December 2019, the European Commission launched its long-term strategy for 2050 with the aim of making carbon-neutral the main block (European Commission, COM (2018) 773) always in line with both the Paris Agreement (COP21 2015) and also with the recent report of the Intergovernmental Panel on Climate Change (IPCC, 2018) on such an economic structure that is neutral to climate change through the use of more effective technology to mobilize all levels of the chain from citizens to countries for a transition to a low carbon emissions action plan to build a viable economy.

In addition, the European Green Agreement as a package of measures obviously serves as a means of promoting the Commission's strategy in a smooth transition to sustainability. In this way, as expected, the efficiency of resources is at the center of global attention, both by organizations and institutions that support policy guidance to create cost-effective economies that link the latter to sustainability through recent initiatives. Sustainable Development Goals (OECD, 2015, UN Environment, 2015).

Undoubtedly, the goal of the Green Deal program is to transform the European economy for a more sustainable future. Initially, the primary goal is to increase the EU's climate ambition for 2030 and 2050. Secondly, supplying clean, affordable, and secure energy. Undoubtedly, one of the most important goals is to mobilize the industry, in this way for a clean and circular economy. So we are essentially accelerating the shift to sustainable and smart mobility. For example, from "Farm to Fork": a fair, healthy, and environmentally friendly food system. All of the above is done in order to achieve the goal which is none other than preserving and restoring ecosystems and biodiversity, with a zero pollution ambition for a toxic-free environment. All this mobilizing research and fostering innovation will be carried out with financial support so that no country is left behind.

Taking into account all the above, EU Directive 2021-2030 in the Member States is to develop a comprehensive strategy for energy efficiency and climate action aimed at aligning with the obligations of the Paris Declaration (ICCP, 2015) and research, innovation and competitiveness among others. Therefore, in this context, the "Resource Efficiency" initiative creates the scene for further improvement of productivity. Focusing on resource efficiency and policymaking, we must keep in mind that various measures that reflect resource efficiency, such as environmental and energy efficiency, can affect each other and increase this argument. Therefore, policy planning to improve resource efficiency needs to dig deeper in this direction.

It is important to note that such policies must be implemented by definition on a heterogeneous basis as well as in an institutional and technological context, which raises several reasonable questions as to whether they can be applied to the economies of countries.

First of all, we are exploring the links between the performance measures that have been neglected so far by recognizing the endogenousness and the insufficient means for its relief. Second, we explore the merit of competitiveness by investigating its association with performance patterns by exploring the research question in segments of competitiveness (i.e. quantiles) to show how the main relationship behaves across the distribution. Such being the case, we emphasize the importance of the relative position of a country on performance. The third and final is necessary for policy proposals. In the vast majority of studies, the key variables we focus on here have been examined individually, leading to a misleading consensus that they are mutually exclusive.

However, this framework has as its main idea that the term performance represents a family of interrelated measures as opposed to the previous literature (eg Pacudan & de Guzman, 2002; Zhang & Wang, 2008; Liddle, 2010; Montalbano & Nenci, 2018). If we were to examine the correlations between different performance measures, this would result in more sophisticated forms of policy planning.

In the energy sector, much of the literature studies through various environmental regulations the relationship between environmental efficiency and competitiveness. All of these studies are based on Porter's case, where environmental regulation may be adjusted over time to reflect updated understanding or new circumstances, and may also improve competitiveness (Porter and Van der Linde, 1995; Shrivastava 1995; Trung and Kumar, 2005, Ambec et al, 2013). Therefore, there is a "win-win" situation as a result of environmental regulation. In contrast, some other researchers (Milliman and Prince, 1989; Palmer et al., 1995; Jaffe et al., 2002) disagree with the optimism of environmentalists. They point out that the private cost of strict environmental regulations affects both competitiveness and productivity.

In addition, it cannot be neglected that performance measures and more specifically environmental performance and productive performance (Tyteca, 1996) are linked as to the same set of production capabilities, although there is an effect of industrial competitiveness on productive performance (e.g. Porter, 1985, Oral et al., 1999). Of course, the analysis of the impact of pollution prevention and environmental compliance on industries, in general, has been studied mainly in a one-dimensional way, with an emphasis on environmental performance, but ignoring the aspect of production efficiency (ie Tyteca, 1996); Triantis and Otis, 2004).

Most studies either take into account industry emissions as poor production (eg Zhou et al., 2008) based on the idea of simultaneously expanding the desired production and limiting unwanted production or suggest measures that integrate these models (Sueyoshi and Goto, 2010) or quantify indicators based on pollution (Tyteca, 1996). However, all of these approaches are ignorant of the productive aspect of performance, as the production of these measures is based on the same set of technology (Triantis and Otis, 2004) and as a result are inherently connected. All of this gives us the opportunity to capture the links between these measures by exploring some intrinsic relationship, although studies investigating whether these measures are evolving have yet to emerge.

On the other hand, we should not ignore the fact that heterogeneous competitiveness standards have been recognized by the literature for their contribution to the difference in performance (Wagner & Schaltegger, 2004; Chiu et al, 2012; Gkypali et al., 2018). For this reason, the multidimensional nature of competitiveness requires an indicator that takes into account many aspects that would otherwise be neglected. The Global Competitiveness Index (GCI) is one such indicator that includes twelve pillars common to all countries, facilitating interstate comparisons. Pillars include Institutions, Infrastructure, Macroeconomic environment, Health and Primary Education, Higher Education and Training, Goods Market Efficiency, Labor Market Efficiency, Financial Market Development, Technological Readiness, Market Size, Business Sophistication, and Innovation. GCI classifies the dynamism of market economies in terms of (i) resources, (ii) efficiency mechanism and (iii) innovation activity guides and is intended to be used as a summary of current market conditions and capabilities (World Economic Forum, Sala-i-Martin & Artadi, 2004; Sala-i-Martin et al., 2008).

As expected, some countries appear to have better environmental performance and this is mainly due to both the structure of the economy and the quality of institutions (Stern, 2012). These differences are evident in all the productive possibilities that affect the performance of an economy because it is logical that the scope of application of each directive differs from country to country.

As most experts claim, a number of factors such as productivity resilience, random shocks, strategic orientation, decisions based on different rules of conduct affecting performance between European countries, add an extra level of heterogeneity. to be taken into account and treated appropriately during the comparative evaluation process. Therefore, the above refutes the idea that performance measures are characterized by simple correlations. Therefore, the need for the development of such a theoretical framework that allows the investigation of the triangle relationship of interest between environmental efficiency, productive efficiency and competitiveness under technological heterogeneity, of course, becomes apparent.

Thus, the handling of technological heterogeneity is realized through the metafrontier framework (Hayami & Ruttan 1970; O'Donnell et al., 2008) that surrounds all those individual frontiers that show us all the relevant technological heterogeneity (Dosi et al., 2010). Thus, such a framework allows us to loosen the case of technological isolation (Tsekouras et al., 2016) between individual technological structures. In other words, at production limits, as all units are known to be evaluated on the basis of a common reference point that represents a technology level without borders, potentially accessible to all units.

In a nutshell, the findings appear to show that productive performance has not only a negative but also a significant effect on environmental performance, while at the same time a very weak endogenous relationship emerges, noting that performance measures are largely detached. An important lever seems to be the quality of the institutions. The findings, however, do not provide support for the Porter case, and competitiveness seems to be a necessary but not a sufficient condition for improving environmental performance. From another perspective, from a political point of view, the tripartite relationship seems to be supported only in highly competitive countries, a binary relationship in the form of a heavy cross as productive performance negatively affects environmental performance for most of the competitiveness sectors examined.

Chapter 2

Literature Review

It is well known that the field of environmental efficiency assessment is a modern and at the same time very active field, with a wave of studies being added to the literature quite quickly. So, it would not make sense to try to present all the existing literature. Our goal is to present a brief but at the same time comprehensive overview of the evaluation methods as well as the empirical studies that have emerged over the years and have helped in the development of this industry.

Several studies have been carried out in the light of the homogeneity of technology. Therefore, those factors that may have a distorting role in environmental performance standards have not been addressed. For this reason, some researchers have decided to consider the heterogeneity of technology. Some of them are Oh (2010), Chiu et al. (2012), Lin et al. (2013), Kounetas (2015), Kounetas and Zervopoulos (2019) and Wang et al. (2016).

Several attempts have been made to study the effects of eco-innovation patterns on a mix of policies in order to enhance various energy-efficient technologies (Costantini et al., 2017). However, not enough attention has been paid to resource efficiency measures. For this reason, Liu et al. (2018) focused mainly on the feedback between the global value chain with energy efficiency and environmental efficiency. Here, however, the possible feedback loops between resource efficiency measures and the role of productive efficiency have once again been neglected.

In 2019, Chatzistamoulou et al. highlighted the prospect of a relationship between performance measures by exploring energy efficiency measures under heterogeneous competitiveness regimes given that productive performance is the driving force behind energy efficiency. In the same vein, Chatzistamoulou and Kounetas (2020), thinking outside the box, studied European environmental performance standards with the assumption that there is technological heterogeneity, thus finding that not only productive performance negatively affects environmental performance but also competitiveness is a necessary but not a sufficient condition for improving efficiency.

Furthermore, Mavi et al., 2019 using the two-step method of DEA analysis with large data, studied eco-innovation and ecological efficiency for OECD countries in order to find the pioneers of each measure. Recent studies have shown that there are links between eco-innovation and industrial performance, agreeing that there is not just one type that can express eco-innovation.

Always speaking at an industrial level, according to Beltrán-Esteve & Picazo-Tadeo, 2015 productivity indicators have been proposed, but not everyone should take into account that there is technological heterogeneity between countries applying the concept of metafrontier in order to determine that policy guidelines should aim to enhance green technologies (Beltrán-Esteve et al., 2019). Of course, some people have been involved in business. More specifically, both eco-innovation and the factors that cause it have attracted a large number of studies both in the study of European countries as a whole (Triguero et al., 2013) as well as for individual cases (Kesidou & Demirel, 2012). In 2000, however, Rennings put eco-innovation in a different perspective in a way that is related to technology, energy efficiency, regulation and market characteristics.

However, the industries are no longer just competing with other domestic industries. A comparison is made with industries abroad that operate under different conditions. Therefore, the problem of technological heterogeneity again arises, with the result that industries must face asymmetrical technological opportunities and be able to take advantage of the knowledge and technological leaks (Tsekouras et al., 2016, 2017). Therefore, the assessment of ecological efficiency in a metafrontier framework paves the way for us to examine the absorptive and innovative capabilities that arise at the European level (Cohen and Levinthal, 1990).

Initially, eco-efficiency was defined as the ratio of GDP to CO_2 emissions (e.g. Glauser and Müller, 1997; Burritt and Schaltegger, 2001; Zhang et al., 2008). Although easy as an indicator, there was a problem. It was completely unaware of the different dimensions of the side effects that could be produced by the production process (Kuosmanen and Kortelainen, 2005; Wang et al., 2011). Therefore, even in this case, it appeared that the solution could be provided by Data Envelopment Analysis (DEA) or Directional Distance Function (DDF) (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005). However, the choice of indicators could be adapted to the entity we want to study (Saling et al., 2002; Hellweg et al., 2005; Scholz and Wiek, 2005. Huppes and Ishikawa, 2007; Managi and Kaneko, 2009).

In many European countries, there has been an increase in emissions, with more and more scientists wanting to study the cause or causes. In 1990 it was presented by Kaya the application of the log mean Divisia Index (LMDI), which was the most popular technique due to some features it had (eg Ang and Pandiyan, 1997; Jung et al., 2012; O'Mahony, 2013; Li et al., 2014; (Streimikienė and Balezentis, 2016; Ma and Cai, 2018).

Energy efficiency plays a vital role in the energy strategy of industries. In 1975 Berndt and Wood dealt with what is energy but also with its substitution elasticity relation with capital and labor. In 1996, Patternson dealt with the different parts of energy efficiency that exist, while at the same time several attempts are being made by various scientists to measure energy efficiency using various methods. The first attempt was made to decompose energy consumption through a framework using Index Decomposition Analysis (IDA), which defined energy as the amount of energy consumed per unit of output (Kounetas et al., 2012). However, the IDA is starting to show some shortcomings on the issue of distribution (Shorrocks, 2013). Finally, as energy intensity does not take into account non-energy inputs in the production process, it results in its establishment as a "partial" measure of energy efficiency.

Some authors have paid special attention to production theory (Filippini and Hunt, 2012). This idea is mainly based on estimating a limit that is essentially optimal in terms of energy use. Therefore, according to Hu and Wang in 2006, energy efficiency can easily be calculated as the difference between actual and projected energy use with the integration of the TFEE index. The SFA-related bibliography section, the extraction of the Shepard distance function, allows the calculation of shadow values (Choi et al., 2012; Lin and Du, 2013; Llorca et al., 2017), the curvature of viability against the length of the frontier (Färe et al., 2005) as well as the production of "underlying energy efficiency" (Filippini and Hunt, 2012).

Of course, one will notice that the largest percentage of studies that already exist for energy efficiency, mainly follows the non-parametric approach aimed at calculating TFEE. Some studies focus on China (Wei et al., 2012; Wang et al., 2013; Shao et al., 2019), while some in India (Paul and Bhattacharya, 2004; Worrell et al., 2009) in both corporate and on an industrial scale. As a result, international organizations such as the OECD as well as the Asia-Pacific Economic Cooperation (APEC) are increasingly concerned with energy efficiency (eg Hu and Kao, 2007; Zhou and Ang, 2008; Voigt et al., 2014).

Generally speaking, TFEE has been calculated mainly using the distance function under an input-output mixture. Two-stage approaches are usually used to identify any relationships between efficiency and external factors using regression methods, based mainly on linear models. Although there is generally significant progress in understanding energy efficiency issues, there is little research examining those factors that affect it. The majority of them use the decomposition analysis to determine energy intensity which consists of a partial energy efficiency index (Ma and Stern, 2008; Metcalf, 2008).

However, even today it is unclear what are the factors that affect energy efficiency. According to Zhang and Broadstock (2016), energy intensity is a broader measure that could be influenced by economic structure, environmental, and other factors. Therefore, we conclude that energy efficiency is more related to the technical characteristics of energy intensity. Of course, the size and location of each factor are likely to vary based on the characteristics of the group of entities being examined each time. Abadie et al. In 2012, they argued that energy efficiency could be affected by adverse, structural, climatic, and, of course, energy factors. In this direction, socio-economic indicators and structural characteristics (Diakoulaki et al., 1999) of a country and industry such as human capital development and income (Zhang and Adom, 2018) and market or environmental regulations (Bigerna et al., 2019) will could be combined in order to create a significant energy efficiency factor. At the industrial level, determinants can be more accurately classified into either technological, sectoral, or specific characteristics of the country (Shao et al., 2011; Pan et al., 2013). Finally, Newell et al. In 1999, they found that the optimization of the industrial structure is probably the main factor that can cause the reduction of energy and consequently the increase of energy efficiency.

Ecological efficiency was initially defined as the ratio of GDP to CO_2 emissions (e.g. Glauser and Muller, 1997; Burritt and Schaltegger, 2001; Zhang et al., 2008). Despite its convenience and simplicity, it completely ignored the different dimensions of side effects that could be produced by the production process (Kuosmanen and Kortelainen, 2005; Wang et al., 2011). Recently, benchmarking techniques, such as Data Envelopment Analysis (DEA) or Directional Distance Function (DDF), to evaluate the eco-efficiency achieved (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005). However, the choice of indicators could depend on the entity we want to review (Saling et al., 2002; Hellweg et al., 2005; Scholz and Wiek, 2005; Huppes and Ishikawa, 2007; Managi and Kaneko, 2009).

Although good progress has been made in understanding energy efficiency assessment issues, only a few studies have been conducted to examine the factors that affect it. Most of them use decomposition analysis to determine the energy intensity consisting of a partial energy efficiency index (Ma and Stern, 2008; Metcalf, 2008). However, it is still unclear what factors can actually affect the measure of energy efficiency. Zhang and Broadstock (2016) point out that although energy intensity is a broader measure that could be influenced by economic structure, environmental and other factors, energy efficiency is more closely linked to the technical characteristics of energy intensity.

In addition, they found that the size and point of each factor could differ based on the characteristics of the group of entities under consideration. In this sense, the determinants of energy efficiency can not be easily identified and determine a broad, common direction. Abadie et al. (2012) argued that energy efficiency can be affected by structural, adverse, climatic, and energy factors. The majority of scholars emphasize the social and economic environment and the shares of production in the economy. In this regard, according to Diakoulaki et al. in1999 socio-economic indicators and structural characteristics of a country and an industry, human capital development and income (Zhang and Adom, 2018) and market or environmental regulations (Bigerna et al., 2019) could be combined to create an important energy efficiency factor. In advance, Cui et al. (2014) added that an amount of tax exemption for high-tech energy companies, as a management indicator, could be beneficial.

On the other hand, some researchers believe that the group of factors that affect a higher level of energy efficiency is that of energy and environmental factors. Climate effects (Filippini and Hunt, 2011), the use of discrete energy sources, known as energy mixes, and energy values cause divergent paths in energy efficiency (e.g. Lin and Long, 2015; Liu and Lin, 2018). At the industrial level, these determinants can be more accurately classified into technological, sectoral, and country-specific characteristics (Shao et al., 2011; Pan et al., 2013). Finally, Newell et al. (1999) found that the optimization of the industrial structure is the main factor that can cause a reduction of energy and consequently an increase of energy efficiency.

Furthermore, Färe et al. in 1996 were the first to introduce the concept of directional distance functions in order to calculate environmental efficiency. Apparently, after that several theories emerged. For example, from radial measures (Färe and Grosskpof, 2000; 2004) to non-radial ones (Zhou et al., 2006; 2008; Färe and Grosskpof, 2010; Mahlberg and Sahoo, 2011; Picazo-Tadeo et al., 2011), Zhou et al., 2008; Chang et al., 2013) and slack-based measures (Tone 2001; Zhou et al., 2006, Choi et al., 2012, Zhang et al., 2014) of combinations of the above (Fukuyama and Weber, 2009).

In addition, in 2000 Zaim and Taskin and nine years later, Cuesta et al., (2009) developed an excessive measure of effectiveness. Also, both Fukuyama et al. (2011), as well as Barros et al. (2012), incorporated the proposed DDFs slack-based measures as well as the weighted Russell DDFs, while Chang and Hu (2010), Färe and Grosskopf (2010) and Cheng and Zervopoulos (2014) introduced a more general non-radial DDF. At the same time, Zhang et al., (2014) presented a detailed framework of successive generalized distance function. However, a Range-Adjusted measurement model for the US coal-fired power plants was introduced in 2010 by Sueyoshi et al., (2010). On the other hand, a different study was conducted. Boyd et al., (2002) and Tyteca (1996) studied environmental efficiency and the impacts of environmental regulation at plant level while in 2000 the environmental effectiveness of OECD countries and regions was investigated from a macroeconomic perspective by Zaim and Taskin.

As most economists claim, the production process of every decision-making unit (DMU) has an economic but also an environmental as well as a social output according to Zhang et al. in 2014. Therefore, a large number of empirical studies have employed DDF to investigate the performance of individual entities (Countries, Companies, etc.).

Chapter 3

Methodology

Many researchers from different fields of knowledge use different methods that fall within the field of Operating Research to answer specific questions. One of these questions concerns whether decision-making units are making appropriate use of their capabilities in order to achieve maximum productivity. This chapter presents both the theoretical background and the methodological framework of the data environment analysis (DEA).

Over the past 40 years, several methods have been used to evaluate Frontiers. Certainly, the best-known methods are Data Envelopment Analysis (D.E.A.) and Stochastic Frontier Analysis (S.F.A.) which include mathematical programming and econometric methods, respectively.

The concept of efficiency plays a key role in how a company manages the productive factors at its disposal because it can measure any waste of resources for a specific and at the same time given production technology. Nowadays, the emerging environment is increasingly characterized by deregulation of markets, liberalization of trade flows and consequently increasing competition, the appreciation of the efficiency of businesses in a particular industry, they offer us a quantitative criterion for the productive performance of that industry. This information is useful information both for the management of these companies because they are given the opportunity to know if there is room to save productive resources that would result in a more efficient operation, but also for policymakers to evaluate and possibly reconsider various policy measures aimed at increasing the competitiveness and efficiency of the industry.

3.1 The concept of technical efficiency

It is clear that in any process of input-to-output conversion, the deviation of the output of a production unit from the limit of the objective possibilities of production technology can be used as a measure of the degree of inefficiency of this unit. The inspirer of this methodological approach was Farrell (1957) and it is the basis of the modern analysis of efficiency.

More specifically, in modern economic research, the overall efficiency of a production unit is considered to include the following according to Fare, Grosskopf, and Lovell in 1994:

- Technical efficiency (T.E.), which refers to the ability of a production unit to operate (or not) to the limit of the objective capabilities of the production technology it uses.

The technical efficiency of a production unit can be measured using as a reference point either the quantities of inputs used or the quantities of outputs produced. Many times, the analysis can be based on the question: "how much should the inputs used be reduced proportionally without changing the amount of output produced?". The measurement of the technical efficiency that results in this way is called input-oriented efficiency (TE^I). Alternatively, measuring the efficiency of a production unit could be based on proportional changes in output, that is, based on the question: "How much can the output flow increase proportionally without changing the amount of inputs used?". Correspondingly here, the measurement of the resulting efficiency is thus called output-oriented efficiency (TE^O).

Obviously, the TE^I is different from the TE^O as the measurement of the first is based on changes in the use of inputs for fixed quantities of produced outputs, while on the other hand in the second in changes of outputs produced for fixed quantities of inputs used. That is, the difference between TE^I and TE^O can easily be represented geometrically in the case of a production technology that employs an input to produce a single output (i.e., a simple production function) such as $y = f(x)$. If we take as a case of declining scale yields, this output function is shown as the hollow OQ curve. By definition, the output function gives the maximum amount of output that can be generated by a given quantity of outputs and is, therefore, the limit of the productive capacity of the technology $y = f(x)$ (see The Figure 1a).

Suppose that a production unit operates at the point P, that is, it uses an input quantity $x_P = OC$ and produces a product quantity $y_P = OA$. Apparently this unit is technically inefficient as it does not operate above the limit of its production capacity (ie, in the OQ curve). The degree of efficiency technique can be measured in two directions. Specifically, we can measure the technical efficiency of inputs, TE^I as factor θ based on which the used input quantity $x_P = OC$ must be reduced to make the minimum input quantity $\bar{x} = \theta \times x = \theta(OC)$ which is capable to produce quantity of OA product. Therefore, $TE^I = \theta < 1$ (since $y_P = f(\bar{x})$) and geometrically the technical efficiency of inputs is given by the ratio, $TE^I = AB/AP$.

Alternatively, we can measure the technical efficiency of outputs, TE^O as the inverse of the factor ϕ based on which the amount produced $y_P = OA$ must be increased to make the maximum possible amount of product $\bar{y} = \varphi \times y_P = \varphi(OA)$ that can be generated by the input quantity $x_P = OC$. Therefore, $TE^O = \varphi^{-1} < 1$ (since $\bar{y} = f(x_P)$ and geometrically the technical efficiency of outputs is given by the ratio, $TE^O = CP/CD$. It is obvious that in general the AB/AP and CP/CD ratios differ and therefore $TE^I \neq TE^O$.

However, these two measurements of technical efficiency coincide in the case where the production technology is characterized by constant returns to scale. This case is shown in Figure 1b where the output function shows constant returns to scale and is therefore represented geometrically by the line OQ. For the production unit operating at point P, of course, $TE^I = AB/AP$ and $TE^O = CP/CD$. However, since the limit of productive potential is the line OQ, one can easily prove using the properties of similar triangles that $AB/AP = CP/CD$ is valid and therefore, $TE^I = TE^O$ when production technology is characterized by constant returns to scale.

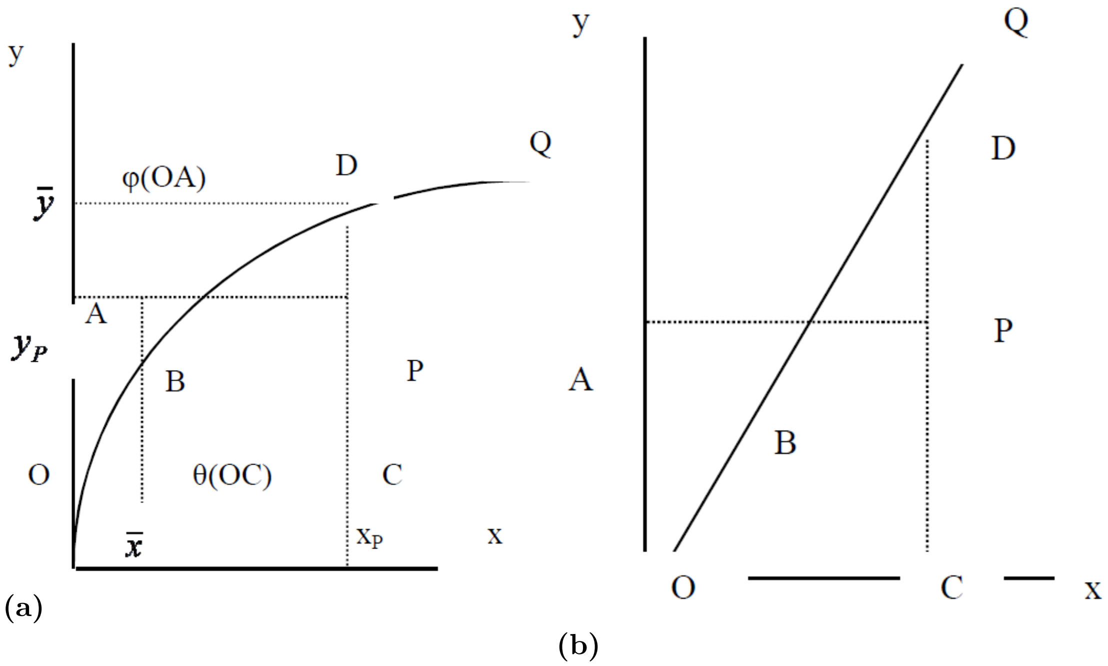


Figure 1: Technical Efficiency and Scale Efficiency

3.2 The Data Envelopment Analysis Methodology (D.E.A.)

3.2.1 The DEA model with Constant Return Scale (CRS)

The original DEA model was developed for production technologies characterized by constant scale returns (CRS) and is also known as the CCR model (as developed by Charnes, Cooper, and Rhodes, 1978). To understand the rationale of the DEA method, let's assume that there are elements available for N production units each of which uses K inputs to generate M outputs through a steady-state output generation technology. The product vector i of the output unit i is denoted by y_I and the corresponding input vector by x_x. The inputs of all together with the production units are included in table x, dimensions (KxN), and all outputs in table Y, dimensions (MxN).

In the literature of the DEA method, the production units are called "Decision Making Units" or DMUs to emphasize the fact that this methodology is not limited to financial units (businesses) but is equally suitable for studying the effectiveness of any in the form of production units that transform all kinds of "inputs" into all kinds of "outputs".

Since there are K inputs and outputs in each DMU, the calculation of the technical efficiency through the word "inputs/outputs" presents obvious application difficulties. The different inputs (outputs) must be grouped into a single amount of input (outputs). An obvious solution, of course, would be to measure the technical efficiency of each DMU using the ratio of the weighted output of the outputs to the weighted input of the inputs using the same weights for the inputs and outputs of all DMUs examined. However, this creates two major problems.

Firstly, there is no objective criterion for selecting these common gravity coefficients and secondly, it would be realistic to assume that different DMUs evaluate their inputs differently, ie they have different significance for them which would require different gravity coefficients for each DMU. The DEA method, recognizing these two problems, selects for each DMU those weight factors that place it in the most favorable position compared to the other DMUs.

Thus, in the context of the DEA method, the technical efficiency (TE) of a DMU, even i, results as the solution of the following linear programming problem:

Maximize the TE of DMU i under the limitation

that: the TE of the other DMU is ≤ 1.

The variables for selecting this problem are the weighting factors for grouping the individual inputs of the i-DMU. In a strictly mathematical formulation, the above problem is written as follows (Model 3.1):

$$max_{u,v}(\frac{u'y_i}{u'y_i})$$

$$\text{s.t. } \frac{u'y_i}{u'y_i} \leq 1 \text{ j} = 1, 2, ..., N$$

$$u, v \geq 0$$

where u, v are the weighting coefficients for grouping outputs and inputs, respectively. The u and v selection variables are defined as positive quantities or very zero so as to avoid the possibility of ignoring the contribution of an input (output) to the calculation of the efficiency of i-DMU.

If the degree of technical efficiency of a particular DMU is equal to the unit then that particular DMU uses production technology in an efficient manner relative to other DMUs that use the same production technology. On the other hand, if the degree of technical efficiency is less than the unit, we understand that some other DMUs are more efficient even when the weighting factors for grouping the inputs of that particular DMU are selected to maximize the degree of technical efficiency.

The problem of maximizing the technical efficiency of i-DMU is formulated in the form of speeches and therefore, it must first be converted to a linear format so that it can be solved by the method of linear programming. Of course, this conversion is easy because when you maximize a speech, what is ultimately interesting is the relative size of the numerator to the denominator and not their absolute values. Therefore, maximizing a speech can be accomplished by setting the denominator equal to a constant value and maximizing the numerator. Therefore, if we impose the constraint $\nu' x_i = 1$, the following linear form of the CRS-DEA model maximizes (Model 3.2):

$$max\ \mu, \nu\ (\mu' y_i)$$

$$\text{s.t. } \nu' x_i = 1$$

$$\mu' y_j - \nu' x_j \leq 0 \ j = 1, 2, ..N$$

$$\mu, \nu \geq 0$$

where gravity coefficients are now denoted by μ and ν instead of u and ν to emphasize the fact that it is a different problem of linear programming.

Furthermore, the second conversion to the original CRS-DEA model in order to take its final form has to do with reducing the number of restrictions to a minimum. It is well known that for every primary linear programming problem we can formulate the corresponding binary problem, using the same statistics. However, the solution to either the primary or binary problem provides the same information for calculating efficiency. The binary problem is formed by corresponding a new variable to each constraint of the primary and developing a new problem (the binary) with respect to these new variables.

The CRS-DEA model as a linear programming problem also has this corresponding binary written as follows (Model 3.3):

$$min_{\theta,\lambda}\theta$$

$$\text{s.t. } y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$\lambda \geq 0$$

where θ is a parameter and λ the dimension $(Nx1)$ vector of the new (binary) variables. Ultimately, this is what is used in applied economic research. The reason is that the primary problem is subject to (N + 1) constraints while the binary to $(K + M)$ constraints. Since the N number of DMUs examined is generally much higher than the number of M outputs and inputs K they use, the binary problem is subject to much fewer limitations than the primary problem. Therefore, the fewer the restrictions, the easier it is to solve them.

The dual minimization problem must be solved N times, that is, for each DMU of the sample under consideration. The value of the parameter θ that results each time from the solution corresponds to the degree of technical efficiency of inputs, TEI, of the specific production unit.

Through Figure 2a we can better understand the TE^I estimates that emerge in this way because it illustrates the simple case of a two-input and one-output technology. Solving the binary minimization problem essentially identifies the SS linear approach to an equilibrium curve. Points C and D represent production units that are technically efficient (and therefore determine the limit of production technology) while point B represents an inefficient unit. Solving the binary problem for unit B gives the degree of technical efficiency of inputs $\vartheta^B (= OB'/OB)$ To measure the technical efficiency of TE^O outputs, the binary model CRS-DEA is written as follows (Model 3.4):

$$min_{\phi,\lambda}\phi$$

$$\text{s.t.} \quad -\phi y_i + Y\lambda \geq 0$$

$$x_{ii} - X\lambda \geq 0$$

$$\lambda \geq 0$$

where $1 \leq \phi < \infty$ and $\phi - 1$ is the proportional increase in outputs that a DMU could achieve by keeping the input quantities constant. The degree of technical efficiency of TEO outputs is given by the ratio $1/\phi$.

In Figure 2b we observe the TE^O estimates obtained in this way that illustrates the simple case of a two-way technology. The solution to the problem of measuring the technical efficiency of TE^O outputs essentially identifies the linear approach of PP a curve of productive potential. Points A and D represent production units that are technically efficient (and therefore determine the limit of production technology) while point P represents an inefficient unit. Its solution for unit P gives the degree of technical efficiency of outputs $TE^O = 1/\phi_P = OP/OP'$.

Approaching the technology limit constructed by the DEA method is a zigzag line (or a zigzag super-surface in the case of multi-input / output technologies), so this can make it difficult to measure the efficiency of some production units. The problem occurs when the projected point of a production unit (above the technology limit) is on the horizontal or vertical part of the zigzag line representing the technology limit.

For example, the TE^I of unit A in Figure 2a is $0A'0A$, but the projected point A 'above the technology limit is doubtful if it is a technically effective point: let us note that we could reduce the amount of inflow used x_2 by the amount of CA' and continue to produce the same amount of outflow. In this case, we say that there is an "input slack" equal to CA' input x2. Similarly, the PE of the R unit in Figure 2b is $0P0P'$, but the projected point P' above the technology limit is doubtful whether it is a technically effective point. Here, we could increase the amount of output y1 produced by the amount of AP' without using more inputs. In this case, we say that there is an "output slack" equal to AR with respect to the output y_1. To address the problem of these "relaxations" in measuring technical efficiency, either the "two-stage DEA" technique or the "multi-stage DEA" technique is applied.

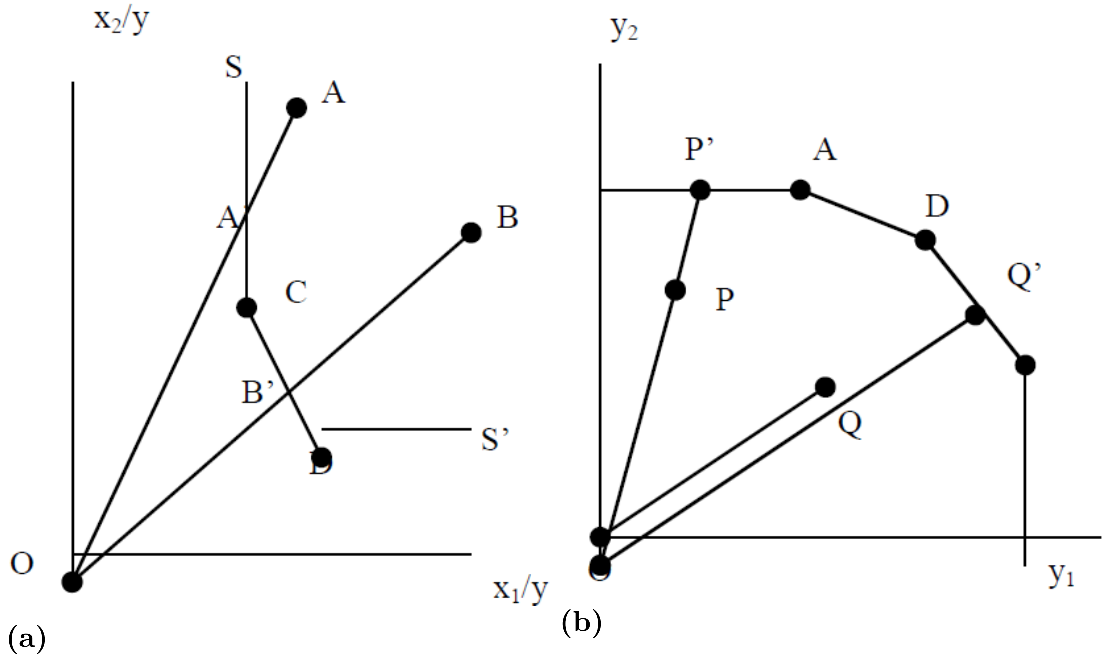


Figure 2: "Slacks" of inputs and outputs.

3.2.2 The DEA model with Variable Return Scale (VRS)

The CRS-DEA model is based on the assumption that production technology is characterized by stable scale yields. However, this assumption is only valid when all the DMUs examined are actually operating at the optimal size and therefore do not have problems with size inefficiencies. In most cases, however, it would be more realistic to assume that some (if not all) of the DMUs examined do not work at the optimal size.

The CRS-DEA model can be modified to take into account variable scale yields. To this modified model, developed by Banker, Charnes, and Cooper (1984) -that is also called the BCC model- it is required to add the curvature limit $N1'\lambda = 1$. Therefore, the VRS-DEA model can be written as follows (Model 3.5):

$$min_{\theta,\lambda}\theta$$

$$\text{s.t.} \ -y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$N1'\lambda = 1$$

$$\lambda \geq 0$$

where N1 is the dimension (Nx1) vector (1,1,.., 1). The VRS-DEA model essentially manufactures a curved surface enclosure that encloses the observations of the test specimen more "tightly" than the CRS-DEA model itself. It follows that the estimates of the resulting technical efficiency (ie the values of the parameter θ) are greater than or at most equal to those of the CRS-DEA model.

The curvature limitation $N1'\lambda = 1$ ensures that an inefficient DMU has effective DMUs of similar size as standard. But this is because the potential limit of production technology is now curved housing and therefore the projected point of an inefficient DMU on this housing is also a curved combination. In contrast, in the CRS-DEA model, where no curvature constraints are imposed, ineffective DMUs are likely to have effective DMUs of very different sizes as models. For this reason, and in this case, the gravity coefficients λ are added to a value greater (or less) of the unit.

Finally, the CRS-DEA model can be modified to take into account non-increasing returns to scale-NIRS. What is required in this case is to replace the curvature constraint $N1'\lambda = 1$ with the constraint $N1'\lambda \leq 1$. Thus, the relevant model can be written as follows (Fare, Grosskopf, and Logan, 1985) (Model 3.6):

$$min_{\theta,\lambda}\theta$$

$$\text{s.t.} \quad -y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$N1'\lambda \leq 1$$

$$\lambda \geq 0$$

The nature of scale returns (if, that is, whether they are increasing or decreasing returns) is ascertained by estimating Model 3.5. If for a particular DMU the degree of technical efficiency calculated on the basis of the case of non-variable scale performance differs from the degree of technical efficiency calculated on the basis of the case of variable scale performance then the technology production of this DMU is characterized by increasing scales. However, it is true that $TE_{NIRS} = TE_{CRS}$ then the production technology of the corresponding DMU is characterized by declining scales. The production technology is characterized by stable scale yields. Therefore, (and based on the technical efficiency of inputs, TE^I) the control of the nature of scale yields is done by estimating in order the Models 3.3, 3.5 and 3.6 and comparing the relative degrees of efficiency.

To measure the technical efficiency of TE^O outputs, the VRS-DEA model is written as follows (Model 3.7):

$$min_{\phi,\lambda}\phi$$

$$\text{s.t.}\ \ -\phi y_i + Y\lambda \geq 0$$

$$x_{ii} - X\lambda \geq 0$$

$$N1'\lambda \leq 1$$

$$\lambda \geq 0$$

where $1 \leq \phi < \infty$ and $\phi - 1$ is the proportional increase of the outputs that a DMU could achieve by keeping the input quantities constant while the degree of technical efficiency of outputs, TE^O is given by the ratio $1/\phi$.

3.2.3 Selection between technical efficiency of inputs (TE^I) and technical efficiency of outputs (TE^O)

As mentioned above, the technical efficiency of inputs (TE^I) refers to the proportional reduction of the quantities of inputs, keeping the quantities of the outflows constant, while the technical efficiency of outputs (TE^O) refers to the proportional increase of the quantities of the outputs, keeping the quantities of inputs constant. These two measurements of efficiency give the same value only in the case of production technologies with stable scale performance (CRS). The question, therefore, arises as to the criterion by which one chooses the type of technical efficiency used in an empirical application.

In modern efficiency measurement research, the prevailing criterion is to choose the type of technical efficiency based on whether a production unit primarily affects its inputs or outputs. In the agricultural sector, for example, production units basically affect the quantities of their inputs from which they try to produce as large amounts of outputs as possible. In this case, the technical efficiency of outflows (TE^O) is more appropriate. In contrast, in other industries (for example, in an oligopolistic electricity industry), production units primarily decide on the amount of outputs they want to produce and then try to produce as little as possible inputs. In this case, the technical input efficiency (TE^I) is more appropriate.

When we use parametric (econometric) models to estimate the limit of a production technology with unstable scale yields, then the estimated frontier resulting from using inputs differs from those obtained by using outputs as a reference point. However, this issue does not exist in the context of the DEA method. Both the DEA models that estimate the degree of technical efficiency in terms of inputs (TE^I) and those that estimate the degree of technical efficiency in terms of outputs (TE^O) calculate the exact same potential limit of production technology and therefore, definition, identify the same DMUs as effective. The only difference is that the technical efficiency levels of inefficient DMUs appear different. Therefore, the choice of model type is of minor importance, at least in terms of identifying technically effective DMUs.

3.3 A Directional Distance Function approach

Suppose we have i DMUs which employ a vector of inputs x, $x \in \Re^n_+$, in order to produce to produce a vector of desirable output y, $y^* \in \Re^m_+$. According to Banker et al. in 1984, the production possibility defined in any given period t can be represented by the closed set: $T = (x, y) : x$ can produce $y \in \Re^{n+m}_+$ while as a set of input we define:$L(y) = \{x \in \Re^n_+ : (x, y) \in \mathrm{T}\}$. However, the input-oriented efficiency regarding T can be measured with reference to the input set through the direct input distance function: $D_I(x, y) = \sup\{\theta > 0 : \frac{x}{\theta} \in L(y)\}$. Therefore, the efficiency for the i-th DMU (x, y) in each of the European countries examined is defined as in Equation 3.1.

$$E\hat{f}f_i(x, y) = \min\left\{\theta \mid \theta > 0, y_i \leq \sum_{i=1}^{n} \gamma_i y_i; \theta_x \geq \sum_{i=1}^{n} \gamma_i x_i\right\} \tag{3.1}$$

for γ_i such that $\sum_{l=1}^{n} \gamma_l = 1; \gamma_i \geq 0, i = 1, 2, \ldots, n$

An input-oriented approach, as opposed to an output-oriented approach, the application of DEA allows us to reduce inputs and more specifically in the case of energy use, as much as possible for a given output level to calculate the TFEE (Total) index. Energy Efficiency Factor). According to the energy efficiency of Hu and Wang (2006) of a country K at time t can be calculated using the following formula:

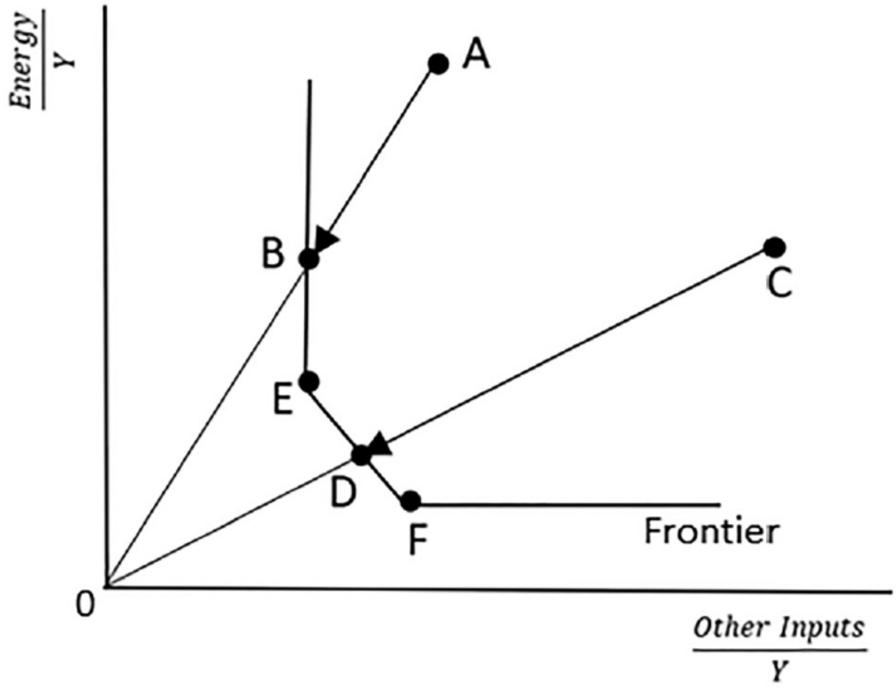
$$\text{TFEE}_{it} = \frac{\text{Target Energy Input}_{it}}{\text{Actual Energy lnput}_{it}} = \frac{\text{Actual Energy lnput}_{it} - \text{Total Adjustments}_{it}}{\text{Actual Energy lnput}_{it}}$$

or

$$\text{TFEE}_{it} = 1 - \frac{\text{Radial Adjustment}_{it} + \text{Energy Input Slacks}_{it}}{\text{Actual Energy input}_{it}} \tag{3.2}$$

where i = 1, 2, ..., I refer to each DMU - country, t = 1, 2, ..., T refers to the time period and K = 1, 2, ... Figure 3 shows a graphical representation of the TFEE which further discusses the theoretical foundations. The amount of total settings is broken down into SAs that are broken down into AB + BE (radial adjustment and amount of loose for energy input respectively) distances for a given output level. Thus, the difference between actual (OA) and total adjustment represents a practical minimum energy inflow level for a given country at a given time t for efficiency with optimal energy consumption efficiency. According to Hu and Wang in 2006, Honma and Hu in 2008 and Zhang et al. in 2011, the TFEE is between zero and unity, and the higher the TFEE value, the more energy is consumed.

Figure 3: Efficiency measurement in an input-oriented model



However, if CO_2 emissions have been included in the production process, we employ a vector of f inputs x, $x \in \Re_+^n$, in order to produce to produce a vector of desirable output y, $y^* \in \Re_+^m$ and an undesirable output b, $y^* \in \Re_+^q$. In this case, the production set in which a unit can produce good and bad outputs using x inputs is defined as: $T^b = (x, y, b) : x$ can produce $(y, b) \in \Re_+^{n+m+q}$.The directional distance function allows the simultaneous existence of good and bad outputs in the production context (Chambers et al., 1998; Färe et al., 2005).

The set of T^b technology, as argued by Shephard (1970), holds a number of axioms. These axioms include: The technology set is closed, curved and demarcated (Chambers et al., 1998), inertia is allowed, "free lunch" is not allowed (Kumar, 2006), good outputs are exposed to strong consumables, good and bad outputs share a "zero connection" and unwanted outputs are involved with poorly discarded use when there are environmental regulations. Therefore, the distance direction function is defined as:

$$\overrightarrow{D_T}(x, y, b; d) = \max\left\{\beta : \left(y + \beta d^y, b - \beta d^b\right) \in P(x - \beta d^x)\right\} \tag{3.3}$$

where $d = (-d^x, d^y, -d^b)$ is a direction carrier that seeks the maximum possible expansion of the desired outputs in the d^y direction and the maximum possible contraction of inputs and unwanted outputs in the d^x and d^b directions respectively. Due to the fact that we wanted to assume that a country is aiming for an increase in the production of good expenditures and a reduction in bad expenditures/inputs at the same time, we used the directional vector d(–1,1,–1). It is important to note that the TFEE follows the same logic as before for its calculation in the DDF approach.

3.4 Environmental efficiency and technology gap

According to the hypothesis of Camarero et al. in 2008 and Kumar and Khanna in 2009 that the distance direction function is separable in both good and bad outputs, we can define the environmental efficiency (EE_F) in relation to each limit taking into account the case where the whole technology has been limited to production only good outputs such as:

$$\mathrm{EE}_F = \frac{\left(1 + \overrightarrow{D_T}\left(x, y, b; g_y g_b\right)\right)}{\left(1 + \overrightarrow{D_T}\left(x, y, b; g_y\right)\right)} \tag{3.4}$$

The environmental efficiency index (EE_F) aims to capture the contraction in increasing outputs by each country, under the potential ability of the production process convention from free disposability to costly disposal of CO_2, taking values between zero and one. More specifically, for a country with environmental efficiency (EE_F)score one, the cost of transforming their production from strong disposability to weak for CO_2 should be zero. On the other hand, EE values lower than zero denotes a significant opportunity cost for this transformation according to Kumar and Khanna, 2009. Furthermore, environmental efficiency has been defined as the ratio of two distances assuming strong and weak disposability of CO_2 emissions. Zaim and Taskin in 2000 said that since the frontier as constructed assuming weak disposability of pollutants envelops the data more closely than the frontier constructed using strong disposability the ratio of these two distances leads to values very close or equal to one.

Chapter 4

Data and Variables

We devise a unique data set by coordinating, mapping, and harmonizing many additional publicly available official sources, including twenty-seven countries of the European Union for a period of eighteen years, from 2000 to 2017. In more detail, not only the dataset includes data for 78 variables obtained mainly from the Eurostat database but also from the Penn World Table version 9.1 database of the University of Groningen. In addition, our total number of observations is 486.

In order to arrive at this dataset, it was first necessary to process and manipulate our data. Within the original dataset, there were other countries for which unfortunately we did not have enough data. In other words, they had high percentages of missing values. We, therefore, considered it right not to include them in our analysis because our results would not be so objective. The same happens for the time period we are examining. Unfortunately here too, there is not enough data before 2000 and after 2017 so we limited ourselves to this time period. Of course, all this was done because the DEA method we followed, can not work with missing values.

We obtain annual data concerning five variables namely GDP (Y), CO_2 emissions (CO_2), capital stock (K), total labor force (L) and finally countries' energy consumption (E). On the output side we used GDP and CO_2 emissions as a rather adequate measure of desirable and undesirable outputs (Chiu et al., 2012; Yu-Ying Lin et al., 2013) respectively. On the other hand, and on the input side capital stock, total labor force and countries' energy consumption were used. Data were collected by combining several distinct databases. Data for GDP, total labor force and energy consumption and CO_2 emissions were obtained from the database of Eurostat while the Penn World Table version 9.1 database from the University of Groningen was used to collect data on capital stock.

More specifically, the Gross Domestic Product (GDP) of each country is measured at current prices, million Euros. The capital stock (K) is measured in current PPPs (in mil. 2011 US $), the labour proxied by the number of persons engaged (measured in thousands.), and the energy captured by the energy use (measured in thousand tonnes of oil equivalent (TOE)).

Last but not least, for the CO_2 emmisions, the indicator measures total national emissions of the so called 'Kyoto basket' of greenhouse gases, including carbon dioxide (CO_2), methane (CH4), nitrous oxide (N2O), and the so-called F-gases (hydrofluorocarbons, perfluorocarbons, nitrogen triflouride (NF3) and sulphur hexafluoride (SF6)). Using each gas' individual global warming potential (GWP), they are being integrated into a single indicator expressed in units of CO_2 equivalents.

Emissions data are submitted annually by the EU Member States as part of the reporting under the United Nations Framework Convention on Climate Change (UNFCCC). The average population of the reference year (calculated as the arithmetic mean of the population on 1st January of two consecutive years) is used as denominator (per capita). The indicator does not include emissions and removals related to land use, land use change and forestry (LULUCF); it does not include emissions reported as a memorandum item according to UNFCCC Guidelines but does include emissions from international aviation as well as indirect CO_2 emissions. All of the above are summarized in Table 1.

Table 1. *Description of Variables briefly*

Variable	Units of measurement
Gross Domestic Product (GDP)	millions Euro
Capital (K)	Current PPPs (in mil. 2011 US $)
Labour (L)	Number of persons engaged in thousands.
Energy consumption (E)	Thousand tonnes of oil equivalent (TOE)
Carbon Dioxide Emissions (CO_2)	Greenhouse gas emissions per capita

A more extensive review of the distribution of inputs and outputs indicates fluctuations between and within the countries. Table 2 and Table 3 represent descriptive statistics of inputs and outputs and the corresponding percentile ranks. The estimated means of each country over the examined period are also displayed in Table A.2, in Appendix A.3 correspondingly. In addition, the estimated growth of each country over the examined period are also displayed in Table A.3, in Appendix A.3 correspondingly.

Table 2. *Descriptive Statistics of Inputs and Outputs (27 Countries, 2000-2017)*

Variable	Observations	Mean	Std. Dev.	Min	Max
GDP	486	470890.4	703927.2	4394.9	3244990
Capital	486	2655384	4018597	20216.83	1.90E+07
Employment	486	8157.239	10540	146.4	44248
Energy	486	65441.21	86406.51	1467.056	359623.6
CO_2 **Emissions**	486	10.56749	4.128679	4.5	30.8

Source: All data retrieved from Eurostat and Penn World Table version 9.1 databases

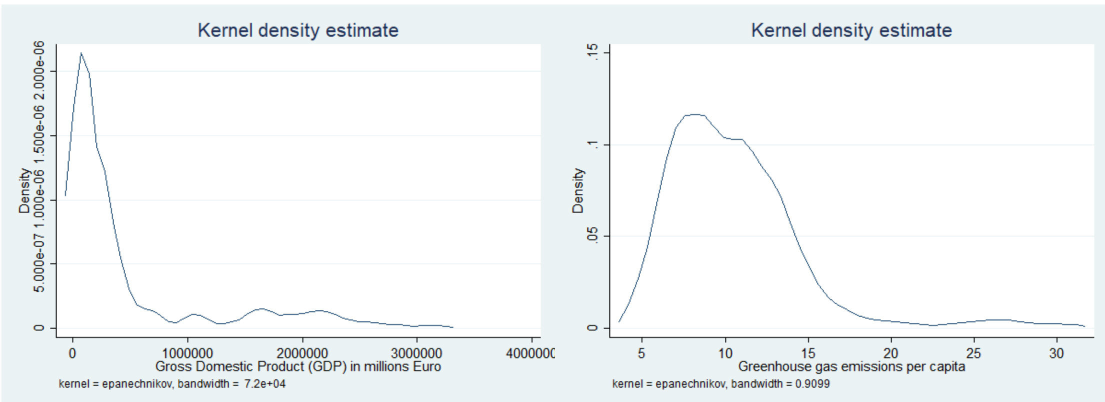
Table 3. *Percentiles of Inputs and Outputs (27 countries, 2000-2017)*

	GDP	Capital	Labour	Energy	Carbon Dioxide Emissions (CO_2)
10%	16826.8	113431.5	406.12	4369.008	6.4
25%	37178.9	282571.3	1416.26	9124.381	7.7
50%	184519.7	1082652	3962.1	28138.01	10
75%	411163.2	2365540	8855	89606.29	12.4
90%	1737000	9471101	26321	201320.8	14.4

Source: All data retrieved from Eurostat and Penn World Table version 9.1 databases

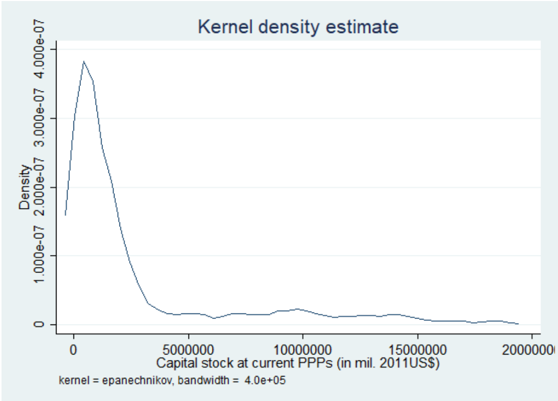
As it is observed both inputs and outputs define asymmetric distributions through the whole sample and specifically the outliers appeared form positive-skew distributions, which can be demonstrated in Figure 4 and Figure 5, which illustrate the estimated kernel densities of the variables.

More specifically, as we can see from the Figure 4 below, the Kernel density estimate of the Gross Domestic Product (GDP) consists of a peak as opposed to Greenhouse gas emissions which consist of two. Respectively, as for the inputs we see that they have single peaks too.

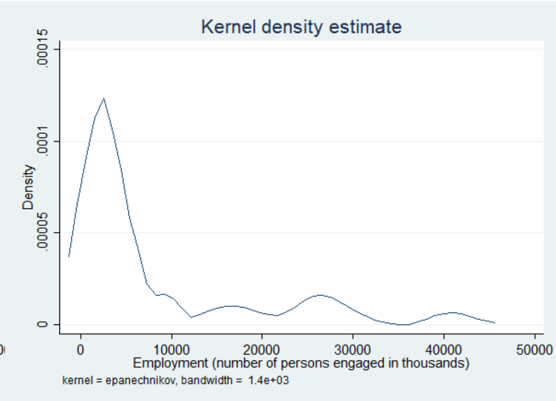


(a) **(b)**

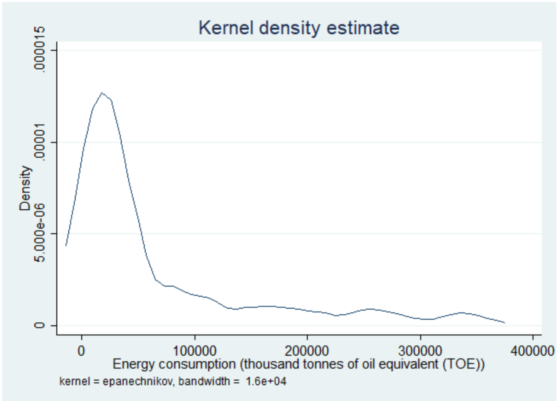
Figure 4: Kernel density of desirable and undesirable outputs produced (27 countries, 2000-2017)



(a)



(b)



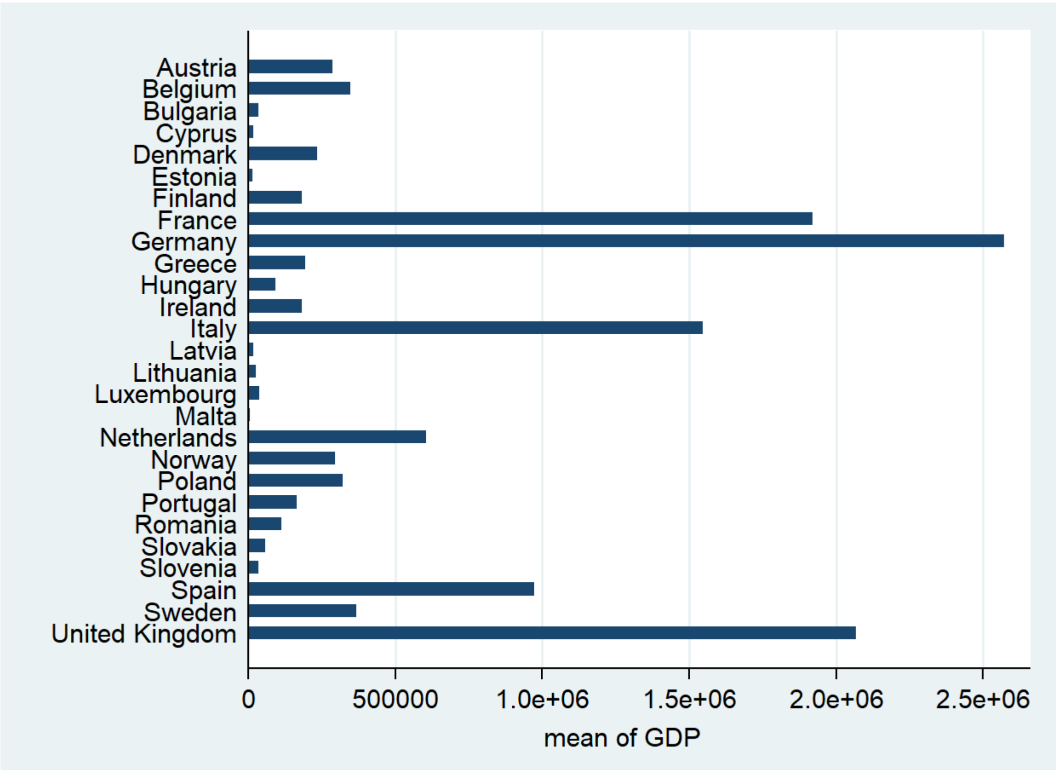
(c)

Figure 5: Kernel density of inputs (27 countries, 2000-2017)

Finally, the Figure 6, Figure 7, Figure 8, Figure 9 and Figure 10 below show us an overview of where each country is in relation to the rest of the variables we have used in our analysis taking data from Table A.2, in Appendix A.3 correspondingly. In terms of GDP, Malta has the lowest average price and Germany has the highest. On average, Estonia has the smallest capital, while Germany has the largest. In terms of the labor force, here again, Germany is first in employment, while the lowest labor force size is held by Malta. Also, for energy consumption, Malta consumes the least energy on average, while the largest consumer is, of course, Germany. Finally, in terms of the level of environmental pollution, Luxembourg appears to emit the most carbon dioxide emissions as opposed to Latvia, which emits the least amount of pollutants.

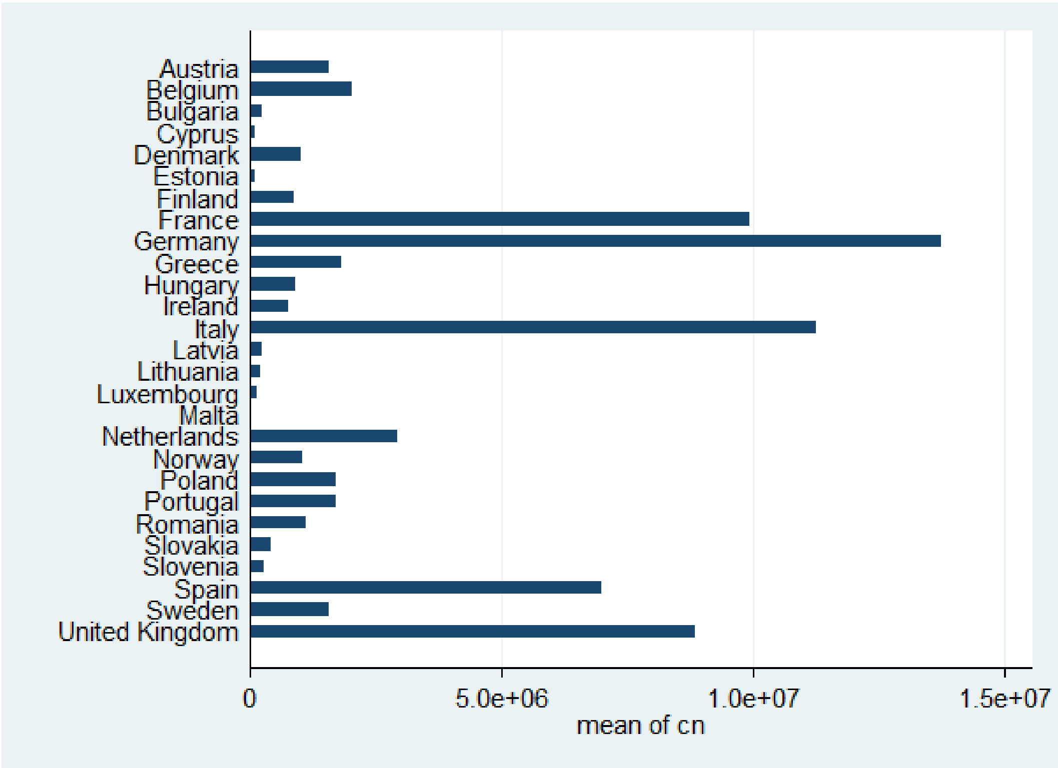
Average Gross Domestic Product (GDP) was formed at 470 trillion throughout the sample, with the highest output levels in Germany, the United Kingdom, France, and Italy. Specifically, the level of production was set at 2.57 trillion in Germany, 2.07 trillion in the United Kingdom, 1.92 trillion in France, and 1.55 trillion in Italy. In contrast, countries such as Bulgaria, Lithuania, Latvia, Cyprus, Estonia, Malta recorded the lowest level of productivity. More specifically, Bulgaria 33.2 billion, Lithuania 27.3 billion, Latvia 18.3 billion, Cyprus 16.5 billion, Estonia 14.8 billion while the latter is Malta with 6.6 billion. Gross Domestic Product stood at less than 37.17 billion, accounting for 25% of observations and less than 411 billion versus 75%.

Figure 6: Mean of GDP per country for all the years



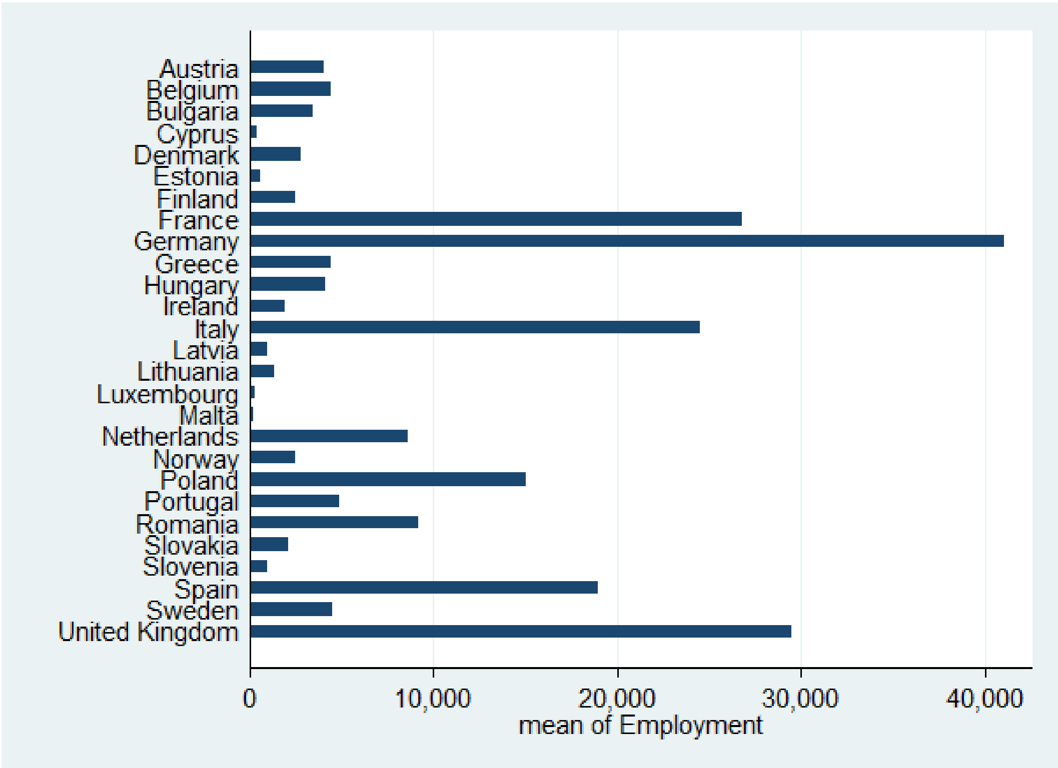
In terms of capital, the average price was 2.6 trillion. The highest prices appeared in countries such as Germany with 13.7 trillion, Italy with 11.2 trillion, France with 9.9 trillion, the United Kingdom with 8.8 trillion, and Spain with 6.9 trillion. On the other hand, the countries with the lowest prices were Lithuania with 21 billion, Luxembourg with 14 billion, Cyprus with 12 billion, Estonia with 11 billion, and Malta with 3.4 billion. Capital prices were below 282 trillion and under 2.3 quadrillion, about 25% and 75% of observations respectively.

Figure 7: Mean of Capital per country for all the years



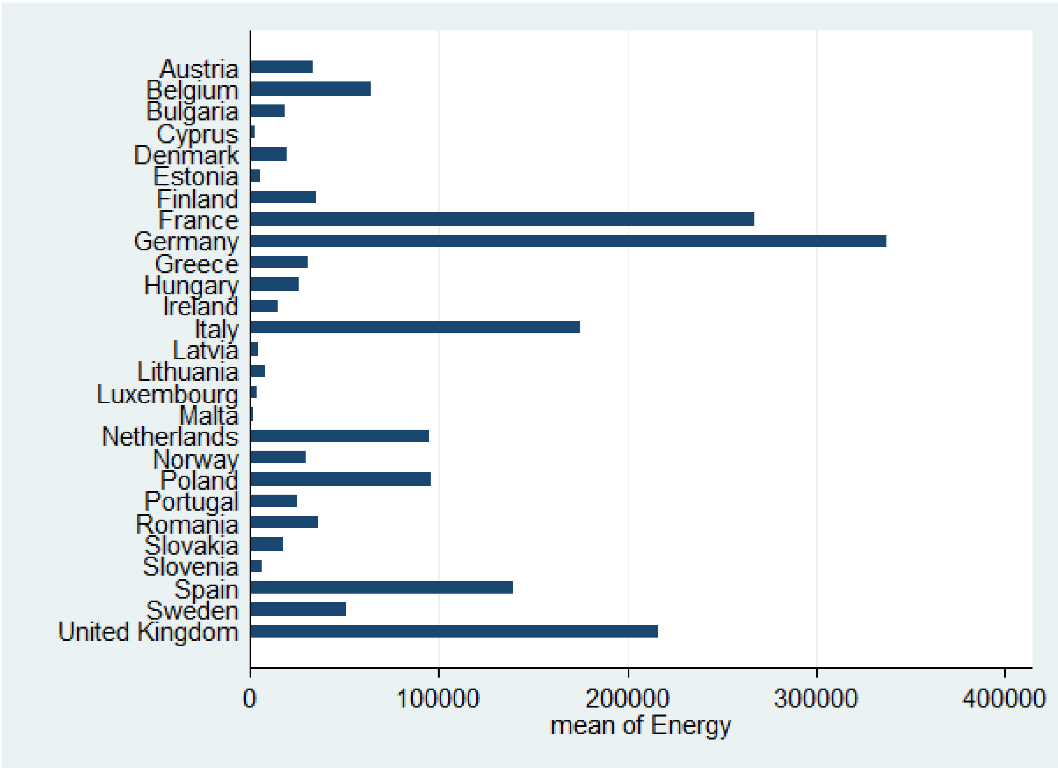
Also, the average price of employment was 8157,239 in thousands of square meters. The highest prices appeared in countries such as Germany with 41095.61, the United Kingdom with 29457.21, France with 26785.67, Italy with 24539.4, and Spain with 18918.17. On the other hand, the countries with the lowest prices in employment were Lithuania with 1359,807, Slovenia with 948,468, Latvia with 930,304, Estonia with 605.55, Cyprus with 372,096, Luxembourg with 346,315 and Malta with 167. Employment prices were below 406.12 per thousand and below 855 per thousand, about 25 % and 75 % of the observations respectively.

Figure 8: Mean of Labour per country for all the years



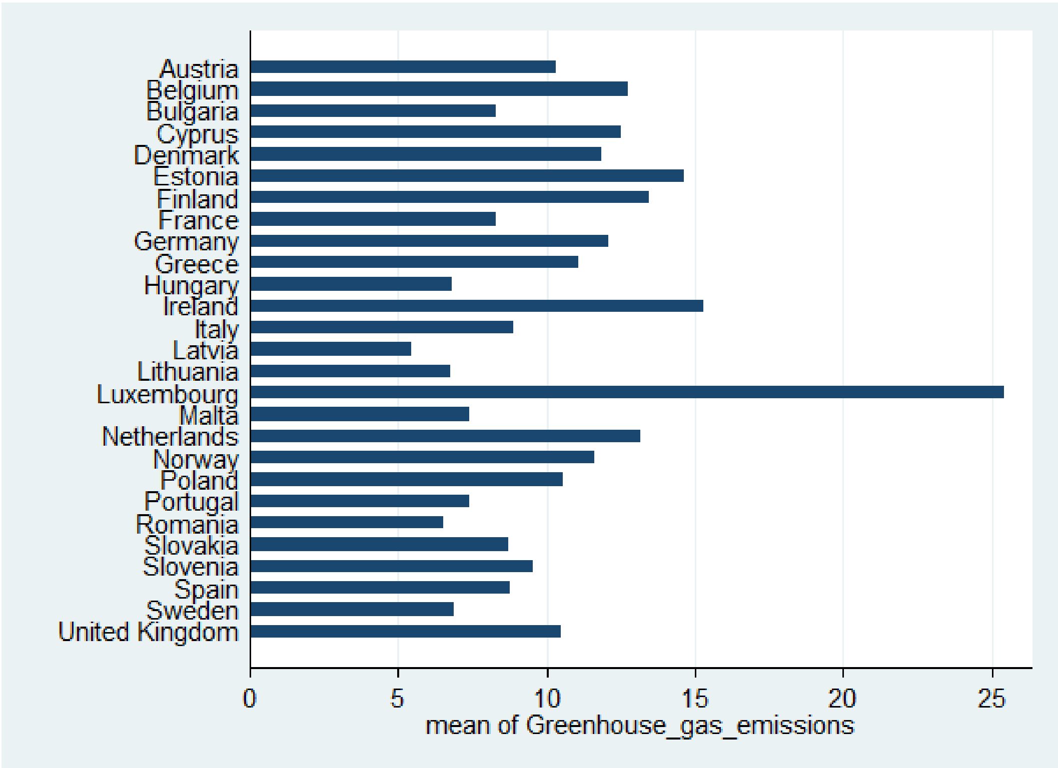
Last but not least, from the side of inputs, the average price of energy consumption was 65441.21 thousand tonnes of oil equivalent. The highest prices appeared in countries such as Germany with 338.000 thousand tonnes of oil equivalent, France with 268000 thousand tonnes of oil equivalent, the United Kingdom with 216000 thousand tonnes of oil equivalent, Italy with 175000 thousand tonnes of oil equivalent and Spain with 139000 thousand tonnes of oil equivalent. On the other hand, the countries with the lowest prices in energy consumption were Lithuania with 8312.932 thousand tonnes of oil equivalent, Slovenia with 7020.15 thousand tonnes of oil equivalent, Estonia with 5640.889 thousand tonnes of oil equivalent, Latvia with 5640,889 thousand tonnes of oil equivalent, Luxembourg with 4366,065 thousand tonnes of oil equivalent, Cyprus with 2772.44 thousand tonnes of oil equivalent and Malta with 2005.8 thousand tonnes of oil equivalent. Employment prices were below 4369,008 thousand tonnes of oil equivalent and below 9606.29 thousand tonnes of oil equivalent, about 25 % and 75 % of observations respectively.

Figure 9: Mean of Energy per country for all the years



Taking into account the undesirable output, fluctuations also occur in the distribution of carbon dioxide emissions, while the average level of emissions was about 10.56 metric tons. The lowest average emissions during the period considered appeared in Malta, Portugal, Sweden, Hungary, Lithuania, Romania, and Latvia, while Luxembourg, Ireland, Estonia, Finland, the Netherlands, and Belgium presented the higher average emissions. Carbon dioxide emissions were below 6.4 and 12.4 metric tons, about 25% and 75% of observations, respectively.

Figure 10: Mean of CO_2 Emissions per country for all the years



Chapter 5

Economic Analysis

5.1 Productive Performance

In this section, we will present the process by which we can perform non-parametric efficiency analysis by applying the Data Envelopment Analysis (DEA) methodology using the software R. The application that will be presented below, concerns real data for 27 countries of the European Union for each year from 2000 to 2017, the technical effectiveness of which we are going to assess through the methodology Data Envelopment Analysis.

From Economic Theory and specifically Producer Theory, we know that the (basic) factors of production are capital, labor, and energy which are combined through the production technology of each country and produce a product, which in the case of countries can be measured through Gross Domestic Product (GDP). However, we go one step further. With the DDF method we take into account that economies as a product not only have what is desired is GDP but also produce an undesirable that is none other than CO_2 emissions In order to estimate the "European" available production technology, ie the European production function, in order to be able to determine the level of technical efficiency of each country separately, we need to collect data on the inputs used by each country as well as the output generated through specialized databases.

In the following sections, the efficiency for the case of input contraction orientation is evaluated, in other words, how much the use of inputs could be reduced given the level of production (without reducing the product produced, ie GDP) and production technology. Below, we will present the estimates of the technical efficiency of our sample countries for variable returns to scale (VRS) scales for the case of input savings orientation using the DEA method and the DDF method. We even calculated both Energy Efficiency with both methods. Finally, we calculated the Environmental Efficiency

5.1.1 Productive Performance for 2000

The Table 4 shows the results as they emerged from our analysis for the year 2000. More specifically, countries such as Denmark, Germany, Ireland, Luxembourg, Malta, Norway, United Kingdom using the DEA method seem to be fully effective for both Resource Efficiency as well as for energy efficiency. Countries such as Sweden, Belgium, the Netherlands, Spain, Greece using the DEA method do not seem to be technically effective. More specifically, Sweden is technically inefficient by 11% while in energy efficiency it is inefficient by 10%. Belgium, respectively, is 17% technically inefficient and 28% inefficient in terms of energy efficiency. At the same wavelength is the Netherlands with 20% and 14% inefficient respectively. But as far as Spain and Greece are concerned, things are changing a bit here. While they are technically inefficient with 36% and 46% respectively, in terms of energy efficiency they are 100% efficient. Probably because they use renewable energy sources taking advantage of their climate and geographical location. Finally, countries such as Hungary, Slovakia, and Romania are the most technically inefficient. Hungary is 67% inefficient while its energy efficiency reaches 96%, Slovakia is 73% inefficient while its energy efficiency reaches 94% while Romania with 75% and 91% respectively.

As for the DDF method, here we have two directions, direction -1, countries are essentially trying to reduce as much as possible the production of the unwanted product, ie CO_2 emissions and direction 0, which you basically just accept that they produce an unwanted product. More specifically, countries such as Denmark, Germany, Ireland, Luxembourg, Malta, Norway, and the United Kingdom that use the DDF method appear to fully resource-efficient and energy-efficient. In contrast, countries such as Finland, Slovenia and Estonia e.g. are technically ineffective. More specifically, Finland is far from fully efficient 595.80, while Slovenia and Estonia 654.21 and 424.99 respectively, while their energy efficiency is 60%, 66%, and 44% respectively. Finally, countries such as Poland, Latvia, and Lithuania are technically inadequate and energy inadequate. Poland is technically inefficient as it is far from the fully efficient 12000.09 and is 45% energy efficient, Latvia is far from the fully efficient 746.08 and is 72% energy efficient, and finally, Lithuania is far from the fully efficient 1194,29 and is 50% energy efficiency.

For the year 2000, most countries appear to be environmentally efficient except for a few such as Belgium which is 16% inefficient, the Netherlands with 5% inefficiency, and Latvia with 4% inefficiency.

Table 4. *Productive Performance for 2000*

	DEA		Directional Distance Function				
Country	T.E. VRS	Energy Eff	Distance fuction (Direction -1)	Energy Eff (Direction -1)	Distance function (Direction 0)	Energy Eff (Direction 0)	Environmental Eff
Denmark	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Germany	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Ireland	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Luxembourg	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Malta	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Norway	1.00	1.00	0.00	1.00	0.00	1.00	1.00
United Kingdom	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Italy	0.92	1.00	4162.68	0.95	4162.68	0.95	1.00
Sweden	0.89	0.90	448.04	0.81	448.04	0.81	1.00
France	0.88	0.87	3052.48	0.76	3052.48	0.76	1.00
Austria	0.88	1.00	788.73	1.00	788.73	1.00	1.00
Cyprus	0.83	1.00	127.20	0.90	127.20	0.90	1.00
Belgium	0.83	0.72	677.18	0.56	570.46	0.55	0.84
Netherlands	0.80	0.86	1700.51	0.69	1622.52	0.68	0.95
Finland	0.75	0.83	595.80	0.60	595.80	0.60	1.00
Spain	0.64	1.00	7062.97	0.73	7062.97	0.73	1.00
Portugal	0.59	1.00	3403.81	0.85	3403.81	0.85	1.00
Greece	0.54	1.00	2502.14	0.74	2502.14	0.74	1.00
Slovenia	0.53	1.00	654.21	0.66	654.21	0.66	1.00
Bulgaria	0.52	0.63	3010.80	0.32	3010.80	0.32	1.00
Estonia	0.50	0.84	424.99	0.44	406.10	0.51	0.96
Latvia	0.50	1.00	746.08	0.72	746.08	0.72	1.00
Poland	0.46	0.81	12000.09	0.45	12000.09	0.45	1.00
Lithuania	0.39	0.94	1194.29	0.50	1194.29	0.50	1.00
Hungary	0.33	0.96	3452.34	0.46	3452.34	0.46	1.00
Slovakia	0.27	0.94	1747.44	0.31	1747.44	0.31	1.00
Romania	0.25	0.91	10157.88	0.48	10157.88	0.48	1.00

5.1.2 Productive Performance for 2006

The Table 5 below, shows the results for the year 2006. According to the DEA method, Germany, Ireland, Luxembourg, Malta, Norway, and the United Kingdom are not only technically efficient but also energy efficient. There are countries that are technically inefficient but at the same time energy-efficient. More specifically, Italy, Denmark, Cyprus, and Austria are technically inefficient by 13%, 9%, 14%, and 25% respectively. However, there are countries that are technically inefficient and energy inefficient. For example, Sweden is 16% technically inefficient and 17% energy inefficient, Poland 38%, and 33% inefficient respectively. However, it is impressive that countries such as Greece, Portugal, and Slovenia, while not technically efficient to a large extent, are instead fully energy-efficient countries. Greece is 44% technically efficient, Portugal 47% and Slovenia 49% respectively. Finally, Hungary is technically inefficient by 57% and energy-efficient by 94%. Respectively, Slovakia 59% and 89%, while Romania 61% and 87% respectively.

According to the DDF method, when the direction is -1, Germany, Ireland, Luxembourg, Malta, Norway, and the United Kingdom show energy efficiency of 1, however, in terms of technical failure, Germany 0, Ireland 0, Luxembourg 0, Malta 0, Norway 0 and United Kingdom 0 respectively. So they are fully effective. In addition, Cyprus is technically inefficient as it is far from fully efficient at 143.97 and is fully energy efficient. Finland is far from the fully efficient 943.71, so it is technically inefficient and 50% energy efficient. Finally, Bulgaria is 3310.59 and is 63% energy efficient. Latvia is far from fully efficient 797.47 and is 23% energy inefficient. But when the direction is 0 then Germany, Ireland, Luxembourg, Malta, Norway, and the United Kingdom show energy efficiency 1, however, in terms of technical inadequacy, Germany 0, Ireland 0, Luxembourg 0, Malta 0, Norway 0, and United Kingdom 0, respectively. Again, here, they are fully technically efficient. In addition, Cyprus is technically efficient as it is far from the fully efficient 143.97 and is fully energy efficient. Finland is 943.71 and is 50% energy efficient. Finally, Bulgaria is 3310.59 and is 63% energy efficient. Latvia is far from the fully efficient 797.47 and is 23% energy inefficient.

For the year 2006, most countries appear to be environmentally efficient except for a few such as Netherlands with 6% inefficiency and the Belgium with 11% inefficiency.

Table 5. *Productive Performance for 2006*

Country	DEA		Directional Distance Function				
	T.E. VRS	Energy Eff	Distance fuction (Direction -1)	Energy Eff (Direction -1)	Distance function (Direction 0)	Energy Eff (Direction 0)	Environmental Eff
Germany	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Ireland	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Luxembourg	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Malta	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Norway	1.00	1.00	0.00	1.00	0.00	1.00	1.00
United Kingdom	1.00	1.00	0.00	1.00	0.00	1.00	1.00
France	0.93	0.80	1907.08	0.73	1907.08	0.73	1.00
Denmark	0.91	1.00	659.76	1.00	659.76	1.00	1.00
Italy	0.87	1.00	4444.36	0.90	4444.36	0.90	1.00
Cyprus	0.86	1.00	143.97	1.00	143.97	1.00	1.00
Sweden	0.84	0.83	1168.09	0.69	1168.09	0.69	1.00
Netherlands	0.79	0.83	1725.11	0.64	1615.22	0.64	0.94
Austria	0.74	1.00	1600.11	0.84	1600.11	0.84	1.00
Finland	0.73	0.75	943.71	0.50	943.71	0.50	1.00
Belgium	0.72	0.79	1207.67	0.52	1070.59	0.53	0.89
Spain	0.69	1.00	7691.99	0.76	7691.99	0.76	1.00
Poland	0.62	0.67	11954.09	0.42	11954.09	0.42	1.00
Bulgaria	0.58	0.60	3310.59	0.37	3310.59	0.37	1.00
Greece	0.56	1.00	2808.94	0.75	2808.94	0.75	1.00
Estonia	0.56	0.91	438.40	0.57	438.40	0.57	1.00
Portugal	0.53	1.00	3574.53	0.81	3574.53	0.81	1.00
Latvia	0.53	1.00	797.47	0.77	797.47	0.77	1.00
Lithuania	0.52	0.87	1146.90	0.55	1146.90	0.55	1.00
Slovenia	0.51	1.00	634.90	0.70	634.90	0.70	1.00
Hungary	0.43	0.94	3308.26	0.50	3308.26	0.50	1.00
Slovakia	0.41	0.89	1697.18	0.42	1697.18	0.42	1.00
Romania	0.39	0.87	8417.70	0.50	8417.70	0.50	1.00

5.1.3 Productive Performance for 2012

Six years later, ie for the year 2012, the results are presented in Table 6 below. According to the DEA method, we observe a big surprise. Cyprus, where all previous years it was almost in the middle in terms of its efficiency both technically and energetically, suddenly here seems to be not only fully technically efficient but also energy efficient. Other countries such as Denmark, France, Germany, Luxembourg, Malta, Norway, and the United Kingdom are moving on the same wavelength, which means they are technically and energy-efficient. Countries such as Austria, which is technically inadequately 30%, Spain, which is 31% technically inefficient, Greece, which is 51% technically inefficient, and Romania, for example, which is 69% technically inefficient, are countries that seem to be fully energy efficient.

With the DDF method, when the direction is -1, Cyprus, Denmark, France, Germany, Luxembourg, Malta, Norway, and the United Kingdom are fully both technically efficient and energy-efficient. Finland is far from the fully efficient 1146.10 and is 51 % energy efficient. Lithuania is far from fully efficient 954.40 and has 64% energy efficiency respectively. Finally, Greece is far from the fully efficient 2765.65 and is 61% energy efficient, while Romania is 7646.74 and is 54% respectively. When the direction is 0 then Cyprus, Denmark, France, Germany, Luxembourg, Malta, Norway, and the United Kingdom are here again both technically efficient and energy-efficient. Finland is far from the fully efficient 1146.10 and is 51% energy efficient. Lithuania is 954.40 away and is 64% energy efficient respectively. Finally, Greece is far from the fully efficient 2765.65 and is 61% energy efficient, while Romania is 7646.74 and is 54% energy efficient respectively.

For the year 2012, most countries appear to be environmentally efficient except for a few such as Netherlands with 16% inefficiency and the Estonia with 8% inefficiency.

Table 6. *Productive Performance for 2012*

	DEA		Directional Distance Function				
Country	T.E. VRS	Energy Eff	Distance fuction (Direction -1)	Energy Eff (Direction -1)	Distance function (Direction 0)	Energy Eff (Direction 0)	Environmental Eff
Cyprus	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Denmark	1.00	1.00	0.00	1.00	0.00	1.00	1.00
France	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Germany	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Luxembourg	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Malta	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Norway	1.00	1.00	0.00	1.00	0.00	1.00	1.00
United Kingdom	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Ireland	0.95	1.00	391.00	1.00	391.00	1.00	1.00
Italy	0.93	1.00	3021.01	1.00	3021.01	1.00	1.00
Sweden	0.82	0.81	1500.86	0.69	1500.86	0.69	1.00
Netherlands	0.76	0.83	2451.40	0.73	2065.44	0.76	0.84
Austria	0.70	1.00	2053.91	0.78	2053.91	0.78	1.00
Spain	0.69	1.00	6331.23	0.92	6331.23	0.92	1.00
Poland	0.67	0.63	12756.67	0.44	12756.67	0.44	1.00
Finland	0.64	0.83	1164.10	0.49	1164.10	0.49	1.00
Latvia	0.61	1.00	608.73	0.78	608.73	0.78	1.00
Belgium	0.56	0.91	1988.96	0.51	1988.96	0.51	1.00
Portugal	0.56	1.00	3384.99	0.74	3384.99	0.74	1.00
Slovenia	0.56	1.00	599.58	0.66	599.58	0.66	1.00
Lithuania	0.52	1.00	954.40	0.64	954.40	0.64	1.00
Slovakia	0.51	0.91	1631.66	0.50	1631.66	0.50	1.00
Estonia	0.50	1.00	357.55	0.55	328.85	0.60	0.92
Greece	0.49	1.00	2765.96	0.61	2765.96	0.61	1.00
Bulgaria	0.48	0.77	3051.02	0.41	3051.02	0.41	1.00
Hungary	0.34	1.00	3228.72	0.48	3228.72	0.48	1.00
Romania	0.31	1.00	7646.73	0.54	7646.73	0.54	1.00

5.1.4 Productive Performance for 2017

Finally, for the last year, we are looking at it is for 2017. Table 7 below presents the results as they emerged. More specifically with the method of DEA, Cyprus, France, Germany, Ireland, Luxembourg, Malta, Norway, Sweden, and the United Kingdom are fully technically and energy-efficient. Countries such as Italy, Spain, Austria, and Greece, as well as other countries, are fully energy efficient. In terms of their technical efficiency, Italy is 10% inefficient, while Spain, Austria, and Greece are 27%, 30%, and 63% respectively. Bulgaria is 52% technically efficient and 24 % energy-inefficient while Romania is 57 % technically inefficient and 14%

energy efficient.

With the DDF method, when the direction is -1, Cyprus, France, Germany, Ireland, Luxembourg, Malta, Norway, Sweden, and the United Kingdom are fully technically efficient but also energy efficient. Belgium is far from fully efficient 791.62 and is 34% energy inefficient. Estonia is far from fully efficient at 359.79 and is 39% energy inefficient. Greece with the DEA method seemed to be fully energy efficient, now with the DDF method, it is 52% energy efficient and is far from the fully efficient 2814.47. When the direction is 0 then Cyprus, France, Germany, Ireland, Luxembourg, Malta, Norway, Sweden, and the United Kingdom are fully technically efficient but also energy efficient. Belgium is far from fully efficient 791.62 and is 34% energy inefficient. Estonia is 359.79 away and is 39% energy inefficient. Greece with the DEA method seemed to be fully energy efficient, now with the DDF method, it is 52% energy efficient and is far from the fully efficient 2814.47.

For the year 2017, most countries appear to be environmentally efficient except for a few such as Netherlands with 17% inefficiency, Belgium with 2% inefficiency and the Estonia with 26% inefficiency.

Table 7. *Productive Performance for 2017*

	DEA		Directional Distance Function				
Country	T.E. VRS	Energy Eff	Distance fuction (Direction -1)	Energy Eff (Direction -1)	Distance function (Direction 0)	Energy Eff (Direction 0)	Environmental Eff
Cyprus	1.00	1.00	0.00	1.00	0.00	1.00	1.00
France	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Germany	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Ireland	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Luxembourg	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Malta	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Norway	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Sweden	1.00	1.00	0.00	1.00	0.00	1.00	1.00
United Kingdom	1.00	1.00	0.00	1.00	0.00	1.00	1.00
Netherlands	0.91	0.76	1269.22	0.82	1058.57	0.75	0.83
Italy	0.90	1.00	3093.03	1.00	3093.03	1.00	1.00
Finland	0.89	0.45	918.85	0.37	918.85	0.37	1.00
Denmark	0.85	0.93	805.66	0.83	805.66	0.83	1.00
Poland	0.85	0.63	11940.40	0.54	11902.72	0.52	1.00
Belgium	0.83	0.81	791.62	0.66	776.99	0.64	0.98
Spain	0.73	1.00	6112.11	0.96	6112.11	0.96	1.00
Austria	0.70	1.00	1428.27	0.99	1428.27	0.99	1.00
Latvia	0.64	1.00	589.25	0.83	589.25	0.83	1.00
Estonia	0.54	1.00	359.79	0.61	266.83	0.69	0.74
Slovenia	0.54	1.00	617.69	0.65	617.69	0.65	1.00
Lithuania	0.51	0.98	991.80	0.62	991.80	0.62	1.00
Slovakia	0.50	0.82	1729.94	0.43	1729.94	0.43	1.00
Bulgaria	0.48	0.74	3099.13	0.39	3099.13	0.39	1.00
Romania	0.43	0.86	7214.48	0.52	7214.48	0.52	1.00
Portugal	0.41	1.00	3355.15	0.55	3355.15	0.55	1.00
Hungary	0.37	0.90	3610.72	0.42	3610.72	0.42	1.00
Greece	0.37	1.00	2814.47	0.48	2814.47	0.48	1.00

5.2 The Wilcoxon Signed Rank Test

The Wilcoxon Signed Rank Test is the non-parametric version of the paired t-test. It is used to test whether or not there is a significant difference between two population means when the distribution of the differences between the two samples cannot be assumed to be normal.

In this case, we will use this test for four factors - variables. More specifically we will use Energy efficiency with DEA Method (DEA_Energ_Eff), Energy efficiency with Direction Distance Function with negative direction (DDF_En_Eff_neg) and with zero direction (DDF_En_Eff_zero), and last but not least the Environmental Efficiency (DDF_Env_Eff). To carry out the above checks, we will examine each year in relation to the previous one to see what changes there were.

5.2.1 The Wilcoxon Signed Rank Test for Energy efficiency with DEA Method

To begin with the DEA_Energ_Eff variable, according to the test results, from 2000 to 2001, it seems that 6 countries achieved better results than the previous year, 6 countries had worse scores, while 15 countries remained stable. The test revealed that there was not a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -0.371, p = 0.7105). These results indicate that there is not a significant effect on the DEA_Energ_Eff. On the other hand, from 2001 to 2002, it appears that 10 countries achieved better results than the previous year, 2 countries had worse scores, while 15 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 2.439, p = 0.0147). These results indicate that there is a significant effect on the DEA_Energ_Eff.

In addition, from 2002 to 2003, it appears that 6 countries achieved better results than the previous year, 6 countries had worse scores, while 15 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 0.080, p = 0.9366). These results indicate that there is not a significant effect on the DEA_Energ_Eff. Furthermore, from 2003 to 2004, it appears that 10 countries achieved better results than the previous year, 2 countries had worse scores, while 15 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 2.439, p = 0.0147). These results indicate that there is a significant effect on the DEA_Energ_Eff.

However, from 2004 to 2005, it appears that 8 countries achieved better results than the previous year, 4 countries had worse scores, while 15 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 1.008, p = 0.3137). These results indicate that there is not a significant effect on the DEA_Energ_Eff. Also, from 2005 to 2006, it appears that 3 countries achieved better results than the previous year, 9 countries had worse scores, while 15 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -1.458, p = 0.1448). These results indicate that there is not a significant effect on the DEA_Energ_Eff.

From 2006 to 2007, it appears that 6 countries achieved better results than the previous year, 6 countries had worse scores, while 15 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -0.159, p = 0.8736). These results indicate that there is not a significant effect on the DEA_Energ_Eff. Furthermore, from 2007 to 2008, it appears that 1 countries achieved better results than the previous year, 11 countries had worse scores, while 15 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -2.996, p = 0.0027). These results indicate that there is a significant effect on the DEA_Energ_Eff.

From 2008 to 2009, it appears that 4 countries achieved better results than the previous year, 6 countries had worse scores, while 17 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -0.544, p = 0.5866). These results indicate that there is not a significant effect on the DEA_Energ_Eff. Thus, from 2009 to 2010, it appears that 4 countries achieved better results than the previous year, 4 countries had worse scores, while 19 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 0.030, p = 0.9761). These results indicate that there is not a significant effect on the DEA_Energ_Eff.

From 2010 to 2011, it appears that 5 countries achieved better results than the previous year, 2 countries had worse scores, while 20 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 1.193, p = 0.2330). These results indicate that there is not a significant effect on the DEA_Energ_Eff. Furthermore, from 2011 to 2012, it appears that 2 countries achieved better results than the previous year, 6 countries had worse scores, while 19 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -1.497, p = 0.1343). These results indicate that there is not a significant effect on the DEA_Energ_Eff.

From 2012 to 2013, it appears that 3 countries achieved better results than the previous year, 5 countries had worse scores, while 19 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -0.809, p = 0.4188). These results indicate that there is not a significant effect on the DEA_Energ_Eff. Moreover, from 2013 to 2014, it appears that 7 countries achieved better results than the previous year, 2 countries had worse scores, while 18 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 1.743, p = 0.0814). These results indicate that there is not a significant effect on the DEA_Energ_Eff.

From 2014 to 2015, it appears that 10 countries achieved better results than the previous year, 3 countries had worse scores, while 14 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 2.197, p = 0.0280). These results indicate that there is a significant effect on the DEA_Energ_Eff. Furthermore, from 2015 to 2016, it appears that 5 countries achieved better results than the previous year, 8 countries had worse scores, while 14 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = -0.689, p = 0.4907). These results indicate that there is not a significant effect on the DEA_Energ_Eff.

From 2016 to 2017, it appears that 7 countries achieved better results than the previous year, 4 countries had worse scores, while 14 countries remained stable. The test revealed that there was a statistically significant difference in mean DEA_Energ_Eff between the two groups (z = 0.814, p = 0.4157). These results indicate that there is not a significant effect on the DEA_Energ_Eff.

5.2.2 The Wilcoxon Signed Rank Test for Energy efficiency with Direction Distance Function with negative direction

Continuing with the DDF_En_Eff_neg variable, according to the test results, from 2000 to 2001, it seems that 6 countries achieved better results than the previous year, 16 countries had worse scores, while 5 countries remained stable. The test revealed that there was not a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = -2.159, p = 0.0309). These results indicate that there is a significant effect on the DDF_En_Eff_neg. In addition, from 2001 to 2002, it appears that 15 countries achieved better results than the previous year, 9 countries had worse scores, while 3 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = 1.972, p = 0.0486). These results indicate that there is a significant effect on the DDF_En_Eff_neg.

From 2002 to 2003, it appears that 2 countries achieved better results than the previous year, 22 countries had worse scores, while 3 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = -4.136, p = 0.0000). These results indicate that there is a significant effect on the DDF_En_Eff_neg. Furthermore, from 2003 to 2004, it appears that 14 countries achieved better results than the previous year, 10 countries had worse scores, while 3 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups ($z = 0.625$, $p = 0.5318$). These results indicate that there is not a significant effect on the DDF_En_Eff_neg.

From 2004 to 2005, it appears that 15 countries achieved better results than the previous year, 8 countries had worse scores, while 4 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups ($z = 2.071$, $p = 0.0384$). These results indicate that there is a significant effect on the DDF_En_Eff_neg. Also, from 2005 to 2006, it appears that 14 countries achieved better results than the previous year, 9 countries had worse scores, while 4 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups ($z = 1.348$, $p = 0.1776$). These results indicate that there is not a significant effect on the DDF_En_Eff_neg.

From 2006 to 2007, it appears that 9 countries achieved better results than the previous year, 16 countries had worse scores, while 2 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups ($z = -1.430$, $p = 0.1527$). These results indicate that there is not a significant effect on the DDF_En_Eff_neg. Thus, from 2007 to 2008, it appears that 3 countries achieved better results than the previous year, 20 countries had worse scores, while 4 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups ($z = -3.901$, $p = 0.0001$). These results indicate that there is not a significant effect on the DDF_En_Eff_neg.

From 2008 to 2009, it appears that 4 countries achieved better results than the previous year, 16 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups ($z = -2.815$, $p = 0.0049$). These results indicate that there is a significant effect on the DDF_En_Eff_neg. Furthermore, from 2009 to 2010, it appears that 17 countries achieved better results than the previous year, 3 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = 3.082, p = 0.0021). These results indicate that there is a significant effect on the DDF_En_Eff_neg.

From 2010 to 2011, it appears that 18 countries achieved better results than the previous year, 3 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = 3.446, p = 0.0006). These results indicate that there is a significant effect on the DDF_En_Eff_neg. In addition, from 2011 to 2012, it appears that 17 countries achieved better results than the previous year, 4 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = 3.301, p = 0.0010). These results indicate that there is a significant effect on the DDF_En_Eff_neg.

From 2012 to 2013, it appears that 4 countries achieved better results than the previous year, 16 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = -2.791, p = 0.0053). These results indicate that there is a significant effect on the DDF_En_Eff_neg. Furthermore, from 2013 to 2014, it appears that 13 countries achieved better results than the previous year, 7 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = 1.796, p = 0.0725). These results indicate that there is not a significant effect on the DDF_En_Eff_neg.

From 2014 to 2015, it appears that 14 countries achieved better results than the previous year, 8 countries had worse scores, while 5 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = 2.086, p = 0.0369). These results indicate that there is a significant effect on the DDF_En_Eff_neg. Moreover, from 2015 to 2016, it appears that 7 countries achieved better results than the previous year, 17 countries had worse scores, while 3 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = -2.669, p = 0.0076). These results indicate that there is a significant effect on the DDF_En_Eff_neg.

From 2016 to 2017, it appears that 11 countries achieved better results than the previous year, 10 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_neg between the two groups (z = 0.738, p = 0.4607). These results indicate that there is not a significant effect on the DDF_En_Eff_neg.

5.2.3 The Wilcoxon Signed Rank Test for Energy efficiency with Direction Distance Function with zero direction

Continuing with the DDF_En_Eff_zero variable, according to the test results, from 2000 to 2001, it seems that 7 countries achieved better results than the previous year, 15 countries had worse scores, while 5 countries remained stable. The test revealed that there was not a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = -1.990, p = 0.0466). These results indicate that there is a significant effect on the DDF_En_Eff_zero. In addition, from 2001 to 2002, it appears that 14 countries achieved better results than the previous year, 9 countries had worse scores, while 4 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 1.974, p = 0.0483). These results indicate that there is a significant effect on the DDF_En_Eff_zero.

From 2002 to 2003, it appears that 4 countries achieved better results than the previous year, 20 countries had worse scores, while 3 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = -3.848, p = 0.0001). These results indicate that there is a significant effect on the DDF_En_Eff_zero. However, from 2003 to 2004, it appears that 13 countries achieved better results than the previous year, 12 countries had worse scores, while 2 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 0.373, p = 0.7095). These results indicate that there is not a significant effect on the DDF_En_Eff_zero.

From 2004 to 2005, it appears that 14 countries achieved better results than the previous year, 8 countries had worse scores, while 5 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 1.966, p = 0.0493). These results indicate that there is a significant effect on the DDF_En_Eff_zero. Furthermore, from 2005 to 2006, it appears that 14 countries achieved better results than the previous year, 9 countries had worse scores, while 4 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 1.445, p = 0.1486). These results indicate that there is not a significant effect on the DDF_En_Eff_zero.

From 2006 to 2007, it appears that 6 countries achieved better results than the previous year, 16 countries had worse scores, while 5 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = -1.966, p = 0.0493). These results indicate that there is a significant effect on the DDF_En_Eff_zero. Also, from 2007 to 2008, it appears that 5 countries achieved better results than the previous year, 18 countries had worse scores, while 4 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = -3.539, p = 0.0004). These results indicate that there is a significant effect on the DDF_En_Eff_zero.

From 2008 to 2009, it appears that 4 countries achieved better results than the previous year, 17 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = -2.914, p = 0.0036). These results indicate that there is a significant effect on the DDF_En_Eff_zero. Furthermore, from 2009 to 2010, it appears that 15 countries achieved better results than the previous year, 4 countries had worse scores, while 8 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 2.585, p = 0.0097). These results indicate that there is a significant effect on the DDF_En_Eff_zero.

From 2010 to 2011, it appears that 18 countries achieved better results than the previous year, 2 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 3.568, p = 0.0004). These results indicate that there is a significant effect on the DDF_En_Eff_zero. Moreover, from 2011 to 2012, it appears that 17 countries achieved better results than the previous year, 4 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 3.301, p = 0.0010). These results indicate that there is a significant effect on the DDF_En_Eff_zero.

From 2012 to 2013, it appears that 5 countries achieved better results than the previous year, 16 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = -2.817, p = 0.0048). These results indicate that there is a significant effect on the DDF_En_Eff_zero. Thus, from 2013 to 2014, it appears that 12 countries achieved better results than the previous year, 8 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 1.553, p = 0.1203). These results indicate that there is not a significant effect on the DDF_En_Eff_zero.

From 2014 to 2015, it appears that 13 countries achieved better results than the previous year, 7 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 2.087, p = 0.0369). These results indicate that there is a significant effect on the DDF_En_Eff_zero. In addition, from 2015 to 2016, it appears that 4 countries achieved better results than the previous year, 16 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = -2.888, p = 0.0039). These results indicate that there is a significant effect on the DDF_En_Eff_zero.

From 2016 to 2017, it appears that 14 countries achieved better results than the previous year, 5 countries had worse scores, while 8 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_En_Eff_zero between the two groups (z = 1.902, p = 0.0572). These results indicate that there is not a significant effect on the DDF_En_Eff_zero.

5.2.4 The Wilcoxon Signed Rank Test for Environmental efficiency.

Last but not least, ending with the DDF_Env_Eff variable, according to the test results, from 2000 to 2001, it seems that 12 countries achieved better results than the previous year, 7 countries had worse scores, while 8 countries remained stable. The test revealed that there was not a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 0.829, p = 0.4069). These results indicate that there is not a significant effect on the DDF_Env_Eff. In addition, from 2001 to 2002, it appears that 7 countries achieved better results than the previous year, 15 countries had worse scores, while 5 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -1.605, p = 0.1086). These results indicate that there is not a significant effect on the DDF_Env_Eff.

From 2002 to 2003, it appears that 10 countries achieved better results than the previous year, 9 countries had worse scores, while 8 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 0.890, p = 0.3734). These results indicate that there is not a significant effect on the DDF_Env_Eff. Furthermore, from 2003 to 2004, it appears that 9 countries achieved better results than the previous year, 8 countries had worse scores, while 10 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -0.346, p = 0.7293). These results indicate that there is not a significant effect on the DDF_Env_Eff.

From 2004 to 2005, it appears that 10 countries achieved better results than the previous year, 10 countries had worse scores, while 7 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 0.243, p = 0.8082). These results indicate that there is not a significant effect on the DDF_Env_Eff. Moreover, from 2005 to 2006, it appears that 3 countries achieved better results than the previous year, 18 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -3.424, p = 0.0004). These results indicate that there is a significant effect on the DDF_Env_Eff.

From 2006 to 2007, it appears that 9 countries achieved better results than the previous year, 9 countries had worse scores, while 9 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -0.086, p = 0.9315). These results indicate that there is not a significant effect on the DDF_Env_Eff. Thus, from 2007 to 2008, it appears that 11 countries achieved better results than the previous year, 8 countries had worse scores, while 8 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 0.452, p = 0.6516). These results indicate that there is not a significant effect on the DDF_Env_Eff.

From 2008 to 2009, it appears that 8 countries achieved better results than the previous year, 11 countries had worse scores, while 8 countries remained stable. The test revealed that there was a statistically significant difference in mean

DDF_Env_Eff between the two groups (z = -0.635, p = 0.5255). These results indicate that there is not a significant effect on the DDF_Env_Eff. In addition, from 2009 to 2010, it appears that 10 countries achieved better results than the previous year, 9 countries had worse scores, while 8 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 0.683, p = 0.4947). These results indicate that there is not a significant effect on the DDF_Env_Eff.

From 2010 to 2011, it appears that 11 countries achieved better results than the previous year, 7 countries had worse scores, while 9 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 0.209, p = 0.8348). These results indicate that there is not a significant effect on the DDF_Env_Eff. Furthermore, from 2011 to 2012, it appears that 4 countries achieved better results than the previous year, 14 countries had worse scores, while 9 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -2.098, p = 0.0359). These results indicate that there is a significant effect on the DDF_Env_Eff.

From 2012 to 2013, it appears that 13 countries achieved better results than the previous year, 5 countries had worse scores, while 9 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 1.804, p = 0.0713). These results indicate that there is not a significant effect on the DDF_Env_Eff. Moreover, from 2013 to 2014, it appears that 9 countries achieved better results than the previous year, 12 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -1.161, p = 0.2456). These results indicate that there is not a significant effect on the DDF_Env_Eff.

From 2014 to 2015, it appears that 9 countries achieved better results than the previous year, 13 countries had worse scores, while 5 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -0.567, p = 0.5708). These results indicate that there is not a significant effect on the DDF_Env_Eff. Thus, from 2015 to 2016, it appears that 17 countries achieved better results than the previous year, 4 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = 2.891, p = 0.0038). These results indicate that there is a significant effect on the DDF_Env_Eff.

From 2016 to 2017, it appears that 8 countries achieved better results than the previous year, 13 countries had worse scores, while 6 countries remained stable. The test revealed that there was a statistically significant difference in mean DDF_Env_Eff between the two groups (z = -0.726, p = 0.4679). These results indicate that there is not a significant effect on the DDF_Env_Eff.

5.2.5 Division of countries into three categories, Champions, Followers and Laggards

Taking into account all the above, we wanted to divide the countries into three categories champion, follower, Laggards. To be precise, we divided the countries each time based on the variable we examined according to the score they achieved in three equal parts 0% - 33% which are the Laggards, 33% - 66% which are the Followers , and 66% - 100% which are the Champions. Table 8 shows the results obtained.

From Table 8 we observe that in terms of the Champions category countries such as Norway, Ireland, Luxembourg belong to all four variables, while some other countries such as e.g. Germany and Denmark appear in three of the four variables. Regarding the Followers category, only Spain appears in all four variables, while countries such as Portugal, Greece, and Slovenia appear in three of the four variables. Last but not least, in terms of the Laggards category, only Bulgaria and Poland appear in all four variables, while countries such as Romania, Slovakia, and Finland appear in all three of the four variables.

Table 8. *Division of countries into three categories*

	Energy Efficiency	**Energy Efficiency (Direction -1)**	**Energy Efficiency (Direction 0)**	**Environmental Efficiency**
Champions	Austria	Germany	Malta	Norway
	Cyprus	Malta	Germany	Ireland
	Germany	United Kingdom	Luxembourg	Denmark
	Greece	Norway	United Kingdom	Luxembourg
	Ireland	Luxembourg	Ireland	
	Italy	Ireland	Norway	
	Latvia	Cyprus	Cyprus	
	Luxembourg	Denmark	Denmark	
	Malta	Italy	Italy	
	Norway			
	Portugal			
	Slovenia			
	United Kingdom			
Followers	Spain	Austria	Austria	Malta
	Denmark	France	France	Austria
	Hungary	Spain	Spain	Spain
	Lithuania	Portugal	Portugal	Finland
	Estonia	Sweden	Sweden	Bulgaria
		Latvia	Latvia	Greece
		Netherlands	Netherlands	Hungary
		Greece	Greece	Latvia
		Slovenia	Slovenia	Lithuania
				Portugal
				Romania

Table 8 continued from previous page

	Energy Efficiency	**Energy Efficiency (Direction -1)**	**Energy Efficiency (Direction 0)**	**Environmental Efficiency**
				Slovakia
				Slovenia
Laggards	Romania	Belgium	Estonia	Sweden
	France	Lithuania	Belgium	Italy
	Slovakia	Romania	Lithuania	France
	Sweden	Estonia	Romania	Germany
	Netherlands	Finland	Finland	United Kingdom
	Belgium	Hungary	Hungary	Poland
	Finland	Poland	Poland	Cyprus
	Bulgaria	Slovakia	Slovakia	Estonia
	Poland	Bulgaria	Bulgaria	Belgium
				Netherlands

Chapter 6

Conclusions

The energy and environmental efficiency dipole has come to the fore for both the research community and the policymaker. It has recently received notable attention due to the flagship resource efficiency initiative as well as the Europe Green Agreement, as resource efficiency is a prerequisite, if not an integral part, for sustainable development. The idea of resource efficiency as well as the scope of performance analysis is largely based on the relative lack of resources to determine the level of performance of each unit under consideration.

Although many countries may be reluctant to implement policies due to high costs, which in turn prevents growth, it is important to note that a huge effort has been made to look for opportunities aimed at reducing their environmental impact and at the same time improving their productivity. In this dissertation, we took into account 27 European countries, with the aim of assessing both their technical and energy and environmental efficiency for a period of 18 years (2000-2017), always keeping in mind that these economies operate below a prism of heterogeneity.

The empirical results presented in this study could also suggest some policy implications. First, the fact that there are significant technological gaps introduces the concept of investing in technology in order for lagging countries to fill this gap to reach the leading countries (Bell and Pavitt, 1993, 1995, Nelson and

Winter, 1982; Nelson and Wright, 1992; Abramovitz, 1986). However, investing in technology and creating technological innovation and knowledge allows shifts in the course of the country (Sagar and van der Zwaan, 2006), but it also remains a complex issue that requires two key additional conditions to be met: R&D efforts and learning through development and dissemination (Carraro et al., 2003).

However, gatherings of research institutes, universities, networks, company R&D departments can provide knowledge for the appropriate solution. More specifically, in the case of alternative raw materials and fuels for the environment (Oggioni et al., 2005) or specialized technologies (eg biomass, photovoltaics, and hydrogen) can be realized (Treffers et al., 2005). Although the role of government in announcing policies that may trigger the right level of R&D investment is vital (Jaffe et al., 2005), the successful penetration and introduction of innovative technologies into the market is another issue that needs to be addressed. seriously considered (Treffers et al., 2005).

Appendix A

Chapter 4

Table A.1. *List of Countries*

ID	Country	ID	Country	ID	Country
1	Austria	10	Greece	19	Norway
2	Belgium	11	Hungary	20	Poland
3	Bulgaria	12	Ireland	21	Portugal
4	Cyprus	13	Italy	22	Romania
5	Denmark	14	Latvia	23	Slovakia
6	Estonia	15	Lithuania	24	Slovenia
7	Finland	16	Luxembourg	25	Spain
8	France	17	Malta	26	Sweden
9	Germany	18	Netherlands	27	United Kingdom

The Table A.2, below presents the descriptive statistics of both inputs and outputs for each country, for the period 2000 to 2017. In particular, we see the average values and standard deviations. The first column shows the countries, the second column is about Gross Domestic Product (GDP), the third column is about capital, and the fourth column is about employment. Finally, the fifth column is related to C02 emissions.

Table A.2. *Descriptive Statistics of the variables per country for 2000-2017*

Countries	GDP	Capital	Labour	Energy	CO_2 Emissions
Austria	288000	1580000	4050.734	33302.65	10.344
	(48,652.94)	(557,000.00)	(213.38)	(1,540.96)	(0.76)
Belgium	348000	2040000	4419.878	64700.71	12.75
	(58,787.14)	(708,000.00)	(197.93)	(2,742.07)	(1.73)
Bulgaria	33271.79	239000	3480.574	19021.76	8.328
	(12,124.77)	(115,000.00)	(174.63)	(983.57)	(0.50)
Cyprus	16593.09	121000	372.096	2772.44	12.522
	(3,076.70)	(38,791.10)	(30.46)	(212.02)	(1.37)
Denmark	234000	1030000	2816.273	20180.87	11.839
	(34,712.89)	(305,000.00)	(62.49)	(1,360.09)	(1.99)
Estonia	14826.23	119000	605.55	5640.889	14.672
	(5,374.11)	(49,617.46)	(26.50)	(499.01)	(1.47)
Finland	183000	866000	2472.656	35506.14	13.433
	(27,021.29)	(218,000.00)	(87.01)	(1,789.32)	(1.98)
France	1920000	9920000	26785.67	268000	8.278
	(252,000.00)	(3,390,000.00)	(622.26)	(7,332.02)	(0.83)
Germany	2570000	1.37E+07	41095.61	338000	12.094
	(350,000.00)	(3,400,000.00)	(1,597.46)	(13,270.65)	(0.59)
Greece	193000	1820000	4419.559	30770.94	11.078
	(28,888.77)	(474,000.00)	(300.05)	(3,365.28)	(1.34)
Hungary	93958.96	918000	4145.47	26089.9	6.833
	(19,273.62)	(343,000.00)	(166.35)	(1,286.81)	(0.63)
Ireland	183000	762000	1931.149	14942.74	15.3
	(49,732.60)	(331,000.00)	(138.93)	(785.35)	(2.26)
Italy	1550000	1.12E+07	24539.4	175000	8.9

Table A.2 continued from previous page

Countries	GDP	Capital	Labour	Energy	CO_2 Emissions
	(142,000.00)	(3,550,000.00)	(610.64)	(13,010.35)	(1.20)
Latvia	18333.04	237000	930.304	4674.179	5.483
	(6,175.18)	(105,000.00)	(65.97)	(276.89)	(0.49)
Lithuania	27363.35	210000	1359.807	8312.932	6.778
	(9,346.17)	(77,699.69)	(62.38)	(1,008.01)	(0.62)
Luxembourg	38317.69	147000	346.315	4366.065	25.45
	(10,929.15)	(48,166.39)	(51.11)	(315.71)	(3.49)
Malta	6660.639	34016.26	168.177	2005.8	7.417
	(2,082.23)	(11,942.08)	(22.34)	(374.40)	(0.97)
Netherlands	606377	2950000	8659.5	94946.38	13.156
	(83,291.97)	(1,010,000.00)	(268.63)	(4,162.54)	(0.89)
Norway	294000	1060000	2509.5	29696.39	11.628
	(71,647.90)	(364,000.00)	(166.65)	(2,483.30)	(0.75)
Poland	321000	1704146	15053.57	96118.75	10.583
	(93,848.06)	(504,000.00)	(886.22)	(4,705.42)	(0.29)
Portugal	166000	1730000	4882.912	25482.13	7.394
	(18,367.35)	(550,000.00)	(236.41)	(1,526.01)	(0.72)
Romania	113000	1110000	9156.683	36174.1	6.533
	(47,184.37)	(522,000.00)	(689.60)	(3,109.30)	(0.57)
Slovakia	56542.79	441000	2168.217	17525.41	8.717
	(21,883.76)	(151,000.00)	(101.69)	(951.43)	(0.74)
Slovenia	33325.06	296000	948.468	7020.15	9.572
	(6,286.76)	(94,974.24)	(25.00)	(355.47)	(0.81)
Spain	973000	6980000	18918.17	139000	8.806
	(155,000.00)	(2,610,000.00)	(1,267.88)	(9,090.03)	(1.21)
Sweden	367000	1580000	4551.994	51740.81	6.911

Table A.2 continued from previous page

Countries	GDP	Capital	Labour	Energy	CO_2 Emissions
	(71,080.03)	(457,000.00)	(206.36)	(1,778.90)	(0.93)
United Kingdom	2070000	8840000	29457.21	216000	10.522
	(252,000.00)	(3,090,000.00)	(1,321.55)	(18,830.69)	(1.71)

Note: Standard Deviations in parentheses

The Table A.3, below presents the growth of used variables for the 27 European countries during the examined period. We observe that significant variations exists in the variables used in this analysis which might be an indicator of uneven economic development across Europe. As we can see, it seems that all countries had an increase in GDP with the smallest increase being 21% from Greece and the largest increase being 78% from Romania. In terms of capital, here too all countries have increased their capital all these years with the smallest increase being from Finland with 48% while the largest 78% from Germany.

Regarding work, some have increased the number of employees while others have decreased. e.g. Luxembourg increased employment by 39% while Romania reduced it by 25%. At the same wavelength is energy. Malta has the largest increase with 50% while the United Kingdom seems to have a decrease in energy consumption with -25%. Finally, in terms of CO_2 Emissions, on average, almost all countries have reduced their emissions, with the largest decrease occurring in the United Kingdom at -64%, while Latvia, in contrast to its emissions in 2000, 2018 has increased them by 26%.

Table A.3. *Annual and growth rates of input and output variables used in this study.*

	2000 period					2017 period					Growth(%)				
	Y	**K**	**L**	**E**	CO_2	**Y**	**K**	**L**	**E**	CO_2	**Y**	**K**	**L**	**E**	CO_2
Output and inputs variables (frontier analysis)															
AUS	213606.5	969076.75	3754.97	29244.842	10.3	370295.8	2518291.5	4413.17	34818.812	9.6	42%	62%	15%	16%	-7%
BEL	256376.4	1129631.875	4109.7	64778.796	15.1	446364.9	3032260.75	4751.4	64476.211	10.5	43%	63%	14%	0%	-44%
BGR	14406.8	90805.5	3239.2	18700.151	7.3	52310	420190.0313	3525.35	19015.844	8.8	72%	78%	8%	2%	17%
CYP	10804.6	71730.29688	314.76	2614.442	13.3	20039.7	172998.5469	406.84	2826.805	11.6	46%	59%	23%	8%	-15%
DNK	178018.1	623113.9375	2755.15	20794.152	13.7	292408	1499052.625	2921.9	18726.344	8.8	39%	58%	6%	-11%	-56%
EST	6179.8	50616.03516	585.3	4837.319	12.5	23775.8	185511.0625	641.5	6062.175	16	74%	73%	9%	20%	22%
FIN	136442	572772.1875	2299.8	33441.182	13.8	225835.9	1102754.375	2561.8	34584.634	10.4	40%	48%	10%	3%	-33%
FRA	1478585	5291587	25602	258868.689	9.3	2295063	15062345	27842	257317.311	7.2	36%	65%	8%	-1%	-29%
DEU	2109090	9432306	39971	344632.692	13	3244990	19033204	44248	324280.628	11.3	35%	50%	10%	-6%	-15%
GRC	142976	1223418.625	4312.79	31500.399	11.9	180217.6	2442296.25	4146.05	26528.764	9.2	21%	50%	-4%	-19%	-29%
HUN	51238.5	437150.8438	4115.82	25230.553	7.2	125603.1	1422003.125	4559.03	26702.693	6.6	59%	69%	10%	6%	-9%
IRL	108380.4	295456.8125	1695.8	14523.37	18.5	297130.8	1298682.625	2144.14	14829.827	13.3	64%	77%	21%	2%	-39%
ITA	1241512.9	6949482.5	23028.6	176185.338	9.9	1736592.8	16525972	25138.3	161815.269	7.3	29%	58%	8%	-9%	-36%
LVA	8605.6	90752	923.69	3872.533	4.5	26797.8	397774.5313	885.99	4811.298	6.1	68%	77%	-4%	20%	26%
LTU	12491.3	107952.7031	1399.19	7441.126	5.6	42269.4	326608.0625	1361.89	7868.518	7.3	70%	67%	-3%	5%	23%
LUX	23079.4	80992.35156	264.05	3656.453	24.4	56814.2	219834.4844	432.71	4330.748	20	59%	63%	39%	16%	-22%
MLT	4394.9	20829.30859	146.4	1467.056	7.9	11284.4	53994.71094	222.33	2919.009	5.5	61%	61%	34%	50%	-44%
NLD	452007	1630074.375	8203	91428.924	14.4	738146	4163233.75	9142	90508.005	12	39%	61%	10%	-1%	-20%
NOR	185788.4	584252.75	2320	26396.774	12.4	353316.4	1574070.75	2747	30810.683	10.3	47%	63%	16%	14%	-20%
POL	186375.9	1112247.5	14516.6	89502.85	10.4	467312.9	2638046	16315	105416.098	11	60%	58%	11%	15%	5%
PRT	128414.4	964867.375	5041.86	26045.024	8.2	195947.2	2398430.5	4802.6	25426.228	7.2	34%	60%	-5%	-2%	-14%
ROU	40594.9	458812.0938	10771.6	36756.989	6.4	187772.7	1857608.25	8631.2	33562.493	5.9	78%	75%	-25%	-10%	-8%
SVK	22389.1	249207.8125	2024.85	17731.325	9.1	84517	689147.1875	2372.26	17247.812	8	74%	64%	15%	-3%	-14%
SVN	21866.8	180383.2031	914.74	6447.869	9.6	42987.1	453280.7188	989.36	7019.692	8.5	49%	60%	8%	8%	-13%
ESP	647851	3282588.25	16706.5	129968.072	9.8	1161878	10450522	19387.9	137450.695	7.7	44%	69%	14%	5%	-27%
SWE	283525.1	1064030.625	4300.8	49065.213	7.9	479605.4	2305795.5	5016.6	52693.154	5.5	41%	54%	14%	7%	-44%
GBR	1797681.6	5031164	27483.29	235338.491	12.6	2363109.3	13221941	32060.17	188151.474	7.7	24%	62%	14%	-25%	-64%

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