Technical University of Crete

Energy Efficiency Assessment in European Union Countries and Industries

A dissertation submitted to the School of Production Engineering and Management at the Technical University of Crete in partial fulfilment of the requirements for the degree of Doctor of Philosophy

Georgia Makridou

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Chania

SUPERVISORS

Michael Doumpos, Associate Professor

School of Production Engineering and Management, Technical University of Crete

Constantin Zopounidis, Professor

School of Production Engineering and Management, Technical University of Crete

Kostas Andriosopoulos, Associate Professor

ESCP Europe Business School, London

Examination Committee

Constantin Mellios, Professor

Sorbonne Management School, University of Paris 1 Panthéon-Sorbonne, Paris

George Atsalakis, Assistant Professor

School of Production Engineering and Management, Technical University of Crete

Chrysovalantis Gaganis, Assistant Professor

Department of Economics, University of Crete

Spiros Papaefthymiou, Assistant Professor

School of Production Engineering and Management, Technical University of Crete

This thesis is dedicated to

the memory of my father…

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SHORT CURRICULUM VITAE

Georgia Makridou holds a diploma in Electronic and Computer Engineering (2009) from the School of Electronic and Computer Engineering and an MSc in Business Administration (2011) from the School of Production Engineering and Management of the Technical University of Crete.

Since 2012, she is a PhD candidate at the Financial Engineering Laboratory at the Technical University of Crete, and a Research Assistant at the Research Centre for Energy Management (RCEM) at ESCP Europe Business School. Georgia's research interests include the evaluation of the EU energy markets on the country and firm levels using sophisticated econometric and multi-criteria methodologies. Besides her research skills obtained so far, since September 2013 she has also worked as a Visiting Lecturer at ESCP Europe Business School in London, teaching at the Master in European Business (MEB), Master in Energy Management (MEM) and Bachelor in Management (BIM) programmes.

Part of her PhD dissertation has been published in international energy-related journals, and has been presented in recognised conferences world-wide (14th IAEE European Energy Conference, 5th International Conference of the Financial Engineering and Banking Society, 38th IAEE International Conference, etc.).

Publications

1. Makridou, G., Andriosopoulos, K., Doumpos, M., and Zopounidis, C. (2016), “Measuring the efficiency of energy-intensive industries across European countries,” Energy Policy, 88, 573-583.
2. Makridou, G., Andriosopoulos, K., Doumpos, M., and Zopounidis, C. (2015), “A two-stage approach for energy efficiency analysis in European Union countries,” The Energy Journal, 36(2), 47-69.
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EXECUTIVE SUMMARY

Due to rapidly rising energy prices in the global market and increased concerns about development sustainability, more and more countries have eagerly been looking into improving energy efficiency. Energy efficiency is considered an essential component of sustainable development policies, which seeks to achieve a well-balanced trade-off between economic growth and competitiveness, energy security, and environmental sustainability. Therefore, many governments all over the world have put energy efficiency on their policy agenda as a top priority issue. Thus, it is not surprising that, in recent years, the assessment of energy efficiency has attracted great interest among researchers. Many approaches and performance indicators have been proposed in literature to this end.

Finding ways to evaluate and explain energy efficiency performance can contribute significantly to its improvement and thus move the world towards a more sustainable energy future. In pursuing this goal, this thesis performs econometric/statistical approaches, multicriteria decision aiding methods, multilevel models as well as efficiency analysis techniques for the energy efficiency analysis. In particular, the aim of this research is the evaluation of energy efficiency in 26 EU countries and ten industrial sectors in 23 EU countries over the period 2000-10 and 2000-09, respectively.

In the first stage of analysis in which the energy efficiency in 26 EU countries is evaluated, we follow a two-stage approach based on Data Envelopment Analysis (DEA) and Multicriteria Decision Aiding approach (MCDA). The proposed approach considers energy efficiency in a multidimensional context, combining multiple energy consumption data, economic outputs and structural indicators. Firstly, DEA is employed under different modeling settings over the period 2000–10 to measure the relative efficiency of the countries and facilitate the identification of the sources of inefficiencies. Then, the DEA efficiency classifications are used as inputs to a MCDA approach constructing an operational model that combines energy efficiency with economic and environmental indicators. The proposed two-stage DEA/MCDA approach can be easily used for benchmarking purposes, allowing for the formulation of a complete ranking of all countries under consideration, as well as the monitoring of the performance of a country over time using data solely at the country level, without having to resort to relative assessments in comparison to data from a set of peer countries.

The results of the empirical analysis indicate that despite the considerable improvements achieved in terms of energy intensity, a more refined view of energy consumption and economic activity data shows that there is still much to be done to improve the actual energy efficiency of European countries. Additionally, the economic crisis of the past few years has had negative effects on energy efficiency. Furthermore, it is has been found that for European countries, the effect due to the consideration of the structure of their economic activity is

stronger than the effect due to the introduction of a breakdown by their energy mix. Taking into account the results of this study, policy makers could identify the main steps that should be implemented to improve the country's energy efficiency. For example, the finding that service-oriented economies are more efficient than industry-oriented ones or the fact that renewable energy sources should gradually displace fossil fuels could help regulators design policies to support certain sectors of the economy or certain energy sources with the aim to improving energy efficiency.

Next, we extend our research to evaluating the energy efficiency trends of ten energy-intensive industries in 23 EU countries over the period 2000–09. Specifically, the performance of the construction, electricity, mining and quarrying, transport, food and tobacco, textiles and leather, pulp and paper, coke and chemicals, other non-metallic mineral and fabricated metal, machinery and equipment is examined. In the first stage, the DEA combined with the Malmquist Productivity Index (MPI) is performed to identify the energy efficiency trends and distinguish between the effects of efficiency and technology changes. In the second stage of our analysis, a two-level cross-classified multilevel modeling is applied to analyse the main drivers behind efficiency performance using a number of sector- and country- characteristics. In particular, the country-level factors include the market share of the largest generator in the electricity market, the energy taxes and electricity prices. For cross-sector differences the examined variables include the contribution of a sector's gross value added to the total gross value of a country, the energy mix, the share of fossil fuels in total gross energy consumption, the real fixed capital stock to gross value added, the real fixed capital stock to number of employees and the productivity defined as the gross value added divided by the total hours worked by employees. The DEA results show that the pulp and coke are the most inefficient sectors, on average. Regarding the decomposition of the MPI, technology change is mainly responsible for the improvements achieved in most of the sectors. The two-level cross-classified model shows that the combination of sector and country levels is the most relevant in explaining the energy efficiency variance. It also shows that energy efficiency is higher for sectors that contribute more to the overall economic activity of a country (high contribution of sector value added to the total of the economy), as well as in a country with a diversified energy mix, and open and competitive energy production market.

Overall, the evaluation models that are developed through this research are of major practical usefulness for monitoring, benchmarking and policy planning purposes. This thesis contributes to the available literature by providing not only energy efficiency estimates but also identifying the drivers behind the observed performance in EU countries and industries. Thus, the conclusions of this research can help policy makers take effective policy decisions for energy efficiency improvement at both the country and industry level.

TABLE OF CONTENTS

CHAPTER 1

Energy Efficiency - Definitions, Measurement and Policy Issues

This chapter presents the theoretical framework of energy efficiency. The definition and benefits of energy efficiency are firstly discussed. Attention is then drawn to energy indicators as well as to the techniques of Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA) that are commonly used for energy efficiency measurement. A discussion about the barriers to energy efficiency, rebound effect and energy efficiency gap is also developed. Last but not least, the energy policies and measures needing adoption for promoting energy efficiency are presented.

1.1 Definition of Energy Efficiency

Undoubtedly, energy is of outstanding importance for satisfying the interrelated goals of modern societies providing directly or indirectly the fundamental source for almost all daily activities.

As energy plays a vital role in many aspects of human life, it is considered a prime agent in the economic development and improvement of standards of living and overall social well-being. Therefore, the meeting of energy demand is a pre-requisite for the satisfaction of societal needs as well as the maintenance of a certain level of human welfare. However, energy use is dramatically increasing mainly due to the fact that the global population and energy needs are increasing hand-in-hand. Furthermore, after the second half of the twentieth century, the industrial revolution also contributed to more energy use. According to the U.S. Energy Information Administration - EIA (2014), energy consumption is expected to increase by 56% and worldwide carbon dioxide (CO_2) emissions by 46% between 2010 and 2040. Thus, it comes as no surprise that increasing energy use is directly linked to the challenges of energy security and climate change facing the world today. Governments are increasingly aware of the urgent need to mitigate these challenges. To this end, their major policy interest is riveted on energy efficiency as it is considered a keystone to addressing these issues. The 1973 Arab oil embargo and later the Iranian Revolution of 1979 played a decisive role in boosting energy efficiency (Sioshansi, 2013). Since then, many countries all over the world have put energy efficiency on their policy agenda as a top priority. But, what is energy efficiency really?

Energy efficiency came onto the world agenda because of its crucial effects toward attaining a sustainable energy future along with environmental sustainability. However, surprisingly, little attention has been given to defining and measuring energy efficiency (Patterson, 1996). There does not seem to be a single commonly-accepted definition.

Energy efficiency is described in past research as maintaining or increasing the level of useful output or outcome delivered, while reducing energy consumption. According to EIA (1995) of US Department of Energy "increases in energy efficiency take place when either energy inputs are reduced for a given level of service or there are increased or enhanced services for a given amount of energy inputs". Energy efficiency is "using less energy to provide the same service" or is "doing more with less" as described by the European Commission (EC) in its Green Paper on Energy Efficiency.

In the Directive on energy end use efficiency and energy services (Directive 2006/32/EC), energy efficiency is defined as a "ratio between an output of performance, service, goods or energy, and an input of energy". The report of World Energy Council - WEC (2010) implies that energy efficiency improvements refer to a reduction in the energy used for a given service or level of activity. The reduction in energy consumption is usually associated with technological changes, but not always since it can also result from better organization and management or improved economic conditions in the sector (non-technical factors). Also, efficiency can refer to how much useful energy we can get from an energy source and the efficiency coefficient is given by the ratio of the output energy to the input energy. Huntington (1994), Lovins (2004) and Boyd (2005) are some other relevant references that deal with the various definitions of energy efficiency.

Energy efficiency is defined differently in international and national literatures. Even in specific scientific fields (e.g. engineering, economics, sociology, etc.) energy efficiency is interpreted in different ways. For engineers, energy efficiency is given by the ratio of the desired output (useful effect) to the required input (used resources) of any system. In economics (WEC, 2010), energy efficiency has a broader meaning: it encompasses all changes that result in decreasing the amount of energy used to produce one unit of economic activity (e.g. the energy used per unit of gross domestic product (GDP) or value added). In that case, energy efficiency is associated with economic efficiency and includes all kinds of technological, behavioral and economic changes that reduce the amount of energy consumed per unit of GDP. For energy efficiency experts, improving energy efficiency reflects the results of actions that aim at reducing the amount of energy used for a given level of services (WEC, 2010). Consequently, different perspectives and ratios can be distinguished concerning energy efficiency. In particular, the ratio between the output of performance (service or goods) and the energy input as well as the ratio between the amount of energy consumption per unit of product (or output/feedstock) are the most commonly used notions for energy efficiency definition. The former ratio is the one that is usually used for defining industrial energy efficiency. In that case, the ratio is known as energy intensity if output is measured in economic units or as specific energy consumption (SEC) if measured in physical units.

Energy efficiency is often confused with other terms such as productivity, conservation, savings, efficacy and effectiveness. Efficiency improvement does not guarantee productivity improvement. Efficiency is a necessary but not sufficient condition for productivity. More often, energy efficiency and energy conservation are used interchangeably in energy policy planning. Although both are referred to as the cheapest and cleanest sources of energy, there are some main differences. The most significant difference is that energy conservation means using less energy and is usually a behavioral change whereas energy efficiency implies meeting a given demand with a lower use of resources and is often a technological change.

Energy savings and energy efficiency should also be differentiated. Energy efficiency refers to the technical ratio between the quantity of primary or final energy consumed and the maximum quantity of energy services obtainable (heating, lighting, cooling, mobility, and others), whereas energy savings addresses the reduction of final energy consumption, through energy efficiency improvement or behavioral change (Oikonomou et al., 2009).

1.2 Benefits of Energy Efficiency

Energy efficiency improvement has become a vital part of energy management and a shared policy goal of many governments. Government, industry, businesses and households can be influenced by energy efficiency at the financial, social and environmental level. Energy efficiency reduces energy costs, increases competitiveness, supports innovation and promotes welfare. Indeed, energy efficiency is widely recognized as the most cost-effective and readily available way of addressing numerous energy-related issues. Among others, ensuring sustainability in all aspects of economic, environmental and social development and reducing the detrimental impacts of CO_2 emissions on the environment. It is also regarded as an effective way for the reduction in greenhouse gas (GHG) emissions from fossil fuels to mitigate climate change as well. In particular, energy efficiency helps to reduce carbon emissions at the lowest cost. According to the Energy Efficiency Market Report (International Energy Agency - IEA, 2014a) a 40% reduction in GHG emissions can come from energy efficiency. Thus, energy efficiency is said to be along with renewable energy one of the “twin pillars” of any sustainable energy policy by decreasing overall energy demand and dependence on imported fossil fuels. In particular, energy efficiency has saved more energy than the total final consumption of any fuel in IEA countries. Based on IEA (2014a) estimates, the energy efficiency market amounts to more than USD 310 billion annually and is increasing over time.

Figure 1 shows a list of the most prominent multiple benefits of energy efficiency (IEA, 2014a). Although the list is not exhaustive, it describes the main socioeconomic outcomes that can arise from energy efficiency improvement. The myriad benefits from energy efficiency could also be categorized according to the nature or character of their impact, their temporal scale and the types of beneficiaries.

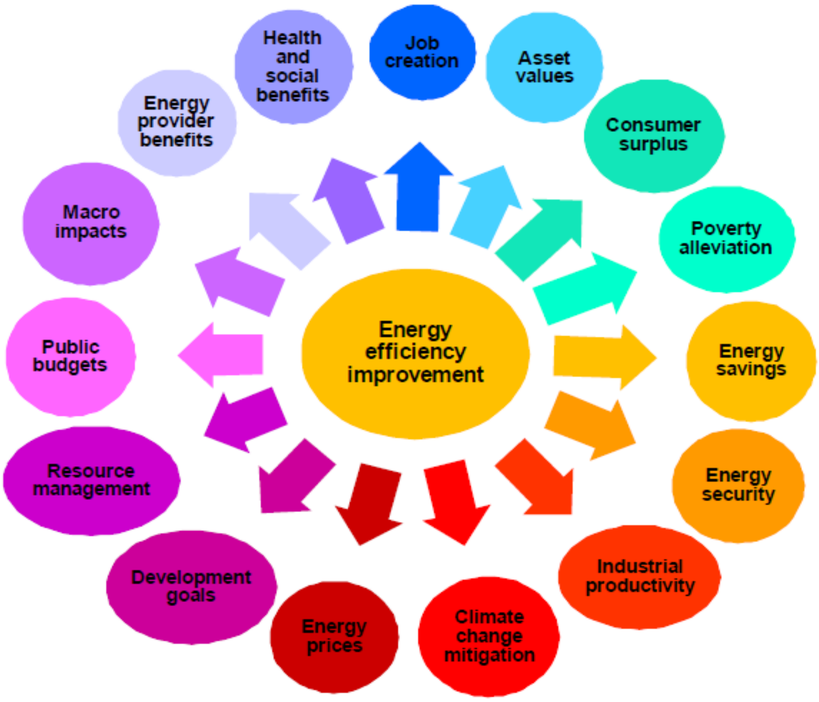


Figure 1.1: The multiple benefits of energy efficiency (IEA, 2014a).

It is obvious that energy efficiency has the potential of influencing beneficially all aspects of society (at the individual, sectoral, national and international level). In particular, the individual benefits include, among others, improved health and wellbeing, energy affordability and access, as well as increased disposable income. The job creation, lower energy-related public expenditures, energy security and macroeconomic effects refer to energy efficiency benefits on a national level. The industrial productivity, competitiveness and increased asset values are some of the sectoral benefits whereas the reduction of GHG emissions, moderation of energy prices and natural resource management are among the most important international benefits. Furthermore, the majority of these benefits can have immediate effect with long-lasting results and operate in both developed and developing countries.

1.3 Measuring Energy Efficiency

1.3.1 Energy Efficiency Indicators

Following the oil crisis of 1973 and due to the multiple benefits of energy efficiency at the national and global level, its evaluation and monitoring became an important part of energy strategy. On top of energy efficiency definition, measuring energy efficiency is also a high priority in energy policy. However, its measurement is an even more difficult task than defining it. Great efforts have been carried out and a number of energy efficiency indicators have been proposed for energy efficiency evaluation. The growing interest in addressing some of the most significant energy related issues on a national and global level, such as the energy security and global warming, also reinforced the development of energy efficiency and environmental indicators.

1.3.1.1 Characteristics of Energy Efficiency Indicators

Due to the fact that there is no single meaningful measure for efficiency performance across all countries and industries, many approaches and performance indicators have been proposed in the literature (Ang, 2004; 2006; Zhou and Ang, 2008a). Energy efficiency indicators are commonly used for a quantitative measurement of any efficiency change that takes place at the cross-country level as well as for international benchmarking.

Whenever an indicator is developed for measuring energy efficiency performance, the first question that should be addressed is the purpose that the indicator is supposed to serve. In particular, a different indicator is used for evaluating environmental, social, economic, or other aspects of energy efficiency because of the different characteristics and objectives that characterize each aspect. Furthermore, a decision regarding the formulation of an aggregate indicator or a more detailed indicator is required. Usually, the aggregated data are very rarely meaningful in monitoring energy efficiency trends, since they can give only a broad overview. Therefore, to build energy efficiency indicators, it is necessary to disaggregate data further, and to understand which sub-sectors or end uses drive energy consumption within each of the sectors.

There are a number of difficulties when proposing and using an appropriate energy efficiency indicator. Firstly, there is often a limitation on the availability of data that are required for its development. Additionally, when international comparisons are desired, differences such as structural, behavioral, and economic characteristics of countries make it more difficult for developing comparative indicators. Some countries have different measures of energy, currencies, inflation, purchasing power parities and income accounting. Thus, even a simple indicator such as energy per GDP for cross-country evaluation is a tough assignment. Therefore, it is not easy to develop an indicator or a set of indicators that will truly represent only the changes in energy efficiency.

Many researchers have analysed the criteria for the selection of appropriate efficiency performance indicators focusing on whether these are measurable, comparable and consistent (Jamasb et al., 2006; 2008; Vaninsky, 2006). It should be noted that a useful indicator, whether it is physical, monetary or qualitative, should be clear in definition as it can then be easily measured and compared over time. However, comparability may be problematic in practice, especially when the data is collected from different countries which are in different stages of economic development, institutional environment and regulatory system (Fang et al., 2009). It is better to express the indicators both in final and primary energy and use physical units rather than economic because by using physical units monetary fluctuations can be avoided from the energy efficiency analysis. It is also worth mentioning that indicators are only estimates. Therefore supporting information on factors affecting the changes needs to be examined in as much detail as possible for a meaningful understanding of energy efficiency performance. The development of energy efficiency indicators is only the first step in evaluating energy efficiency trends. They can also help in drawing conclusions regarding past and future trends in energy efficiency. However, a set of several indicators are needed for an accurate energy efficiency evaluation as each indicator has its own characteristics, purpose and limitations.

1.3.1.2 A Pyramidal Approach for Energy Efficiency Indicators

Indicators built to understand trends in the consumption of a sub-sector or an end use could be more or less aggregated and sophisticated based on data availability. The indicators can be presented for each sector and then for each sub-sector or end use following a “pyramidal approach”. The energy indicator pyramid is portrayed as a hierarchy of energy indicators and it is often used for conceptualizing the energy efficiency level (Shipper, 1997; Asia Pacific Energy Research Centre - APERC, 2001; IEA, 2014b).

The “pyramidal approach” (Figure 1.2) refers to the identification of sub-sectors or end uses that consume energy and the recognition of factors (e.g. economic, structural, etc.) resulting in possible changes on the way energy is consumed. It includes energy indicators from most detailed (the most disaggregated level) at the bottom of the pyramid, to least detailed at the top (the most aggregated level). Its main characteristic is that in each level the indicators are disaggregated and so a deeper analysis regarding the factors that affect energy efficiency is assessed. At a macro level (top of pyramid), economic ratios are used for measuring energy efficiency at a high level of aggregation (e.g. whole economy or sector). In particular, the ratio of energy consumption to GDP or to another macro-economic variable such as population is usually used for providing a general idea of the reasons behind energy consumption trends. However, this ratio is often affected by structural and activity effects and therefore leads to misleading conclusions. Therefore, more disaggregated indicators from sub-sectoral levels (lower levels in pyramid) are used for a safer evaluation of energy efficiency trends and a policy-relevant analysis on how to influence these trends. These indicators are based on calculations of techno-economic ratios such as energy consumption to activity measured in physical or consumption terms. The lower rows in the pyramid represent the sub-sectors or end uses of each sector and give detailed information about these. Although the bottom up approach gives a deeper understanding of the true energy efficiency trends it requires more data and more complex analysis to re-aggregate back up to a higher level.

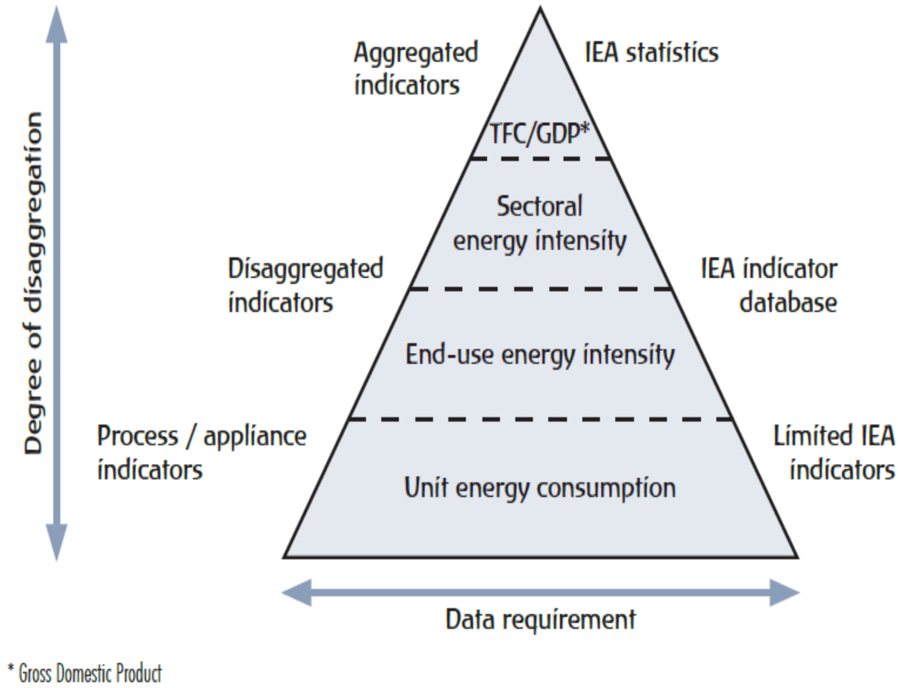


Figure 1.2: Schematic representation of the IEA energy indicators pyramid (IEA, 2014b).

1.3.1.3 Categories of Energy Efficiency Indicators

Energy Efficiency Indicators (EEI) can be expressed in energy units (consumption of a sector or of an end use), in ratio terms (litres per 100 kilometres), as well as in percentage (share of the industry sector in total energy consumption). According to Patterson (1996), they are grouped into four categories: thermodynamic indicators, physical-thermodynamic indicators, economic thermo-dynamic indicators and economic indicators. Their main difference is based on the consideration of inputs and outputs and more specifically on the units used for their measurement. Nevertheless, all types of indicators can be used for measuring true energy efficiency.

The WEC (2010) categorized the energy efficiency indicators into three types namely, techno-economic ratios, indicators of diffusion and economic ratios. Techno-economic ratios are used for energy efficiency evaluation at a disaggregated level (sub-sector or end-uses). In particular, energy consumption is related to an indicator of activity measured in physical terms or to a consumption unit. Indicators of diffusion are used for estimating the effect of energy efficient technology on a market whereas the economic ratios are the most commonly used indicators. The economic ratio, commonly known as energy intensity, is often used in macro-level analysis for measuring energy efficiency at the level of the whole economy or of a sector (high level of aggregation). Energy intensity is defined as the ratio between energy consumption (measured in energy units) and indicator of economic activity (measured in monetary units at constant prices). Thus, it can be used to assess the effect of economic and technical driving factors such as energy prices, GDP and new technologies on energy consumption and CO_2 emissions (de la Rue du Can et al., 2010). Energy intensity indicators can be also used to analyse historical trends, for benchmarking, examination of policy progress over time, and as input to economic and technological models. It is also known as an efficiency indicator because it is considered to be the reciprocal of energy efficiency. This means that a reduction in energy intensity may lead to energy efficiency improvement. However, due to the fact that energy intensity is influenced by factors that are not directly linked to "true" energy efficiency (e.g. economic structure, behavioral changes, energy mix, climate, etc.), energy intensity is more an indicator of "energy productivity" than a true indicator of efficiency (WEC, 2010). Moreover, although easily calculated, its interpretation is sometimes misleading. This is more obvious when it is used for cross-country comparisons mainly because of the possible informality in some countries' economic performance.

There are two main categories of EEIs that have been widely used for evaluating energy efficiency at the sector and national level. These involve economic and physical indicators. Economic indicators, often referred to as Economic Energy Intensity (ECI) indicators, are based on monetary values and thus are defined as the energy demand per unit of sectoral value added or GDP. On the other hand, physical indicators (or Specific Energy Consumption (SEC) indicators) are calculated by the ratio of energy use (expressed in energetic units) to the amount of output expressed in physical units (e.g. ton of product). Of both, the former has gained more popularity mainly because economic data are more readily available than physical production data for energy efficiency comparisons. Nevertheless, ECI indicators present a difficulty in their interpretation as their value is affected by many factors (e.g. structural change, energy price change) other than energy efficiency. On the other hand, SEC indicators are characterised by higher reliability in energy efficiency evaluation and are most appropriate for measuring energy efficiency trends in energy intensive industries. SEC are widely used in industry for measuring the energy efficiency of different processes (Phylipsen et al., 2002; Siitonen et al., 2010).

Energy efficiency indicators can also be categorized into two groups: macro-indicators used for measuring energy efficiency performance of an economy as a whole or in main sectors or sub-sectors and the micro-indicators used for energy efficiency evaluation at a micro-economic level (e.g. firms or households). Furthermore, indicators that are used for analyzing the energy efficiency performance and evolution are known as descriptive indicators whereas those that explain the factors affecting energy efficiency performance are called explanatory indicators.

The development of EEIs for national energy efficiency monitoring has been attracting growing interest internationally (Ang, 2006). Many EEIs have been developed for measuring the impacts of various energy efficiency policies and making meaningful cross-sector and cross-economy comparisons. More specifically, many national energy agencies and international organizations such as IEA (1997; 2004; 2007; 2014b), APERC (2001), Energy Efficiency and Conservation Authority of New Zealand – EECA (2006), Natural Resources Canada – NRC (2006), and ODYSSEE (2009) have proposed a number of energy efficiency indicators and monitoring systems. In particular, the IEA has played a pioneering role in the development of EEIs for providing and analyzing information regarding energy consumption trends, assessing energy efficiency at a quantitative level and developing effective energy policies, among others. ODYSSEE is another database that contains more than 600 comparable EEIs based on economic and physical variables. The ODYSSEE-MURE project has proposed the ODEX indicator that is most useful for measuring energy efficiency at an aggregate level as it is not affected by factors not related to energy efficiency (ODYSSEE, 2009). ODEX is defined as a weighted average of sub-sectoral indices (e.g. industrial or service sector branches or end-uses for households or transport modes) of energy efficiency progress. A number of energy efficiency indicators have also been developed by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (DOE/EERE). In particular, the DOE/EERE has established a new system of indicators for assessing energy intensity trends over time at the national level. Enerdata also proposed around 50 indicators for reviewing energy efficiency trends and helping decision makers and analysts monitor these trends in the main world regions and WEC member countries[1].

EEIs can be used not only for cross-country comparisons but for cross-sector measurements as well. Appropriate indicators have been developed and applied in numerous studies for estimating the energy efficiency of energy-intensive sectors such as the iron and steel sector (IEA, 2009a, Siitonen et al., 2010), chemical and petrochemical sector (Saygin et al., 2011), manufacturing sector (Neelis et al., 2007) and others (Oda et al., 2012).

The IEA (2007) has also developed a number of indicators for measuring energy efficiency in the manufacturing, household, service and transport sectors of 20 IEA countries over the period 1990-2004. The IEA indicator approach grouped the indicators into three main

[1] The World Energy Council has Member Committees in nearly 100 countries, including the largest energy-producing and energy consuming nations.

categories namely sectoral activity levels, structure (the mix of activities within a sector) and energy intensities (energy use per unit of sub-sectoral activity). IEA performed a factorial decomposition method based on the Laspeyres Index to separate the effect of each component by using the following relation:

$$E = A * \sum S * I \qquad (1.1)$$

where E represents total energy use in a sector, A the overall sectoral activity, S the sectoral structure or mix of activities within a sub-sector and I the energy intensity of each sub-sector (or end-use).

1.3.1.4 Decomposition Methods

Decomposition analysis has gained popularity in energy and environmental analysis as well as in industrial energy demand analysis over the last decades. It has been widely used to study the driving forces of changes of an aggregate indicator over time. Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA) are the two widely applied decomposition techniques for policymaking on energy and environmental issues.

There are both similarities and differences between IDA and SDA in terms of study scope, method formulation, data requirements and the results given (Hoekstra and van den Bergh, 2003; Su and Ang, 2012). IDA is often adopted for a better understanding of the drivers of energy use and energy-related emissions in a specific energy consumption sector. However, SDA is used primarily by those who are familiar with input–output (I–O) analysis in order to study changes in energy consumption or emissions in the economy (Su and Ang, 2012). Decomposition in IDA is equivalent to the one-stage decomposition model, while SDA can have a one-stage or two-stage model because of the inverse matrix involved. SDA as relies on the I–O model framework can account for the indirect effect while IDA can only deal with direct effect. Indirect effects emerge when a direct demand increase in one sector leads to increases in the demand for inputs from other sectors. The indicator forms (absolute and intensity) as well as the decomposition forms of additive and multiplicative are in IDA, while only absolute indicator and additive decomposition form are often used in SDA literature. The simplicity of IDA allows considerable flexibility in problem formulation whereas the fact that SDA is linked to the I–O tables reduces its flexibility but helps to introduce some special features that are not applicable to IDA. SDA can distinguish between a range of technological effects and final demand effects that are not possible in the IDA framework (Hoekstra and van den Bergh, 2003). IDA requires only data at the sub-sector level thus the data requirements depend to a very large extent on the level of sector disaggregation. IDA approach is used to decompose a change in energy consumption over time in a sector into several predefined effects that contribute to the change. One of them can be the intensity effect which is estimated based on changes in the energy intensities of the sub-sectors (Ang et al., 2010). However, SDA is generally more data intensive and decomposition is often conducted for a specific timeframe (Casler and Rose, 1998; Munksgaard et al., 2000; Zhou and Ang, 2008b).

Rose and Casler (1996) as well as Miller and Blair (2009) conducted a detailed review of SDA and its features. Several ideal SDA decomposition methods have been adopted by researchers such as the four ideal decomposition methods, namely D&L, LMDI-I, LMDI-II and MRCI (Su and Ang, 2012). Among these, D&L and MRCI belong to the Laspeyres family while the logarithmic index methods of LMDI-I and LMDI-II belong to the Divisia family (Ang, 2004).

A large number of studies have applied the IDA method for CO_2 emission decomposition (Ang and Zhang, 1999; Wang et al., 2005; Wu et al., 2005; Lin et al., 2006; Diakoulaki and Mandaraka, 2007). Ang (2004) reported a number of publications that use IDA in areas such as energy demand and supply, energy-related gas emissions, material flows and dematerialization, national energy efficiency trend, and cross-country comparisons. IDA-based energy efficiency studies mainly focus on measuring the energy efficiency changes of a specific country or sector over time. However, there are only a few studies that use IDA method for benchmarking the energy efficiency performance across different entities (Zhou and Ang, 2008a). Data envelopment analysis (DEA) and Stochastic Frontier Analysis (SFA) are the methodologies that have been widely used for analyzing the energy efficiency performance across different entities.

IDA has also been used for the construction of a composite energy efficiency index based on the bottom-up approach. In particular, this index considers the decomposition of changes in energy use or aggregation of energy intensity into different factors and then the aggregation of the impacts of energy intensity changes on energy end-use or sub-sector level (Ang, 2006). The two most widely used IDA methods include those based on the Laspeyres and the logarithmic mean Divisia index methods (LMDI-I and LMDI-II). The former index is linked to the concept of percentage change whereas the latter to the concept of log change. In the last 20 years both approaches have gained ground in energy management and environmental planning. For example, the Divisia index has been used by many organizations such as the US Department of Energy (Wade, 2002) and ODYSSEE (2009) for the construction of aggregate energy efficiency indicators. On the other hand, the Office of Energy Efficiency (2002) and IEA (1997) have performed the Laspeyres index in their energy indicators formulation whereas the APERC (2001) has used both of them.

Despite the differences between SDA and IDA in terms of the nature of decomposition, there has been convergence in the basic methods used in both techniques (Su and Ang, 2012). For example, LMDI, the most widely used decomposition method in IDA, has lately been adopted in SDA as well. The above as well as more similarities and differences between IDA and SDA have been analyzed in detail. In particular, the review by Hoekstra and van den Bergh (2003) includes SDA and IDA methods up to 2001, whereas the literature survey conducted by Su and Ang (2012) is concentrated on studies published from 1999 onwards.

1.4 Barriers and Gap to Energy Efficiency

Due to many obstacles raised for energy efficiency improvement, energy efficiency is often underestimated. IEA (2013) estimated that more than half of the potential savings in industry and a whopping 80% of opportunities in the buildings sector worldwide remain untapped. This could be explained by the unwillingness of societies and countries to adopt energy efficiency or the energy efficiency barriers in general.

But what is energy efficiency barrier? Although the concept of energy efficiency barrier is widely used, it is confused especially regarding its importance and the way it should be addressed. The term energy efficiency barrier refers to a mechanism that inhibits a decision or behaviour that appears both energy and economically efficient (Sorrell et al., 2004; Rohdin and Thollander, 2006). Thus, a barrier refers to factors that either hamper the adoption of cost-effective energy-efficient technologies or slow down their diffusion in the market (Fleiter et al., 2011).

According to a number of studies, the major barriers to energy efficiency include, among others, high investment costs, lack of finance for energy efficiency investments, lack of awareness, cost of production and risk of production disruptions (WEC, 2010). The barriers are categorised into structural barriers and behavioural barriers (Hirst and Brown, 1990). The structural barriers include, among others, distortion in fuel prices, uncertainty about future fuel prices, limited access to capital, government policies that encourage energy consumption rather than energy efficiency, codes and standards that lag behind the development of efficient technologies and supply infrastructure limitations. On the other hand, the behavioural barriers refer to attitudes toward energy efficiency, perceived risk of energy-efficiency investments, lack of information on the performance of energy-efficient technologies and lack of life-cycle thinking on costs and savings. A different categorization of barriers is proposed by Jaffe and Stavins (1994). According to them, barriers are grouped into market failures (e.g. imperfect information) and non-market failures (heterogeneity and inertia of consumers, uncertainty about future energy prices and actual savings from energy efficiency investments).

Furthermore, the International Chamber of Commerce – ICC (2014) noted that there are two main categories of barriers that hold back energy efficiency investments: the barriers to deployment of energy efficiency measures and to scaling up energy efficiency measures. The former category refers to the fact that the benefits of energy efficiency investments are perceived as marginal and to a perceived risk and uncertainty for investing time and resources in energy efficiency improvement (ICC, 2014). The second category includes the possible high upfront costs and transaction costs required for energy efficiency improvements, the structural problems due to divergent incentives between owners and occupants of buildings, the lack of knowledge regarding the available efficient technologies and the lack of capability of delivery. To overcome all these barriers, governments need to reward energy-efficient options and encourage investment and innovation (ICC, 2014).

Many researchers have also grouped the barriers into economic, behavioural (psychological) and organisational types (Sorrell et al., 2004; Thollander and Palm, 2012). In particular, the economic-related barriers refer to the market barriers including the heterogeneity of the area of application, hidden costs, access to capital, risk regarding payback periods and market failures including imperfect information and competition, incomplete markets and, principal-agent relationships (Jaffe and Stavins, 1994; Sorrell et al., 2004).

The study of energy efficiency barriers is a multi-disciplinary field. There are many factors that vary widely from one country, sector and technology to another and this makes it more difficult to overcome barriers to energy efficiency. No single policy instrument could address all these and therefore a package of policy instruments is required. In particular, a targeted policy mix including best practices schemes, training initiatives, market-based instruments, energy audit programs, labelling schemes and minimum energy performance standards for the energy efficiency of equipment are of the most common means of overcoming barriers to energy efficiency. Subsidies, preferential loans, research and development (R&D) funds for energy efficiency investment and awareness contribute to reduce barriers. Public-private financing instruments are also useful in overcoming market barriers to motivate people to invest in energy efficiency.

1.5 The Rebound Effect

Most governments are seeking ways to improve energy efficiency in pursuit of their energy policy goals. However, the potential energy savings from improved energy efficiency are sometimes undermined. What takes place is that additional services are employed due to the savings stemming from an existing service becoming increasingly energy-efficient. This is the so-called rebound effect (also called the take-back effect or Jevons' Paradox). In particular, the rebound effect expresses the difference between expected energy savings due to energy efficiency improvement and actual energy savings. This difference could be explained by the behavioral and economic response (saved incomes, reduced costs, more demand, etc.) to energy efficiency increases. In quantifiable terms, the rebound effect is defined as the ratio of energy savings after the installation of the energy-efficient appliances/energy savings without the new energy-efficient devices.

The rebound effect is still an under-researched and controversial topic. It is mainly driven by an energy consumption price tag that is imposed on some of the energy efficiency benefits associated with it such as health improvements, consumer surplus and development goals, energy prices and industrial competitiveness being some of the many benefits that there are. It can be also attributed to the way energy is used and to increased spending and investment across the economy.

The direct, indirect and macroeconomic or economy-wide rebounds are the three rebound effects related to energy efficiency. In the case of direct rebound the efficiency improvement in a certain type of service (or production) leads to increased consumption in the same type of service (or production). In particular, the consumer or producer invests in energy efficient equipment in order to reduce the energy cost and then increases production or consumption using the proceeds from the energy saved. However, in the indirect rebound the improvement increases the consumption in another type of service/production and thus the consumer invests the savings gained by energy efficiency improvements in other goods. In macroeconomic or economy-wide rebound the economic and technological improvement due to efficiency leads to increased energy productivity and economic growth.

The rebound effect is a phenomenon based on economic theory and long-term historical studies, but as with all economic observations its magnitude is a matter of considerable dispute. Although a rebound effect's size is uncertain, its existence has been proven and analyzed by several authors (see among others, Brännlund et al., 2007; Holm and Englund, 2009; Sorrel, 2009). The rebound effect should always be taken into account when energy efficiency is evaluated even when it is not strong enough to outweigh the savings of energy efficiency improvement. Failure to take account of rebound effect could also contribute to shortfalls in the achievement of energy and climate policy goals.

1.6 The Energy Efficiency Gap

A number of studies have pointed to a difference between the cost-minimizing level of energy efficiency and the level of energy efficiency actually realized (Painuly et al., 2003; Sardianou, 2008; Shi et al., 2008). This difference is known as the 'energy efficiency gap' or 'energy efficiency paradox' (DeCanio, 1998; Jaffe and Stavins, 1994; van Soest and Bulte, 2001; Dyer et al., 2008) and was first originated by Eric Hirst and Marilyn Brown in 1990. Its definition can be more complex than it may seem at first glance. Linares and Labandeira (2010) tried to explain it in detail. According to the literature, the fact that we do not often act rationally in decision making, the lack of knowledge about energy saving measures, the capital constraints that make it difficult to acquire energy efficient equipment, the time preference and the uncertainty about the effectiveness of the measures are only some points that explain this gap. Some studies have also focused recently on estimating the existence and the magnitude of the principal-agent problem (Davis, 2012). This refers to the case where a renter decides about energy use and pays the bills but the decisions regarding the equipment installed are taken by the owner who opts for the cheapest alternative. Thus, in this case the most cost efficient combination may not be chosen.

The existence of energy efficiency gap suggests that society has cut out cost-effective investments in energy efficiency (Painuly et al., 2003; Sardianou, 2008). It is attributed to barriers that exist in energy efficiency and mainly to market failures. More than 30 years of literature has tried to define the size of this gap but it remains unclear. It is noted that that the gap may be much smaller than estimated or there may be no gap at all (Metcalf and Hassett 1999; Smith and Moore 2010). On the other hand, it is noted that the gap may be over-estimated mainly due to hidden costs, consumer heterogeneity, uncertainty, over-estimated savings and the rebound effect. Furthermore, there are also several market failures such as the imperfect information, principal-agent issues, credit constraints, and regulatory failures suggesting that the energy efficiency gap is real (Gillingham and Palmer, 2014).

Energy efficiency gap exists in various sectors and therefore many policies and programmes have been developed towards closing this gap. Among others, subsidies and incentives for energy-efficient technologies, tax subsidies, loan guarantees, minimum building and equipment efficiency standards, information campaigns, the EU's labelling scheme and other voluntary labelling programs contribute to narrowing the gap. A summary of these energy efficiency policies can be found in a number of publications (Geller et al., 2006; IEA, 2008; 2011).

1.7 Energy Efficiency Policies

The world population is expected to increase from 6.6 billion to 9 billion between now and 2050 resulting in higher energy demand. Following the increase in energy use, various negative effects such as climate catastrophe, volatility of energy prices and energy resource depletion are also arising that seek urgent attention. Therefore, the adoption of an energy policy framework that could address all these challenges, that are becoming even more severe over time, is a necessity. Today, one by one and in ever increasing numbers, governments are embracing energy efficiency as a way to tackle these issues. Energy efficiency is widely considered as the "holy grail" of energy policymakers mainly due to its various benefits in many aspects. Improving energy efficiency is the most economic and readily available means of ensuring a better use of the world's energy resources. In the 1970s and early 1980s, energy efficiency was a growing policy priority in many EU countries mainly due to its importance in energy supply security and economic development. However, after the counter-oil shock of 1986, the environmental degradation due to the high levels of GHG emissions caused by increasing energy use was the main reason for the energy efficiency promotion. A decline in energy efficiency interest was observed during the 1990s, but energy efficiency rapidly became an important component of global energy policy. Since then, many measures and programs have been developed for the adoption of energy efficiency on a national and global level.

In the following, we focus on EU policies as the aim of this thesis is the evaluation of energy efficiency in EU countries and industries. This is mainly because of the data availability and also the importance of EU performance at the global level.

1.7.1 Directives

Over years, a number of EU directives have been developed dealing with energy efficiency. These include, among others, the following directives (Bleischwitz and Andersen, 2009):

- Energy efficiency of hot-water boilers (1992/42/EEC)
- Household appliances labeling directive (1992/75/EEC)
- Energy efficiency of domestic refrigeration appliances directive (1996/57/EC)
- Ballasts for fluorescent lighting directive (2000/55/EC)
- Energy performance of buildings directive (2002/91/EC)
- Cogeneration directive (2004/8/EC)
- Ecodesign for energy-using appliances directive (2005/32/EC)
- Energy end-use efficiency and energy services directive (2006/32/EC)
- Promotion of Clean and Energy Efficient Road Transport Vehicles (2009/33/EC)

In December 2008, the EU also adopted an integrated energy and climate change policy known as 20 20 20 - 2020 goals. Its aim is a 20% reduction in GHG emissions, a 20% share of energy from renewable sources and a 20% increase in energy efficiency by the year 2020 (European Union - EU, 2009). These 2020 targets are the basis for a sustainable, secure and affordable energy system. The first two of these targets were implemented by a binding legislation known as the "climate and energy package" that became law in June 2009. Regarding the third target, the non-binding national target for energy efficiency improvement, the 2012 Energy Efficiency Directive (EED) came into force on 5 December 2012. It repeals the Cogeneration Directive (2004/8/EC) and the energy end-use efficiency and energy services directive (2006/32/EC) whereas it amends the Ecodesign directive (2009/125/EC) and the Energy Labelling Directive (2010/30/EU). The 2012 EED firmly places energy efficiency at the heart of the EU 2020 energy strategy aiming for an EU primary consumption level (minus non-energy uses, e.g. for pharmaceuticals) of 1474 Mtoe or 1086 Mtoe of final energy consumption in 2020. The Commission, having this number in a directive, can monitor the progress towards it and propose further measures if necessary. All EU countries, under this directive, are required to use energy more efficiently at all stages of the energy chain from transformation to distribution and final consumption. To this end, each EU country has set its own indicative national energy efficiency action plans (NEEAPs) for saving energy. Each Member State (MS) is required to develop energy efficiency obligation schemes and measures to reduce energy use in industry, transport and households. Based on the EED plan, a fifth of Europe's annual energy consumption can be saved by 2020 compared with conducting "business as usual" by improving the energy efficiency of energy-using products, services and buildings.

In addition, to the aforementioned directives, the EC has established the voluntary energy labelling programs of "Energy Star" and "EU Ecolabel" for the promotion of energy efficiency[2]. The former is an international standard for energy efficient consumer products originated in the United States. It was created in 1992 by the Environmental Protection Agency and the Department of Energy and since then, Australia, Canada, Japan, New Zealand, Taiwan, and the European Union have adopted the program. Devices carrying the Energy Star service mark, such as computer products, kitchen appliances, buildings and other products, generally use 20–30% less energy than required by federal standards[3]. The "EU Ecolabel" scheme is used for identifying products and services that have a reduced environmental impact throughout their life cycle. There are over 37.000 products and services on the market that display the "EU Ecolabel" covering everything from detergents to shoes and paints to paper. The "EU Energy Label" is another labelling scheme that gives information about the energy efficiency performance, total energy consumption and other characteristics of a product (e.g. water consumption, noise levels etc.). Contrary to "Energy Star" and "EU Ecolabel", the "EU Energy Label" is a mandatory scheme. All labelling schemes help consumers to buy energy-efficient and environmentally friendly products and services. Moreover, the labelling logos add value to manufacturers' products by increasing the product's reputation and giving their products a competitive advantage in the growing green marketplace.

1.7.2 Measures

The EC's action plan for energy efficiency proposes a number of measures aimed to put the EU on track towards saving 20% of its energy by 2020. Energy efficiency policy can be considered in a broader context including regulation for appliances, equipment and buildings

[2] http://ec.europa.eu/environment/gpp/eu_related_en.htm [Accessed 23 October 2015]
[3] https://en.wikipedia.org/wiki/Energy_Star [Accessed 14 November 2015]

(performance standards and labelling), energy efficiency awareness for consumers and stakeholders, economic support though loans, subsidies or tax reduction, deployment of specific financing mechanisms, as well as R&D and dissemination of expertise in the field of energy efficiency (WEC, 2010).

The energy efficiency measures could be organized into regulations, financial and fiscal measures. Regulations include mandatory policies that are usually applied to equipment. The Minimum Efficiency Performance Standards (MEPs) for new appliances, new cars and new buildings, efficiency labels, mandatory energy audits, energy saving obligations and mandatory training for professionals are some regulations. Regulations are widely used, partly because they have been proven effective in lowering energy consumption of specific appliances and equipment and speeding up the diffusion of energy-efficient equipment, energy-saving investments and practices. These measures can be set nationally, for a group of countries or at sub-national, regional level. The financial measures include subsidies for audits, soft loans and funds for energy efficiency investment and other economic incentives. For example, public–private partnerships, international cooperation and banks are called on by the EC for funding new energy-efficient technologies and eco-innovations. The fiscal measures refer to tax credit and tax reduction for products and/or services based on their efficiency performance. Taxes are mainly imposed on the CO_2 emissions of vehicles, use of high energy-consuming products and fees/charges on fuels and energy utility charges. Fiscal incentives also include measures to reduce the annual income tax paid by consumers who invest in energy efficiency (WEC, 2010). Taxation is an effective way of reducing GHG emissions and promoting energy efficiency as many people choose tax-efficient products to avoid being taxed.

The evidence of great potential for cost-effective efficiency-derived reductions in energy use and GHG emissions from industries has prompted governments to implement numerous policies and measures aimed at improving industrial energy efficiency. The energy efficiency measures applied in industry are divided into regulations/standards, fiscal policies and agreements/targets (Abdelaziz et al., 2011). Agreements are usually voluntary agreements between government and industry and are used for meeting specific energy use or energy efficiency targets. As the industrial sector accounts for a large share of total energy consumption, new business models have been developed as part of an integrated approach for energy efficiency improvement. The Energy Service Companies (ESCOs) are an example of the scope for greater energy efficiency through cost-effective projects. ESCOs perform an analysis of the property, provide a broad range of energy solutions and ensure energy savings during the payback period. The EU’s Emission Trading Scheme (ETS), the first large GHG emissions trading scheme in the world, is also an overarching method for boosting energy efficiency performance on the electricity sector[4]. It was launched in 2005 to fight Global warming and is a major pillar of EU climate policy. Its main aim is the reduction of CO_2 emissions by allowing companies to buy or sell allowances in order to emit CO_2.

Since the 1970s, various energy efficiency measures have also been applied in buildings including, among others, regulatory (e.g. building codes, minimum energy performance standards, energy certificates, etc.), economic, informative and voluntary approaches (e.g. passive house standard, energy efficiency commitment schemes, etc.) (Buildings Performance Institute Europe – BPIE, 2011; Global Energy Assessment - GEA, 2012). Buildings are responsible for a high percentage (about 40%) of the EU's energy consumption. Nevertheless, there is a potential of reducing the energy use in buildings by around 11% by investing in energy efficiency. The Commission estimates that emissions from buildings could be reduced by around 90% in 2050[5]. Based on the first Energy Performance of Buildings Directive (2002/91/EC), all MSs are required to set minimum energy performance requirements of new and existing buildings whereas new buildings and major renovations shall be "nearly zero-energy buildings" on a cost-optimal level.

Energy efficiency policies have also been developed for improving energy efficiency performance in transport and more specifically for promoting environmentally friendly and energy-saving forms of transportation. Transport is one of the fastest growing sectors accounting for almost one fifth of the EU's total energy consumption and a large rate of worldwide CO_2 emissions. Therefore, various energy efficiency measures such as congestion charges, promotion of public transport, intelligent control of traffic lights, car-sharing and a higher tax rate for less-fuel-efficient vehicles are applied in the transport sector for meeting its increasing energy use and minimizing GHG emissions. The EU-wide car fuel efficiency labelling also helps consumers to choose more energy-efficient vehicles and incentivizes producers to manufacture cleaner and environmentally friendly vehicles. Furthermore, subsidies are given to the owners of the hybrid-electric vehicles (HEVs) as these can increase energy security, improve fuel economy, and reduce emissions.

Over the last decades, the number of energy efficiency measures, applied in developed and developing countries has increased. According to the WEC survey (WEC, 2013) that identifies recent trends in energy efficiency performance in 85 countries and economies from all over the world, regulations are predominant representing around 70% of all measures in 2013. This is due to the fact that regulations are more powerful compared to other measures

[4] http://ec.europa.eu/clima/policies/ets/index_en.htm [Accessed 23 October 2015]
[5] http://ec.europa.eu/clima/policies/strategies/2050/index_en.htm [Accessed 23 October 2015]

as they do not leave any choice for consumers. Furthermore, regulations are used worldwide and have been proved effective in reducing energy use of equipment. Labelling and MEPs are the most important regulatory measures accounting for 42% and 40% of total regulations on average, respectively. Furthermore, regulations are dominant in the residential and service sectors. The survey also showed that fiscal or financial measures have been implemented in two thirds of the surveyed countries. Of them, financial measures are the most dominant measures, especially in industry.

1.7.3 Effectiveness of Energy Efficiency Policies and Future Trends

The WEC (2010) proposed a set of strategies and action plans for improving energy efficiency. Among others, sustainable institutional support, incentive prices, financing schemes, regulations, promotion of energy efficient equipment and services, consumer awareness, and international and regional cooperation are needed to make investments in energy efficiency attractive and cost effective.

The implementation of energy efficiency measures is expected to reduce global energy intensity by 1.8% per year through to 2035 (IEA, 2013). IEA (2009b) recommended a number of policy measures that could be applied to 25 fields in areas such as the cross-sectoral activity, buildings, appliances, lighting, transport, industry and power utilities. Based on the IEA (2013) estimates, if these recommendations were implemented fully by all 28 IEA Members they could save USD 1 trillion in annual energy costs as well as deliver incalculable security benefits. According to the annual report of the IEA (2014a), the global energy efficiency market is worth at least USD 310 billion a year and growing. This confirms the position of energy efficiency as the world's "first fuel". It also reports that energy efficiency finance is becoming an established market segment, with innovative new products and standards helping to overcome risks and bringing stability and confidence to the market.

Over the past years energy efficiency improvements have led to a reduction in global energy use and CO_2 emissions. Without energy efficiency improvements, the OECD nations would have used approximately 49% more energy than was actually consumed as of 1998 (Geller et al., 2006). Minimum efficiency standards, voluntary agreements, financial incentives, and eliminating subsidies for fossil fuels have been proved to be a very effective strategy for stimulating energy efficiency improvements on a large scale, for reducing industrial energy use and CO_2 emissions in a number of countries. Government-funded R&D also contributed to the development and commercialization of a number of new energy efficiency technologies in some countries and sectors. Moreover, labelling, information dissemination, and training have also increase awareness of energy efficiency measures and improved know-how with respect to energy management.

Efficiency pessimists believe that there is little potential for further energy efficiency improvements as we have been harvesting the low-hanging fruit. Thus, the only solution to meet the future energy needs is through the power plants, transmission lines and distribution systems. On the other hand, efficiency optimists contend that energy efficiency is an endless energy source. Most probably the truth is somewhere in between. Therefore, more policy instruments should be applied including among others information, standards, technological change and financing.

Despite the progress made in energy efficiency until today, IEA assessments show that under existing policies as much as two-thirds of the economically viable energy efficiency potential will remain unrealized between now and 2035 (IEA, 2013). That so much energy is simply wasted should be deemed unacceptable. The Energy Efficiency Communication of July 2014 noted that the 20% target will be missed by 1% - 2% if EU countries do not implement all existing energy efficiency measures. Therefore, the efficiency button needs to be pushed and governments are often in the best position to make this happen. They need to overcome any barrier to the implementation of energy efficiency. To do that, governments have to help people to understand the costs and benefits of energy efficiency and make energy efficiency more visible and affordable to everyone. To this end, governments need to provide financing instruments and incentives. Information and communication campaigns are needed to change people's behavior towards more sustainable energy consumption. Furthermore, energy efficiency measures can play an important role in energy efficiency improvement. The sooner measures are put in place, the more effective they will be. It has been proven that the cost of taking action is less than the price of failing to act which amounts to 1% of world GDP. Thus, the EU needs to develop an overarching context with mandatory and voluntary policies and strategies for energy efficiency adaption. It is also important the EU countries' implementation of energy efficiency measures be monitored and energy efficient activities of all MSs to be supported through funding mechanisms. Greater coordination and information-sharing between MSs should also be promoted through strategy support actions. Furthermore, the EU should encourage the transition to a low-carbon economy through investing in energy efficiency and renewable energy. A low-carbon economy is helping to enhance job creation, strengthen Europe's energy security and reduce its dependence on imports. Businesses should also develop innovative and energy efficient financing incentives. They need to set standards and benchmarks and improve industry professionalism for promoting energy efficiency. In addition to these, governments need to raise their level of ambition, and commit to investing in energy efficiency without delay even if there are in fact "hidden costs" towards achieving energy efficiency.

The year 2030 is the next crucial milestone in energy policy. The EC has launched a public debate on what energy policies and measures the EU should apply in 2030. In particular, in October 2014, EU countries agreed to cut GHG emissions by at least 40% (from 1990 levels), to boost the share of renewables to at least 27% of EU energy consumption and to a 27% or greater energy efficiency improvement by 2030[6]. The EU expects a reduction in EU energy use by 30% in 2050 due to energy efficiency. The EU has also committed to keeping global warming below *2* °C by cutting its emissions by 80-95% of 1990 levels by 2050.

[6] http://ec.europa.eu/clima/policies/strategies/2030/index_en.htm [Accessed 23 October 2015]

CHAPTER 2

Energy Efficiency Evaluation Models

This chapter presents the main methodological tools, which are relevant for the energy efficiency assessment framework considered in this thesis. These include input-output models such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), as well the multidimensional evaluation framework of Multiple Criteria Decision Aid (MCDA). The basic characteristics of these methodologies are described as they are the most popular techniques used for efficiency analysis with many applications in energy management and environmental planning. In the context of this thesis, DEA is used for obtaining efficiency estimates, whereas MCDA approach is used to build an operational model that combines energy efficiency with economic and environmental indicators. An extended literature review regarding the fields in which these models are applicable is also presented.

2.1 Parametric and Non-parametric Approaches

During the past several decades, in addition to energy efficiency indicators, many methods have been developed to monitor and measure energy efficiency trends. These methods can be classified into two broad categories, namely parametric and non-parametric approaches (Fried et al., 1993; Sadjadi and Omrani, 2008). The measurement of efficiency and productivity in the case of multiple inputs and outputs can only be performed by using these techniques. Thus, both approaches are mainly used for aggregating inputs and outputs in a single "index of inputs" and "index of outputs", respectively (Coelli et al., 2005).

Each approach has its own characteristics, strengths, and weaknesses. Parametric models are based on econometric estimation techniques whereas non-parametric ones use operations research and management science (OR/MS) models. The main difference between these two aforementioned approaches lies in their fundamental assumptions. Although, both use a measure of distance between the observed data and the "best practice" efficient frontier (which serves as a norm for the productivity efficiency evaluation), they differ in whether they estimate a cost or production function (parametric models) or not (non-parametric models). In particular, the specification of a production function (most commonly a cost function) is a necessity only for parametric models. Non-parametric approaches are more flexible compared to parametric ones. However, parametric models can distinguish the various sources of randomness such as the measurement and specification of error from inefficiency (Bauer et al., 1998). Furthermore, parametric models are characterized by higher scores as they consider statistical noise and exhibit less variability.

The Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are the most popular parametric and non-parametric methods, respectively. DEA is widely recognized having certain advantages over SFA. In particular, DEA, contrary to SFA, provides simultaneously both an efficiency score and benchmarking information through efficient targets. It does not require any prior assumptions on the relationships between input and output data (Seiford and Thrall, 1990; Zhou et al., 2008) but only physical quantities for evaluating technical and scale efficiency indicators. This is especially useful when the relationship is not known or specified by theory (Fang et al., 2009). Also, DEA can be used as a multi-factor analysis model without formulating any functional form on the relationship between variables (Thakur et al., 2006; Fang et al., 2009). Its preference over SFA is also well-known when dealing with very small samples since DEA performs better in these situations (van Biesebroeck, 2007; Krüger, 2012). A literature review to a sample of energy production papers that adopted these models can be found in Barros (2008).

2.2 Stochastic Frontier Analysis

SFA is used in a large body of literature related to production, cost, revenue, and profit efficiency. It is a method of economic modelling that was first introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977). A Stochastic Frontier Model (SFM) is often known as “composed error model” since the error term comprises two components. The one component captures the effects of inefficiency as regards the stochastic frontier and the other captures the effects of external factors that are beyond the producers’ control such as statistical noise and measurement error. The SFM can be represented as:

$$y_i = f(\mathbf{x}_i; \boldsymbol{\beta}) + \varepsilon_i \tag{2.1}$$

where y_i is the single output of the producer i $(i = 1,...,N)$, $\mathbf{x}_i$ is a vector of M inputs used by producer i, $f(\mathbf{x}_i;\boldsymbol{\beta})$ is the deterministic component of the production function that is common to all producers, $\boldsymbol{\beta}$ is a vector of technology parameters to be estimated, and ε_i is the composite error term that can be defined as follows:

$$\varepsilon_i = \upsilon_i - u_i \tag{2.2}$$

The economic logic behind this specification is that the production process is subject to statistical noise (randomness) represented by υ_i and technical inefficiency represented by u_i. Thus, contrary to general regression analysis that estimates an average function with a normal error distribution, SFA calculates the best practice technology of production (e.g. cost function, or distance function) with a two-part error term.

Under the assumption that $f(\mathbf{x}_i; \boldsymbol{\beta})$ is of Cobb-Douglas type, the stochastic frontier model in (2.1) can be written in logs as (Kumbhakar and Lovell, 2000):

$$\ln y_i = \beta_0 + \sum \beta_n \ln x_{ni} + \upsilon_i - u_i \tag{2.3}$$

Many studies have used SFA for energy efficiency measurement. For instance, Feijoo et al. (2002) as well as Buck and Young (2007) applied SFA to evaluate the energy efficiency performance of Spanish industrial and Canadian commercial buildings respectively. Managi et al. (2006) used SFA to examine the impact of technological change on the exploration of oil and gas, whereas Farsi et al. (2007) used it to investigate the cost efficiency of Swiss gas distribution companies. Boyd et al. (2008) also employed SFA to develop a statistical benchmarking tool (energy performance index), which is used in the Energy Star program of the US Environmental Protection Agency. Growitsch et al. (2009) and See and Coelli (2013) applied SFA to examine the efficiency of electricity distribution networks. SFA was also applied for estimating the energy efficiency performance in 47 Japanese regions (Honma and Hu, 2014a) and 117 agricultural and 43 manufacturing enterprises in Hungary (Piesse and Thirtle, 2000). Finally, Zhou et al. (2012) used SFA to estimate the economy-wide energy efficiency performance of 21 OECD countries at a macro-level.

2.3 Data Envelopment Analysis

2.3.1 Basic DEA Model

DEA, first introduced by Charnes, Cooper and Rhodes (1978), is a well-established methodology for evaluating the relative efficiencies of a set of comparable entities known as decision making units (DMUs, i.e., countries, sectors, firms). The DMUs transform multiple inputs (energy and non-energy inputs) into multiple outputs (desirable and undesirable). Relying on linear programming techniques, and without having to introduce any subjective or economic prices (weights, costs, etc.), DEA provides a non-parametric estimate of the efficiency of each DMU compared to the best practice frontier constructed by the best-performing DMUs (Zhou and Ang, 2008a). The multidimensional efficiency frontier provides a reference for benchmarking the efficiency of all DMUs.

DEA produces relative, rather than absolute, measures of technical efficiency for each DMU under consideration due to the fact that the technical efficiency score of each DMU depends on the performance of the sample of which it is a part (Pardo Martínez and Silveira, 2012). A DMU is technically efficient if it has the best ratio of any output to any input or according to Cooper et al. (2006) if and only if it is not possible to improve any input or output without worsening some other input or output.

The assessment of energy efficiency in the context of DEA can be derived from a production theory point of view. In particular, in accordance with Zhou et al. (2012), assume that energy (E) and non-energy inputs (NE) are used to produce outputs (Y) in an economy wide context and let $T = \{(N, NE, Y) / (N, NE) \text{can produce } Y)\}$ be the production technology set, which describes the feasible transformations of the inputs to outputs. From an energy efficiency point of view, the goal is to minimize energy use while keeping all inputs and outputs within the production technology set. Thus, the Shephard distance function can be described as follows:

$$D(E, NE, Y) = \sup\{a : (E / \alpha, NE, Y) \in T\} \tag{2.4}$$

Using the above function, an energy efficiency index can be defined as $\theta = 1 / D(K, L, E, Y)$, which ranges in [0, 1]. If the energy efficiency index is less than 1, then the country/sector is inefficient as its energy use could have been decreased within their production technology set. Furthermore, the higher the value of the index, the better the energy efficiency performance with a value equal to 1 indicating that the unit under consideration (country, sector, firm) is located on the best performance frontier.

To implement this framework in the context of DEA, assume that there are data on K_E energy inputs, K_{NE} non-energy inputs, and M outputs for N (DMUs (countries, sectors, firms). For the i_{th} unit, the corresponding data are denoted by the vectors $\mathbf{x}_i^E, \mathbf{x}_i^{NE}$, and $\mathbf{y}_i$, respectively. The $K_E \times N$ matrix $\mathbf{X}_E$ for the energy inputs, together with the $K_{NE} \times N$ matrix $\mathbf{X}_{NE}$ for the non-energy inputs, and the $M \times N$ output matrix $\mathbf{Y}$ represent the data for all available units. Then, the energy efficiency of unit i is estimated through the solution of the following linear program which is known as the CCR model from the initials of the authors Charnes, Cooper and Rhodes (Charnes, Cooper and Rhodes, 1978):

$$\begin{array}{ll} \min & F = \theta_i - \varepsilon(\mathbf{1s}_i^E + \mathbf{1s}_i^O) \\ \text{Subject to:} & \mathbf{X}_E\boldsymbol{\lambda} - \theta_i \mathbf{x}_i^E + \mathbf{s}_i^E = \mathbf{0} \\ & \mathbf{X}_{NE}\boldsymbol{\lambda} \le \mathbf{x}_i^{NE} \\ & \mathbf{Y}\boldsymbol{\lambda} - \mathbf{s}_i^O = \mathbf{y}_i \\ & \boldsymbol{\lambda}, \mathbf{s}_i^E, \mathbf{s}_i^O \ge \mathbf{0},\ \theta_i \in \mathbb{R} \end{array} \tag{2.5}$$

where $\mathbf{1}$ denotes a vector of ones. The solution of this linear program provides the energy efficiency estimate $\theta_i = 1/D(E, NE, Y)$ for each unit i relative to other unit in the data, from the perspective of reducing the energy inputs, in accordance with the production framework discussed above. $\mathbf{s}_i^E$ and $\mathbf{s}_i^O$ are vectors of slack variables for the energy inputs, non-energy inputs and outputs, respectively, indicating the improvements that an inefficient unit should achieve to become efficient. In the objective function $\varepsilon \approx 0$ is a small, positive constant that allows the solution procedure to give first priority to the optimization of θ_i. Denoting by F^* the value of the objective function of problem (2.5) at its optimal solution, unit i is classified as efficient if and only if $F^* = 1$ (i.e. if the efficiency score is $\theta_i = 1$ and the slacks are zero).

The above model (2.5) assumes constant returns to scale (CRS). Variable returns to scale (VRS) can be introduced by simply adding the convexity constraint $\mathbf{1}\boldsymbol{\lambda} = 1$ which ensures that each DMU is compared only to DMUs of similar size. The resulting model is known as the BCC model (Banker, Charnes and Cooper, 1984).

Within the DEA framework, the technical efficiency can be measured by an input or output oriented model. In general, the technical efficiency in input and output oriented models can be measured as the ratio of the efficient level of input and output divided by the actual input and output, respectively. The main difference between these types of models is that an input-oriented approach considers the technical inefficiency by assessing the reduction of all inputs that would set a unit technically efficient while keeping all outputs fixed. On the other hand, an output orientation focuses on the expansion of all outputs while keeping inputs fixed. This model is the most appropriate in case there is a priori assumption that energy input has a strong complementarity with other inputs. Although the CCR model is invariant to the orientation of the modelling approach (i.e., input/output oriented), in the BCC model the orientation plays an important role. Most studies dealing with applications of DEA models in energy efficiency and other related areas have adopted an input-oriented approach. This is line with the nature of energy efficiency management, as a country or organization has more control over its available resources (energy, labour, capital, etc.), rather than the level of outputs (e.g., GDP). Cook and Seiford (2009) surveyed several DEA applications focusing on the various models for measuring efficiency, while covering issues related to the selection of input/output variables, and the modeling of various data settings.

DEA is also one of the most widely used methodologies in surveys of energy and environment. Regarding the energy sector efficiency evaluation, it should be noted that papers which are based on this methodology are steadily increasing from 2000 and afterwards (Vlontzos et al., 2014). The literature of DEA studies dealing with environmental aspects of production is even larger than the that dealing with energy issues (Ang and Zhang, 2000; Färe et al., 2004; Ramanathan, 2005; Hu and Kao, 2007; Zhou and Ang, 2008a; Fang et al., 2009; Vlontzos et al., 2014). A literature survey by Zhou et al. (2008) listed a total of 100 studies published from 1983 to 2006 using DEA in energy and environmental analysis. According to the survey, 72 of these studies were published between 1999 and 2006, which shows a rapid increase in the number of studies using DEA. Sueyoshi and Goto (2012) also presented a number of DEA studies published in Energy Economics from 2006 to 2010.

DEA has also been widely applied to assess the energy efficiency performance of different countries/regions from the viewpoint of production efficiency (Wei et al., 2007; Honma and Hu, 2008; Zhou and Ang, 2008a; Chang and Hu, 2010; Mukherjee, 2010; Zhou et al., 2012). Ramanathan (2005) used DEA to analyse the performance of 17 countries in the Middle East and North Africa for the period 1992–1996, whereas Lozano and Gutiérrez (2008) used the DEA method to measure energy efficiency in 21 OECD countries from 1990 to 2004.

DEA has also been used for evaluating energy efficiency trends in energy intensive industrial sectors (Jamasb et al., 2008; Mukherjee, 2008a). For example, it has been used for evaluating the performance of industrial sectors such as pulp and paper (Blomberg et al., 2012), cement (Mandal, 2010; Oggioni et al., 2011; Riccardi et al., 2012), chemicals (Saygin et al., 2011, Broeren et al., 2014), power (Vaninsky, 2006; Wang et al., 2007) and transport (Ramanathan, 2005; Cui and Li, 2014; Zhou et al., 2014).

Most of DEA-related energy efficiency studies do not take into account undesirable outputs such as CO_2 and GHG emissions (Wu et al., 2012). However, this omission may lead to biased energy efficiency values (Zhou and Ang, 2008a; Mandal, 2010). Firstly, Zhou and Ang (2008a) incorporated undesirable outputs in the production process for evaluating energy efficiency. Since then, more and more studies consider both desirable and undesirable outputs for energy efficiency analysis (Bian and Yang, 2010; Mandal, 2010; Shi et al., 2010; Yeh et al., 2010; Sueyoshi and Goto, 2011; Wu et al., 2012). It is found that the results can be biased if undesirable outputs are excluded from the analysis (Watanabe and Tanaka, 2007; Zhou and Ang, 2008a; Mandal and Madheswaran, 2011; Sueyoshi and Goto, 2011; Riccardi et al., 2012; Wu et al., 2012; He et al., 2013; Ramli and Munisamy, 2013).

Table 2.1 presents a brief overview of other studies using DEA for measuring energy efficiency at the country and sectoral level. From Table 2.1, it can be concluded that labour, capital and energy are defined as the inputs in most papers. For outputs, most papers' energy efficiencies contain GDP and CO_2 emissions.

Table 2.1: Studies that use DEA to measure energy efficiency

at the country and industry level.

Authors	**Period**	**Sample**	**Inputs**	**Outputs**
Azadeh et al. (2007)	1991-1998	manufacturing sectors of Iran and some OECD countries	final fuel consumption, electricity consumption	gross output, value added
Chien and Hu (2007)	2001–2002	45 countries	labor, capital stock, energy consumption	GDP
Mukherjee (2008b)	1970-2001	U.S. manufacturing sector	labour, capital, energy, materials, services	gross output
Wang and Zhou (2008)	1993-2005	28 Chinese regions	labour, capital, energy,	gross product value of industrial enterprises
Fang et al.	2001–2005	coal mining	operating cost, total	earnings per share,

(2009)		companies in China and the US	assets, number of employees	operating revenue, net profit before tax
Ramos-Real et al. (2009)	1998–2005	18 Brazilian electricity distribution firms	length of electricity grid, number of employees, losses	sales, number of customers
Shi et al. (2010)	2000-2006	28 Chinese regions	labour, fixed assets, energy consumption	industrial added value, industrial waste gas
Pardo Martínez (2011)	1998-2005	non-energy intensive sectors in Germany and Colombia	labour, energy, capital, materials	gross value of manufacturing deflated by the wholesale price index
Wei et al. (2011)	1980-2007	156 countries	labor, capital, energy consumption	GDP
Zhang et al. (2011)	1980–2005	23 developing countries	labor force, energy consumption, capital stock	GDP
Pardo Martínez and Silveira (2012)	1993–2007	19 sub-sectors in the Swedish service sectors	labour, capital, materials, energy	production value, CO_2 emissions
Sueyoshi and Goto (2012)	2005-2009	9 Japanese electric power firms	generation asset, transmission asset, distribution asset, operation cost without labor cost, number of employees	amount of electricity sold, number or customers
Tao et al. (2012)	1999-2009	China's industry	number of employees, energy consumption, capital stock	gross industry output, CO_2 emissions
Vlahinić-Dizdarević and Šegota (2012)	2000-2010	26 EU countries	labor, capital stock, energy	GDP
Wu et al. (2012)	1997-2008	industrial sectors in 28 Chinese regions	labor force, capital stock, energy	industrial value added, CO_2 emissions
Bampatsou et al. (2013)	1980-2008	EU-15 countries	energy consumption of fossil, non fossil fuels, nuclear energy	GDP
Lu et al. (2013)	2005-2007	32 OECD	value-added industry, population	GDP, fossil-fuel, CO_2 emissions
Honma and Hu (2014b)	1995–2005	14 developed countries	labour, capital stock, energy, non-energy intermediate inputs	value added
Vlontzos et al. (2014)	2001–2008	primary sectors in 25 EU countries	labor, capital, energy consumption	output (millions of euro), CO2 emissions, gross nutrient balance

Zhou et al. (2014)	2003-2009	transport sector of China's 30 regions	labour, energy inputs (coal, gasoline, kerosene, diesel oil, electricity, other energy)	passenger kilometres and tonne-kilometers for passenger and freight services, CO_2 emissions

2.3.2 Malmquist Productivity Index

Index number approaches such as the Malmquist Productivity Index (MPI) have been developed to measure changes in productivity and its components. Productivity is an important component for monitoring and analysing performance. It evaluates the performance of economic entities that convert inputs (e.g. labour, capital, materials, energy) into outputs (e.g. products and services). Productivity changes over time due to changes in technical efficiency, technology, and scale of operations. Measuring the changes in productivity is of great importance at all levels of economic activity. The most commonly used categories of productivity ratios are the partial productivity, total factor productivity, and total productivity (Christopher, 1993; Sumanth, 1998). The classic measure of productivity is the ratio of output produced per unit of input expended. Therefore, the productivity ratios are measured by the ratio of output to a single input, the ratio of output to capital and labour services and the ratio of output to all combined inputs including labour, materials, capital, energy and other inputs respectively. However, the ratios that measure productivity trends –changes in productivity over time - are commonly converted into an index. The first two sources of productivity change are known as efficiency change and scale efficiency change, whereas the last one is known as technical change and it is associated with shifts of the frontier (technical progress or regress). Contrary to other index approaches, MPI can distinguish between two sources of productivity growth: efficiency change and technical change but it does not adequately account for scale change. MPI uses input or output oriented distance functions. However, input- and output-oriented MPIs coincide if the technology exhibits constant returns to scale.

The concept of the MPI was originally introduced by Malmquist (1953) whereas Färe et al. (1992) constructed a MPI directly from input and output data using DEA. It is an efficient-frontier based (mostly DEA) measure of total factor productivity used for analysing the effect of efficiency and technology change on energy efficiency performance (Pombo and Taborda, 2006; Perez-Reyes and Tovar, 2009; Zhou et al., 2010). In the non-parametric framework of

DEA, MPI is measured as the product of catch-up (or recovery) and frontier-shift (or innovation) terms. Thus, the DEA-based MPI firstly constructs an efficiency frontier over the whole sample realized by DEA and then computes the distance of individual observations from the frontier. It can be defined as follows (Färe et al., 1992):

$$MPI_i(t,\ t+1) = \frac{\theta_i^{t+1}(\mathbf{x}_i^{t+1}, \mathbf{y}_i^{t+1})}{\theta_i^{t}(\mathbf{x}_i^{t}, \mathbf{y}_i^{t})} \times \sqrt{\frac{\theta_i^{t}(\mathbf{x}_i^{t+1}, \mathbf{y}_i^{t+1})}{\theta_i^{t+1}(\mathbf{x}_i^{t+1}, \mathbf{y}_i^{t+1})} \times \frac{\theta_i^{t}(\mathbf{x}_i^{t}, \mathbf{y}_i^{t})}{\theta_i^{t+1}(\mathbf{x}_i^{t}, \mathbf{y}_i^{t})}} \tag{2.6}$$

where $\theta_i^{t'}(\mathbf{x}_i^t, \mathbf{y}_i^t)$ is the efficiency score obtained by benchmarking the unit's data for period t against the sample data for period $t+1$. $MPI_i(t,t+1) > 1$ indicates an increase or improvement in the total factor productivity of the DMU from the period t to $t+1$, while $MPI_i(t,t+1) = 1$ and $MPI_i(t,t+1) < 1$ indicate the status quo (no change) and decline in productivity, respectively.

The first term in (2.6) indicates the catch-up (or recovery) effect and relates to the degree that a DMU attains for improving its efficiency. Thus, it identifies the change in the distance of observed production from best-practice production (i.e., between periods t and $t+1$). This ratio is greater than, equal to, or less than unity as the relative performance of a DMU is improving, unchanging, or declining. Conversely, the square root term represents the technological change that indicates the frontier-shift (innovation) effect between consecutive periods. It shows whether the best-practice frontier relative to the DMU in question is improving, stagnant, or deteriorating. This second term is greater than, equal to, or less than unity as technical change is positive, zero, or negative, on average.

The DEA-based MPI has proven to be a useful tool for measuring the productivity change of DMUs over time and has been successfully applied in many sectors (Yörük and Zaim, 2005; Wei et al., 2007; Xue et al., 2008; Greer, 2008; Perez-Reyes and Tovar, 2009; Zhou et al., 2010; He et al., 2013). For example, DEA-based MPI has been employed for evaluating the performance of electricity distribution utilities (Giannakis et al., 2005; Abbott, 2006; Barros and Peypoch, 2008; Sueyoshi and Goto, 2012), iron and steel industry (Wei et al., 2007; He et al., 2013). A number of studies that used MPI in energy efficiency measurement are listed in Table 2.2.

Table 2.2: Studies that use MPI to measure energy efficiency.

Authors	Period	Sample	Inputs	Outputs
Hattori et al. (2003)	1985- 1998	electricity distribution systems in the UK and Japan	operating expenses, capital expenditures	units of energy delivered, number of customers, length of network, maximum demand
Estache et al. (2004)	1996-1999	Mexico’s 11 main ports	capital, labour	volume (in tons) of merchandise handled in each port
Abbott (2006)	1969-1999	Australia's electricity supply industry	capital stock, energy used, labour employed	amount of electricity consumed
Estache et al. (2007)	1998-2005	12 countries around the Southern African Power	installed capacity, labour	generation, number of customers, sales
Wang et al. (2007)	1978–2003	Hong Kong electricity supply industry	labour, capital expenditure	sales of electricity delivered, customer density
Barros (2008)	2001–2004	Portugal hydroelectric energy generating plants	capital, number of workers, operational costs, investment	production, capacity utilization
Perez-Reyes and Tovar (2009)	1996-2006	14 electricity distribution companies in Peru	number of workers, distribution power losses, medium-voltage and low-voltage network kilometres, number of substations, monetary value of the active capita	sales, number of customers
Cui et al. (2014)	2008–2012	9 countries	number of employees, energy consumption, energy services amount	CO_2 emissions per capita, industrial profit amount

2.3.3 Statistical Inference - Bootstrap Methodology

Many efficiency and productivity analysis studies based DEA have suffered from lack of appropriate tests for analysing the sensitivity of the results as the estimates from conventional

DEA analyses offer no information on the variability of the obtained estimates. Statistical resampling techniques provide a possible remedy to this problem (Odeck, 2009). Bootstrap, first introduced by Efron (1979) and further explored by Efron and Tibshirani (1993), is such an approach which is widely used as an alternative to classical inference and hypothesis testing.

The combination of the bootstrap techniques with DEA was first proposed by Simar and Wilson (1998) who used bootstrap to extract the sensitivity of DEA efficiency scores towards sampling variations. In DEA the distribution of (in)efficiency scores is the source of variability while the estimated parameters are the efficiency scores of the DMUs in the sample. In particular, the idea in bootstrapping DEA scores is to evaluate the sensitivity of a DMU towards changes of the reference set against which its efficiency score is assessed. The efficiency score of a DMU obtained by DEA is deemed as a sample estimate of the population value. DEA is applied repeatedly and its efficiency scores are resampled by keeping the outputs fixed (assuming input orientation). The random resampling of efficiency scores suggests that any DMU in the sample could achieve any of the observed efficiency scores. Ultimately, the bootstrapping process involves using the original sample to construct an empirical distribution of the variables of interest by repeated sampling of the original data set and then applying the estimation process to the re-sampled data and then calculating relevant statistics such as means and standard deviations (Odeck, 2009).

Among the main characteristics of bootstrap DEA is that it is asymptotically consistent. The most commonly used assumption in bootstrap DEA is that the bootstrap bias is asymptotically equal to the DEA bias (or model bias). The bootstrap bias refers to the difference between the bootstrap mean and the model's estimated parameters and occurs mainly due to the randomness in the resampling process. On the other hand, the model bias is the difference between the estimated parameters and their "true" value or population value and occurs due to sampling variations but it can also be caused by model misspecification or measurement errors. Thus, bootstrap DEA can be used to uncover the population or "true" efficiency score of any DMU by correcting twice for bootstrap bias or to construct low-variance confidence intervals that centre this "true" efficiency score (Simar and Wilson, 1998; 2000). Further developments and extensions of bootstrap DEA have also been applied. Among others, the bootstrap Malmquist index, the introduction of bootstrap tests on returns to scale and the implementation of two-stage bootstrap DEA to account for environmental variables (Simar and Wilson, 2007).

2.4 Multiple Criteria Decision Analysis

The field of multiple criteria decision aid (MCDA) has developed rapidly over the past decades. The rapid development in the field of multicriteria modelling resulted in an exponential increase in the number of real-world applications that use MCDA approaches for problem structuring, problem solving and decision making (Greening and Bernow, 2004).

MCDA combines quantitative and qualitative techniques. It is involved with decision problems under the presence of multiple (conflicting) decision criteria, which require the selection of the best alternatives, the ranking of the alternatives according to their overall performance, or their classification into predefined performance groups. At its core, MCDA is useful for dividing the decision into smaller parts, analysing each part and integrating the parts to produce a meaningful solution. MCDA models enable decision makers to grasp the inherent conflicts and trade-offs among the distinct aspects of evaluation and to rationalize the comparison among different alternative solutions. Thus, MCDA methods are useful when problems involve multiple, conflicting and incommensurate axes of evaluation (Diakoulaki et al., 2005).

The first historical applications of MCDA proved the strengths of the methodology and its capacity to be adapted in many different decision problems (Kavrakoglu and Kiziltan, 1983; Siskos and Hubert, 1983; Schulz and Stehfest, 1984; Diakoulaki et al., 2005). The applications of MCDA are numerous and cover a wide range of different fields. Among others, the energy sector is one of the most active and areas in applied MCDA research. MCDA has been extensively used for energy planning and efficiency evaluation (Diakoulaki et al., 1999; 2005; Mavrotas and Trifillis, 2006; Zhou et al., 2006; Qin et al., 2008; Neves et al., 2009; Streimikiene and Balezentis, 2013; Haydt et al., 2014; Javid et al., 2014) as these are characterized by uncertainty, long time frames, capital-intensive investments and many conflicting criteria. During the 1970s, little effort was made in the formal planning of energy systems aiming at exploring the energy–economy relationships established in the energy sector. However, after the oil crisis of 1973, more emphasis was placed on identifying efficient supply options, energy conservation and energy substitution. During the 1980s, growing awareness and the apparent conflict between economic and environmental objectives pushed energy planners towards the use of MCDA methods. Energy planning and selection (Begic and Afgan, 2007; Buchholz et al., 2009; Jovanovic et al., 2009), energy resource allocation (Chedid et al., 1999; Afgan et al., 2007), energy exploitation (Goumas and Lygerou, 2000), energy policy (Greening and Bernow, 2004; Kablan, 2004), building energy management (Wright et al., 2002; Wang et al., 2008), and transportation energy systems

(Yedla and Shrestha, 2003) are some of the applications areas of MCDA. Multi-objective programming and fuzzy MCDA methods are usually adopted for considering the alternative plans and uncertainties in energy planning (Pohekar and Ramachandran, 2004).

MCDA methods have now been widely applied to social, economic, agricultural, industrial, ecological and biological systems in addition to energy systems (Wang et al., 2009). The field is so large and comprises developments so heterogeneous that it is almost impossible to make an exhaustive review of the research and practice of MCDA in the energy sector. Zhou et al. (2006) attributed the increased popularity of MCDA, especially in decision-making for sustainable energy, to the multi-dimensional nature of the sustainability goal and the complexity of the socio-economic and biophysical systems. Loken (2007) conducted a literature review on the most important MCDA methods that have been proposed over the years for energy planning purposes. He argued that MCDA can be a very useful tool for the planning of local energy systems with multiple energy carriers and multiple energy resources. Wang et al. (2009) reviewed the corresponding methods in different stages of multi-criteria decision-making for sustainable energy, i.e., criteria selection, criteria weighting, evaluation, and final aggregation. Greening and Bernow (2004) presented a survey of the use of multicriteria decision making in the design of coordinated energy and environmental policies recommending the implementation of several MCDA methods in an integrated assessment framework. MCDA can also be used for constructing composite indicators that evaluate the energy performance and efficiency of a country and the impact of energy efficiency programs (Munda and Saisana, 2007; Emerson et al., 2012).

CHAPTER 3

Energy Efficiency Analysis at the Country Level

This chapter presents an analysis of energy efficiency performance in EU countries. It begins with an introduction which places the work in context. A literature section that reviews previous studies that use similar methodologies is then presented, followed by the aims and objectives of the analysis, the main methodological tools, as well as the data and variables. Finally, the results are presented and the chapter ends with some concluding remarks.

3.1 Introduction

The last decades have seen radical changes in the world's energy scene. The most dramatic occurrence was the energy crisis of the '70s. At almost the same time, the sharp increase of energy prices and environmental considerations reflecting either the concern for the depletion of energy resources or the need to cope with the ongoing environmental degradation imposed a shift towards energy efficiency.

In the 1970s and early 1980s, energy efficiency emerged as a major issue for sustainable economic growth. Even after the 1986 counter oil shock and the decline in oil prices, environmental concerns continued to rise, especially in the context of the growing debates on global warming and climate change, which gave energy efficiency improvement a new perspective. The latter, along with the world energy crisis in the beginning of 1990s, and in combination with the sharp increase in oil prices during the 2000s, today have put energy efficiency on the policy agenda of many countries as a top priority issue. This can be explained by the fact that governments are increasingly aware of the urgent need to make better use of energy due to the various benefits of more efficient energy use. These include among others, reduced investments in energy infrastructure, lower fossil fuel dependency, increased competitiveness, improved consumer welfare and reduced GHG emissions and air pollution. Thus, energy efficiency has now been recognized as an essential component of sustainable development policies, which seek to achieve a well-balanced trade-off between economic growth and competitiveness, energy security, and environmental sustainability. Therefore, it is not surprising that tracking economy-wide energy efficiency trends is being undertaken in many countries on a regular basis (Ang et al., 2010).

Many studies show that the evaluation of energy efficiency in a global context is extremely difficult because of the different economic, environmental and social conditions of each country. Data used for cross-country comparisons are often heterogeneous and the interpretations even of similar ratios or indicators used for assessing energy efficiency may diverge considerably. Therefore, a structure for the purpose of assessing energy efficiency across countries should be set up that uses harmonized data and a common methodology of energy efficiency assessment for all participating countries.

This thesis suggests the evaluation of energy efficiency based on a multidimensional context that considers a disaggregated view of energy consumption and economic outputs. It also considers the introduction of an evaluation model that enables policy makers and analysts to consider the trade-offs between the different benefits of energy efficiency. This is in line with the framework proposed by Ryan and Campbell (2012) who adopted a broader socioeconomic perspective which enables policy makers to generate accurate impact assessments considering a comprehensive range of benefits and costs that result from energy efficiency programs.

On the methodological side, at the first stage, DEA is performed to assess the relative efficiency of the countries under different modeling settings. At the second stage, the efficiency estimates obtained from DEA are used to build a MCDA evaluation model, which is used to build an operational model that combines energy efficiency with economic and environmental indicators. Two-stage approaches are often employed in an explanatory setting to identify relationships between efficiency estimates and external factors using parametric regression methods (e.g., ordinary least squares (OLS), truncated or tobit regression), based mainly on linear models. Instead, in this study we follow a decision-making approach based on a non-parametric multicriteria additive model. The additive model retains the simplicity and transparency of linear models, but it provides the flexibility needed to consider possible nonlinear relationships between energy efficiency and a set of multiple factors that describe its drivers and benefits. The construction of the additive MCDA model is based on a non-parametric approach using linear programming, thus being in accordance with the non-parametric framework of DEA. The resulting multicriteria model complements and enhances the technical efficiency estimates of DEA through the introduction of a transparent composite indicator that enables the evaluation of all countries in a common setting. Thus, the proposed two-stage DEA/MCDA approach provides a framework that policy makers can use to construct a standardized and comprehensible composite energy efficiency and performance evaluation indicator, which can be easily used for benchmarking purposes, allowing the formulation of a complete ranking of all countries under consideration, as well as the monitoring of the performance of any country over time, without having to resort to relative efficiency analyses every time an evaluation is sought. The introduction of the multicriteria approach also enables policy makers to evaluate different types of benefits that result from energy efficiency programs, without restricting the analysis solely to an input/output energy-economic context.

Overall, through the proposed methodologies, this analysis contributes to the existing literature by introducing a unified and integrated approach considering the multidimensional character of energy performance evaluation at an aggregated level such as countries. Thus, all the evaluation models developed through this research are expected to be of major practical usefulness for monitoring, benchmarking and policy planning purposes.

3.2 Literature Review

A rich body of research has emerged that measures energy efficiency changes over time at the economy-wide level and permits the cross-country comparisons. On one hand, various efficiency-related indicators have been developed, with the ratio of total national primary energy consumption to GDP (energy intensity) among the most popular ones. On the other hand, most researchers focus on developing methods to decompose accurately the aggregate energy intensity into the true change in intensities at the disaggregated sectorial levels, and to understand the effects of structural changes in the economy. Another line of research examines energy efficiency within a framework where energy is one of the many inputs of production, with the most widely used technique being DEA.

Bampatsou and Hadjiconstantinou (2009) used DEA to develop an efficiency index, which combines economic activity, CO_2 emissions, and energy consumption of the production process in 31 European countries for 2004. The study also provides estimates for the capability of the countries to achieve sustainable economic development through the reduction of their reliance on fossil fuels. Lanfang and Jingwan (2009) proposed a non-parametric method based on DEA to measure energy efficiency, taking into account undesirable factors such as water, gas, and solid wastes. Ceylan and Gunay (2010) analyzed Turkey’s economy-wide energy efficiency and its energy-saving potential with cross-country comparisons and benchmarking with EU countries, for the period 1995–2007, using a non-parametric frontier approach. Wei et al. (2011) applied DEA by using the labor, capital stock and energy as inputs and the GDP as output for measuring the energy efficiency performance of 26 and 156 countries during the period 2000–10 and 1980–2007, respectively. Table 2.1 presents a brief overview of studies that used DEA for measuring energy efficiency at the country level.

In addition to DEA models, multicriteria decision-analysis has been used extensively to evaluate energy management and efficiency. For example, Diakoulaki et al. (1999) used a multicriteria methodology to determine the relative contribution of different factors such as socio-economic indices, structural characteristics, and energy mix of countries in reaching a desired level of energy efficiency. The authors' analysis focused on 13 EU countries and the United States in three points in time, namely, 1983, 1988, and 1993, using data on economic growth, energy consumption, and its breakdown into energy forms and sectors. Appropriate pricing policies (mainly on electricity) and long-term structural changes in the energy system were the main effective means used to achieve efficient energy use in the late 1980s and early 1990s. These remarks agree with existing qualitative estimates about the relative importance of various factors related to energy efficiency at the national level, proving the capability of the proposed methodology to emphasize the examined problem through a detailed quantitative analysis. Moreover, Mavrotas and Trifillis (2006) used basic principles from DEA to facilitate the evaluation of the environmental performance of 14 EU countries through a MCDA approach. The analysis was based on energy intensity, emission intensity, acidifying gases intensity, and other indicators related to the composition of the countries' energy mix, use of land, and recycling. The results show that the overall evaluation of countries with dispersed performances along the criteria is more sensitive to modifications in the relative importance of the evaluation criteria. Furthermore, Zhou et al. (2006) attributed the increased popularity of MCDA, especially in decision-making for sustainable energy, to the multi-dimensional nature of the sustainability goal and the complexity of the socio-economic and biophysical systems. For example, Qin et al. (2008) developed an MCDA-based expert system to tackle the interrelationships between climate change and adaptation policies in Canada, and to facilitate the assessment of climate-change impacts on socio-economic and environmental sectors, as well as the formulation of relevant adaptation policies in terms of water resources management and other watersheds.

Adler et al. (2002) provided a comprehensive review of different DEA-based ranking techniques, but according to Bouyssou (1999) many of these approaches (e.g., cross-efficiency and super-efficiency models) have significant methodological shortcomings. MCDA techniques, on the other hand, are particularly useful for evaluation problems under multiple criteria. MCDA models enable the consideration of a wider set of additional socio-economic issues related to the benefits and impacts of policy decisions. However, in the MCDA framework the construction of evaluation models requires preferential information from the decision/policy makers (e.g., trade-offs and value judgments), which is often not available due to cognitive or time limitations. Thus, DEA (and other frontier analysis techniques) and MCDA constitute useful tools for quantifying and measuring energy efficiency, each adopting a different perspective. Nevertheless, despite the differences, the combination of these approaches provides the advantages of both while addressing their limitations. Possible ways of combining the two paradigms have already been explored (Doyle, 1995; Sinuany-Stern et al., 2000; Lahdelma and Salminen, 2006). These approaches have focused either on introducing new multicriteria evaluation procedures inspired from ideas in DEA or on enhancing DEA with ideas from MCDA.

This overview indicates that despite the rich literature on the use of DEA and MCDA for energy efficiency analysis and planning, there has been almost no attempt to combine, in a unified context, the capabilities that the two approaches provide. Thus, this study contributes to the literature by adopting a two-stage DEA/MCDA approach. On the one side, the DEA model results provide efficiency classification estimates and facilitate the identification of the sources of inefficiencies. On the technical side, however, efficiency scores often have limited discriminating power when used for evaluation and do not allow a full ranking of the countries, which is important for benchmarking and comparative analyses purposes.

3.3 Data and Methods

At the first stage, DEA is performed to measure the efficiency performance of the countries. The DEA methodology was described in detail in chapter 2. An input-orientation for the constant returns-to-scale (CCR) and variable returns-to scale (BCC) model is applied as a country has more control over its available resources (energy, labor, capital, etc.), rather than the level of outputs (e.g., GDP).

In this study, an up-to-date panel data set is used, consisting of 286 country-year observations for 26 EU countries[1] over 11 years (2000-10). Based on a common frontier that characterizes the efficiency of the countries over all years, this approach takes into account the correlation between the observations from a same country over whole period of the analysis. The

[1] Malta is excluded due to unavailability of some data.

adopted approach allows the comparison of the efficiency results over time and the identification of the observed efficiency trends.

During the period under consideration, the EU formulated an energy policy based on the Kyoto Protocol, through numerous directives and actions plans focused on improving energy efficiency. At the same time, the introduction of the Euro has changed the economic environment and the global financial crisis that started at the end of 2007 had a strong negative effect, mainly in eastern and southern European countries that experienced recession, significant budget deficits, and high sovereign debt. In light of these events, it is particularly interesting to examine energy efficiency in European countries over the selected period.

All data were obtained from Eurostat, except for labor force data, which were collected from the World Bank, and capital stock, which was obtained from the AMECO database of the European Commission. Choosing an appropriate set of indicators and evaluation criteria was clearly an important issue. The multidimensional character of energy efficiency and its multiple aspects (environmental, socio-economic, and technical) make it very difficult to specify a comprehensive set of relevant measurement indicators universally applicable under all contexts. In this study, the input and output variables, presented in Table 3.1, were selected based on data availability and the existing literature. All the economic variables are measured in constant prices, thus allowing comparisons over time eliminating the effect of inflation.

Table 3.1: Input and output variables.

Type	**Variable**	**Unit**	**M1**	**M2**	**M3**	**M4**
Outputs	Gross domestic product	Million euros*	✓	✓		
	Industry, value added	Million euros*			✓	✓
	Services, value added	Million euros*			✓	✓
Inputs	Total energy consumption	Thousand tons of oil equivalent	✓		✓	
	Fossil fuels energy consumption	Thousand tons of oil equivalent		✓		✓
	Other fuels energy consumption	Thousand tons of oil equivalent		✓		✓
	Labor force	Economically active population	✓	✓	✓	✓
	Domestic material consumption	Thousand tons	✓	✓	✓	✓
	Capital stock	Billion euros*	✓	✓	✓	✓

Note: * Constant prices

In the analysis, we consider two different settings for the input variables and two different settings for the output variables, thus leading to four DEA models (henceforth denoted as M1, M2, M3, and M4).

The first setting for the output variables uses only GDP, whereas in the second setting GDP is replaced by the value added from the industry and the services sectors, thus providing more detailed insight into the economic output of each country. Generally, the industry sector is more energy intensive than the service sector. Therefore, a structural shift from high-energy-consumption secondary industry to low-energy-consumption tertiary industry may lead to an improvement in overall energy efficiency, solely due to structural changes in the economic activity of a country. Yu (2010), using the variations in the share of value-added from the industry and services sectors, in terms of GDP, showed that the service share has a significant positive impact on energy efficiency. However, he also showed that the industry share has an insignificant, small positive effect (less than 0.25%) and, as a result, may not affect energy efficiency at the country level substantially. Wei et al. (2009) as well as Zhao et al. (2010) examined energy efficiency in China and found that it is negatively associated with the secondary industry share in GDP, and that the simultaneous improvement of energy efficiency in energy-intensive sectors is mainly due to industrial policies. Furthermore, Zhao et al. (2010) found that low energy prices have directly contributed to high industrial energy consumption, and indirectly to the heavy industrial structure. Arcelus and Arocena (2000) compared the multifactor productivity levels and the changes across countries and across time, using a nonparametric model. The evidence obtained from a sample of 14 OECD countries indicates a high degree of catching-up among the various countries for the total industry, manufacturing, and services sectors. Hu and Kao (2007) claimed that a newly industrialized economy will have lower total-factor energy efficiency than agriculture-dominant and service-dominant economies. Hence, the industrial structure of an economy is a crucial factor for energy efficiency, and thus the energy-saving ratio; an industry-dominant economy can improve its energy efficiency and save energy more efficiently and effectively by shifting the economy structure toward services. Therefore, it is important to decompose the influence of the value added to GDP by the industry and services sectors.

Similar to the outputs, two settings are also used for modeling the inputs. In particular, the first setting has four inputs, involving total energy consumption, capital stock, labor force, and materials consumption. Capital, labor, and material force are used as the non-energy (non-discretionary) inputs, in accordance with the KLEM production function framework. The specification of these variables as non-discretionary inputs assumes that even though a country's outputs are produced through the utilization of such resources, the obtained energy efficiency estimates are obtained solely from the perspective of minimizing energy consumption. In the second setting, total energy consumption is replaced by fossil fuel consumption and the consumption of other energy sources (renewables and nuclear), thus providing a more refined view of the energy mix that each country uses. The majority of studies that measure energy efficiency using the DEA framework choose inputs such as energy consumption, capital, and labor (see the studies listed in Table 2.1). Ramanathan (2005) also used fossil fuel energy consumption as a minimization indicator, in the sense that countries with lower values in this indicator are more preferred. Mandal (2010) used data related to capital, energy, labor, and raw materials as inputs, and claims that environmental regulation has the potential to positively affect energy use. Zhou and Ang (2008a) presented several DEA-type linear programming methods for measuring economy-wide energy efficiency performance using labor, capital stock, and energy consumption as inputs, and GDP as the desirable output. Moreover, Hu and Wang (2006) observed a high correlation among the inputs (labor, capital stock, energy consumption, and total sown area of farm crops) and the single output (real GDP). In the same vein, Hu and Kao (2007) showed that labor employment, capital stock, and energy consumption actually do correlate with GDP performance. They also found that energy efficiency can be over-estimated or under-estimated if energy consumption is taken as a single input with a certain portion of GDP output produced not only by energy input but also by labor and capital. Hence, using a multiple-inputs framework is important to evaluate energy efficiency correctly (Hu and Wang, 2006).

Figure 3.1 presents the evolution of the selected variables aggregated over all countries over the period of the analysis. As far as the energy-related variables are concerned, the consumption of other fuels shows a steady increase throughout the examined period, mainly due to the increased use of renewable sources. However, the total energy consumption and the consumption of fossil fuels increased slightly up to 2005–2006, followed by a decrease in the subsequent years. Regarding the economic variables, the GDP and the services value added increased considerably up to 2008, before falling in 2009 due to the global economic crisis. On the other hand, the capital stock increased considerably over the examined period (about 25% increase overall).

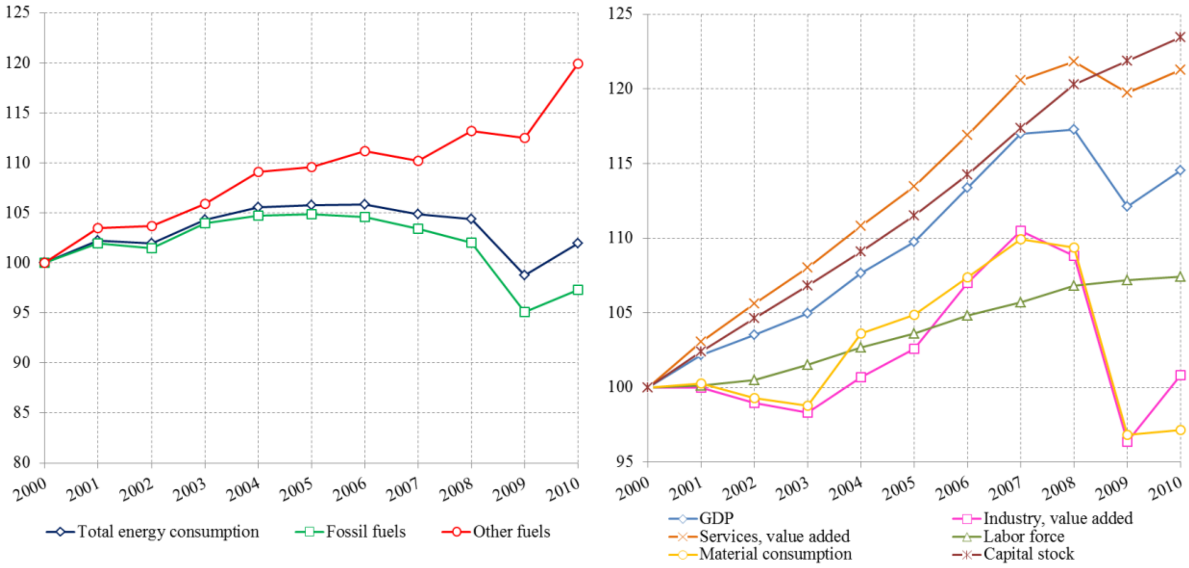


Figure 3.1: Evolution of the selected variables over the period 2000–10 (year 2000=100).

Figure 3.2 illustrates the time trends for the relative shares of the two energy inputs to the total energy consumption (fossil and other fuels – decomposed into nuclear and renewables). It is clear that the share of renewables in the energy mix has followed an increasing trend, starting from 2003. During the same period (2003–2010), the share of fossil fuels has declined, but it still ranges in levels that exceed 76%. The share of nuclear energy has also followed a slightly declining trend.

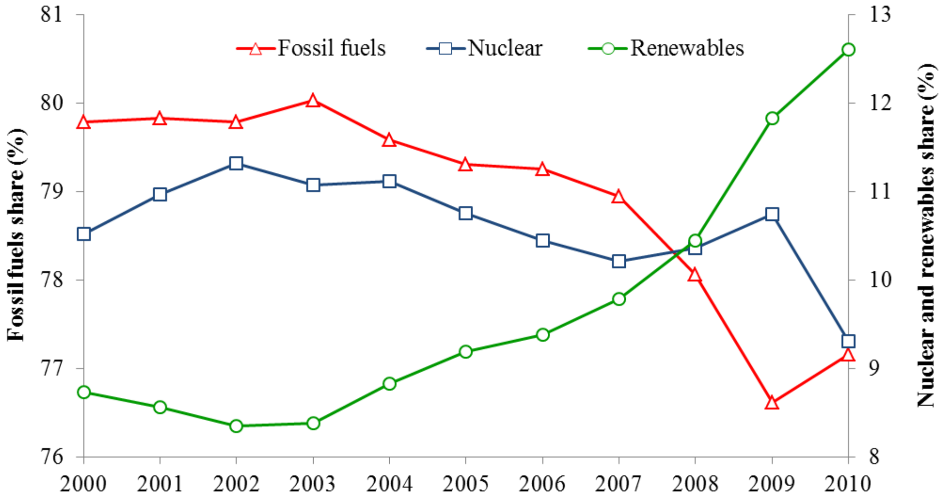


Figure 3.2: Evolution of the shares of fossil fuels, nuclear, and renewables to total energy consumption over the period 2000–10.

As described earlier, in this study the results from the input/output frontier framework of DEA are combined with an MCDA modeling approach. The scope of the latter is to build an overall energy efficiency and composite performance indicator that will enable the evaluation of all countries in a common and standardized setting. Furthermore, such an indicator will have enough discriminatory power to allow the complete ranking of all countries (both DEA-efficient and inefficient). DEA efficiency scores often lack discriminatory power, as they do not differentiate among efficient cases (they all receive the same efficiency score). This difficulty also applies to inefficient cases, as making direct comparisons among such DMUs are generally meaningful only for those belonging to the same facet of the efficient frontier (Kao and Hung, 2005). Furthermore, increasing the number of input and output variables inflates the efficiency scores (thus yielding upward biased efficiency estimates) and leads to efficiency results with diminishing discriminating power (as more DMUs appear fully efficient). On the other hand, the multicriteria model is appropriate for benchmarking purposes, allowing the consideration of all pertinent factors that describe (direct or indirectly) energy efficiency and its multiple benefits, and enabling comparisons to be performed over time (for a single or multiple countries) based on a well-defined functional model without having to resort to relative estimates such the ones used in DEA. Of course, the linear programming formulations of DEA do not pose any computational issues as they are easy to solve. Nevertheless, the sample-dependent character of the relative efficiency estimates obtained with DEA is not an appealing feature in a benchmarking and evaluation context, as it makes it difficult to perform direct comparisons whenever the set of data observations is altered or the available data are updated. In contrast to DEA, the multicriteria model enables analysts and policy makers to perform evaluations and monitor the performance of a country over time using data solely at the country level, without having to resort to relative assessments in comparison to data from a set of peer countries.

The second stage of the analysis is implemented using a multicriteria classification technique. In particular, the efficiency classifications, as defined from the DEA results, are used to build the multicriteria evaluation model. The countries are classified as efficient or inefficient according to their DEA efficiency scores and a multicriteria model is then constructed, which combines n criteria, so that the model's classifications are as close as possible to DEA's efficiency classification. The UTADIS multicriteria method is used for this purpose (Doumpos and Zopounidis, 2002). The UTADIS method leads to the development of an additive value function of the following form:

$$V(\mathbf{x}_i) = \sum_{j=1}^{n} w_j v_j(x_{ij}) \in [0,1] \tag{3.1}$$

where w_j is a non-negative trade-off constant for evaluation criterion j and $v_j(x_j)$ is the corresponding marginal value function normalized between 0 and 1. The marginal value functions provide a decomposition of the aggregate result (global value) in terms of individual assessments at the criteria level. According to its global value, a country i is classified as efficient if and only if $V(x_i) > t$, where t is a cut-off point that distinguishes efficient countries from inefficient ones. The additive value function and the optimal cut-off point are estimated through linear programming techniques (a brief description is given in the Appendix). In contrast to parametric regression techniques, the use of linear programming provides flexibility to analysts and policy makers in building models that are not only based on historical trends and statistical relationships, but also take into account their expert judgments and policy objectives with respect to the properties of the final evaluation model (e.g., the trade-offs between energy, socio-economic, and environmental factors).

Although the selected input and output variables are meaningful in the context of DEA, they are not useful in a multicriteria setting, as they do not allow for direct comparisons among the countries. In particular, in DEA the countries are compared based on a ratio defined by each country's aggregate outputs to its aggregate inputs. However, the multicriteria evaluation context relies on the use of a set of indicators on which the countries are directly comparable. The multicriteria modeling framework provides flexibility in the specification of these indicators. In this study, their selection is based on the framework introduced by Ryan and Campbell (2012), who emphasized the need to analyze energy efficiency in a context much broader than the usual input/output energy-economic production model. Based on this framework, we use indicators that are relevant to the input/output modeling context discussed earlier for the DEA models, but also cover additional issues that policy makers may consider relevant for evaluating the impacts of energy efficiency programs as pointed out by Ryan and Campbell (2012). In particular, the second stage of the analysis is based on a set of ten evaluation criteria. Similar to the modeling approach used in DEA, the selected criteria (Table 3.2) combine energy efficiency indicators, economic growth and competitiveness indicators, environmental indicators, and two original indicators related to the primary energy source and the focus of the economy in each country. Furthermore, the selected indicators cover the top three levels (international, national, sectoral) in the hierarchical structure of energy efficiency benefits presented in Ryan and Campbell's work (2012). In particular, energy intensity is used as the main proxy for energy efficiency as it is widely adopted by policy makers for assessing energy efficiency. GDP growth is used as the main indicator for measuring economic development, thus enabling the evaluation of the economy-wide impact of energy efficiency. However, economic output and growth are affected by many factors beyond energy use, and as explained, energy efficiency has multifaceted benefits. To consider these issues, we use additional variables, including resource productivity (for the effect of materials' use)[2], gross fixed capital formation/GDP (the effect of investments), and current account balance/GDP (competitiveness)[3]. In addition, we control for the effect of environmental taxes, which affect energy costs and consumption, as well as the labor dimension (unemployment rate). Furthermore, following the existing literature, we consider the environmental effects of energy use and economic activity, by considering the level of GHG emissions in relation to GDP. Ryan and Campbell (2012) also noted similar dimensions (GHG emissions, job creation, macroeconomic effects, competitiveness, among others) as important impacts of energy policies that must be introduced in a comprehensive evaluation framework. Finally, to control for the energy and economic mix, two additional indicators are introduced. The primary energy source indicator is used to consider the energy mix of a country in a particular year, indicating whether renewables, nuclear, natural gas, solid fuels, or petroleum consumption was the main energy source for the country. Economy focus is modeled as a binary indicator, designating whether the value added by the industrial sector of a country (as a percentage of GDP) in a given year is above or below the overall average of all countries. Introducing this indicator in the analysis enables the consideration of the differences among the various countries in terms of their level of industrial development (as industry is generally more energy intensive than services). The combination of the selected indicators in an additive evaluation model not only provides policy makers and analysts with a comprehensive efficiency evaluation model, but also enables them to explore the trade-offs among the multiple aspects of energy efficiency (i.e., energy, economic, and environmental indicators).

[2] Resource productivity is measured by Eurostat as the ratio of GDP to domestic material consumption and is reported in euros per kg. The same definition is also employed by OECD (2008). According to OECD this is a type of economic physical measure which is suitable when the focus is on the decoupling of value added and resource consumption. Alternatively, physical or economic approaches can also be used to measure resource productivity (using physical or money values, respectively, for both the nominator and the denominator). The economic approach is more suitable when the focus is on the minimization of input costs, whereas the physical approach focuses on the maximization of outputs for a given level of inputs and a given technology. Dahlström and Ekins (2005) however, argue that such a physical measure is a resource efficiency indicator, rather than a measure of productivity.

[3] Policies for improving energy efficiency can have a positive effect on current account balance through reducing energy dependency and energy imports.

Table 3.2: Evaluation criteria for building the second stage multicriteria model.

Energy intensity (Kgoe / €1000)	Current account balance / GDP
Gross fixed capital formation / GDP	Unemployment rate
Environmental taxes / GDP	Greenhouse gas emissions / GDP
GDP growth	Primary energy source indicator
Economy focus indicator	
Resource productivity (GDP/domestic material consumption, €/kg)	

3.4 Results

3.4.1 DEA Results

Figure 3.3 illustrates the average CCR and BCC efficiency scores of the four models over the entire period of the analysis. The differences between the CCR and BCC scores are generally limited in most countries, thus indicating that overall the scale effect is weak (the scale efficiency defined by the ratio of CCR to BCC efficiency is on average more than 80% for the vast majority of the countries). However, some smaller countries such as Estonia, Bulgaria, and Cyprus, exhibit scale efficiency consistently below 65%, thus indicating that their scale size is a limiting factor.

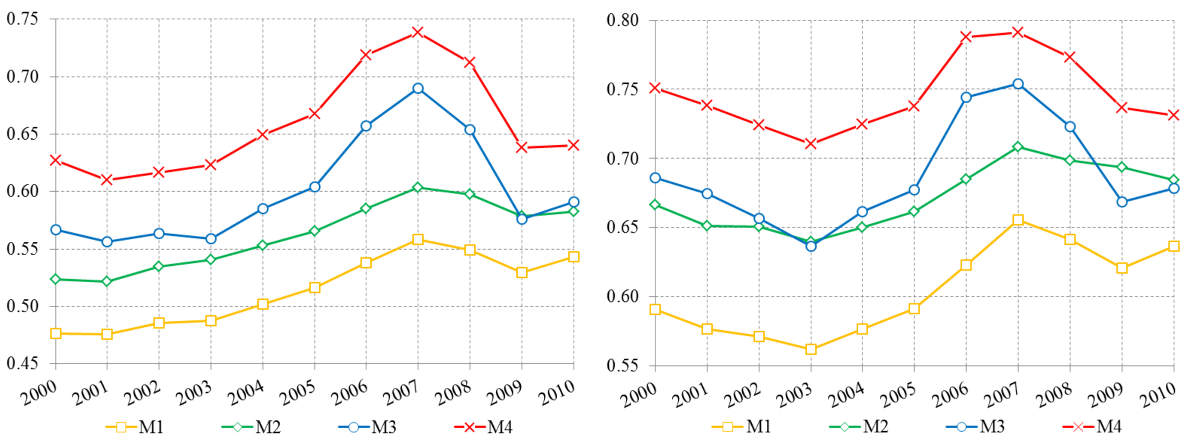


Figure 3.3: Average efficiency scores for the four models (CCR left, BCC right).

As far as the differences between the four models are concerned, it is evident that the models with more inputs and outputs lead to higher efficiency estimates, but this is fairly common in

DEA (i.e., the DEA efficiency scores generally increase with the number of inputs and outputs). Generally, there are high correlations among the results of the four models. The correlations are stronger for the pairs M1-M2 (about 97% correlation for the CCR models and 94% for the BCC models) and M3-M4 (about 95–96% correlation coefficient under the CCR and BCC models). However, the similarities between each model M1 and M2 to M3-M4 are lower (correlation coefficient 84–92%). The pair of models M1-M2 differs from M3-M4 in the way that the outputs are defined, with the latter providing a more detailed breakdown of the economic output (M1-M2 consider only GDP, whereas M3-M4 consider the value added by services and industry as separate outputs). Thus, for European countries, the effect due to the consideration of the structure of their economic activity appears to be stronger than the effect due to the introduction of a breakdown by their energy mix.

When the efficiency estimates under the four modeling settings are compared with the energy intensity of the countries in the panel data set (Table 3.3), strong negative correlations are observed in all cases (all correlations are significant at the 1% level). The correlations are stronger for models M1 and M2, which use GDP to measure economic output (similarly to energy intensity). The same negative relationship between energy intensity and the obtained efficiency estimates was also observed (at different magnitudes) for each of the countries particularly under the CCR models, whereas for the BCC models the discrepancies were higher. However, in accordance with the suggestions of Filippini and Hunt (2011), the relationship between energy efficiency estimates obtained by frontier techniques and energy intensity needs further analysis, possible over extended time periods to derive conclusive evidence on the characteristics of the countries for which energy intensity might be a poor proxy for energy efficiency.

Table 3.3: Correlations between the DEA efficiency scores and energy intensity.

	CCR				**BCC**			
	M1	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
Pearson correlation	-0.79	-0.80	-0.74	-0.75	-0.69	-0.72	-0.64	-0.68
Kendall's τ	-0.83	-0.74	-0.64	-0.57	-0.62	-0.54	-0.46	-0.45

When the efficiency trends are examined over time, the period 2000–07 is characterized by increasing global (CCR) efficiency scores according to models M1 and M2. A similar trend is also observed for models M3 and M4, particularly after 2003. The BCC efficiency scores obtained with the assumption of variable returns to scale also follow an increasing trend for the period 2003–07. However, both during 2000–03 and 2007–09 an efficiency decline is evident. In both the CCR and BCC results the effect of the global economic crisis is clearly shown by the significant decrease of the efficiency scores during 2008–09 (under all modeling settings), whereas signs of minor recovery are evident in 2010. The 2008–09 decline is larger under the models M3-M4.

Overall, the results indicate that when the structure of the economy is explicitly considered (i.e., separation of GDP into the value added by the industry and services in models M3 and M4), then the efficiency improvements appear to be more conservative. Based on these findings, the subsequent analysis focuses on model M4, which provides the most comprehensive consideration of the economic outputs of the countries and their energy mix.

Table 3.4 presents the countries' global CCR efficiency scores averaged over all 11 years of the analysis, as well as the percentage changes over the entire period of the analysis and during the recent economic crisis (2008–2010).

Table 3.4: Overall CCR efficiency scores (averaged over 2000–10) and percentage changes (model m4).

	Average	**2000–10**	**2008–10**		**Average**	**2000–10**	**2008–10**
Luxembourg	0.998	0.0	0.0	**Finland**	0.749	-29.2	-44.4
Ireland	0.993	-4.4	-4.4	**Poland**	0.738	8.1	-19.8
Netherlands	0.978	0.0	1.7	**Greece**	0.591	26.4	2.1
Denmark	0.969	0.0	0.0	**Cyprus**	0.582	12.5	0.1
UK	0.967	0.0	0.0	**Spain**	0.561	10.8	5.2
Sweden	0.908	16.1	0.0	**Portugal**	0.523	12.0	10.5
Germany	0.859	13.3	-8.5	**Belgium**	0.505	6.9	-6.5
Latvia	0.850	-26.6	-47.5	**Romania**	0.296	24.0	-59.0
Austria	0.847	1.9	-0.9	**Slovakia**	0.287	107.3	-28.2
Slovenia	0.843	-49.8	-49.6	**Hungary**	0.252	16.8	3.5
Italy	0.832	1.2	-8.9	**Czech Rep.**	0.226	36.0	4.8
Lithuania	0.758	2.8	-48.3	**Estonia**	0.147	16.4	-16.3
France	0.751	30.0	10.8	**Bulgaria**	0.107	81.3	-5.5

Luxembourg, Ireland, the Netherlands, Denmark, and the United Kingdom (UK), achieved the highest efficiency scores overall, whereas Bulgaria, Estonia, the Czech Republic, and Hungary have the lowest scores. Similar efficiency estimates are reported for European countries in the recent study by Halkos and Tzeremes (2013), who applied DEA to 25 European countries using data from 2010. Similar to our results, the authors found countries such as Sweden and the UK had high efficiency scores, whereas countries such as Greece, Hungary, the Czech Republic, and Spain performed poorly (the correlation of our results with those reported in Halkos and Tzeremes (2013) for the CCR model M4 is 0.35). In another study, Vlahinić-Dizdarević and Sĕgota (2012) examined a set of 26 European countries (not identical to those in our study). Similar to our results, they found countries such as the UK, Luxembourg, Ireland, and Denmark performed consistently well over the period 2000–10, whereas Bulgaria, the Czech Republic, Greece, and Hungary performed poorly. Chien and Hu (2007) reported similar results using DEA in a sample of OECD countries for 2001–2002 (e.g., Luxembourg, the UK, Denmark, Ireland had high efficiency). In contrast to these DEA-based studies, Filippini and Hunt (2011) used stochastic frontier analysis for a panel data set of 29 OECD countries over the period 1978–2006, using set of explanatory variables related among others to energy consumption, climatic conditions, GDP, energy prices, and country size. Their results differ from the ones reported in the present study and other DEA-based studies. Except for the longer time period used by Filippini and Hunt, the discrepancies could be due to the differences in the variables used, the different sample of countries and of course the method used for the analysis.

Table 3.5 summarizes the estimated energy inputs and economic outputs improvements (averaged by year) that inefficient countries should seek to achieve to improve their efficiency status (under the BCC model). The figures reported for the input variables involve the percentage reductions required for a country in a particular year to become efficient, whereas for the output variables the reported improvements involve the target percentage increase in the level of economic activity (industry/services value added). In terms of energy conservation, the results indicate that inefficient countries should implement policies that focus on energy consumption from non-fossil fuels (i.e., renewables and nuclear). A closer examination further indicates some time trends, which highlight the increasing importance of the consumption of non-fossil fuels, particularly after 2007 (the most recent time trends are clearly more relevant for policy making purposes). On the other hand, the inefficiencies of the countries with respect to the consumption of fossil fuels have followed a declining trend, and at the same time the suggested improvements with respect to other fuels increased. Thus, even though there has been an improvement of the energy mix from an environmental perspective (i.e., promotion of renewables), energy conservation still remains a challenge, with the relative importance of renewables increasing over fossil fuels. On the output side, the improvement targets for the services sector are consistently higher compared to the industry sector. This is in accordance with the increasing importance of services for the economic activity in EU countries, as evident by the time trends illustrated in Figure 3.1. Nevertheless, it should be noted that the design and implementation of policies for improving energy efficiency should also consider the interactions and synergies among different actions, the economic and environmental trade-offs, as well as complementarity and substitutability effects (Frondel and Schmidt, 2002; Neumayer, 2003), which may differ from country to country.

Table 3.5: Suggested average changes in inputs and outputs (% changes).

	Industry value added	**Services value added**	**Fossil fuels**	**Other fuels**
2000	0.80	6.01	-0.70	-2.22
2001	0.92	5.21	-0.60	-1.03
2002	1.61	5.60	-0.45	-1.49
2003	1.62	3.75	-0.51	-1.29
2004	1.78	4.91	-0.23	-0.32
2005	1.52	3.86	-0.15	-0.43
2006	1.15	3.25	-0.16	-1.05
2007	1.56	3.17	0.00	-0.44
2008	2.10	4.26	0.00	-0.68
2009	1.96	6.47	0.00	-3.70
2010	0.34	6.33	0.00	-2.08
Average	1.40	4.80	-0.26	-1.34

3.4.2 The Multicriteria Model

For the reasons explained in the previous subsection, the development of the multicriteria evaluation model in the second stage of the analysis is based on model M4. Given the CCR efficiency scores obtained with model M4, all countries are classified as efficient (efficiency score equal to 1) or inefficient (efficiency score lower than 1). The UTADIS multicriteria method is used to fit a model on the efficiency classifications of DEA, combining the selected set of criteria presented in Table 3.2.

Overall, the sample includes 49 efficient country-year observations and 237 inefficient cases. Table 3.6 presents the means of the selected indicators for each group. Most differences are statistically significant at the 5% level according to the non-parametric Mann-Whitney test, with the exception of the environmental taxes to GDP ratio. These comparative results indicate that energy-efficient countries have lower energy intensity, employ material resources in a more productive manner, experience higher GDP growth, are more competitive (lower current account deficits), have lower unemployment rates, lower GHG emissions, emphasize the use of renewables, and are more services-oriented.

Table 3.6: The mean of the selected indicators for efficient and inefficient countries.

	Efficient	**Inefficient**
Energy intensity (Kgoe/€1000)	188.08	356.95
Gross fixed capital formation/GDP	3.32	3.12
Environmental taxes/GDP	3.08	2.63
Resource productivity (€/kg)	1.61	1.14
GDP growth (%)	4.00	2.42
Current account balance/GDP	0.88	-3.05
Unemployment rate (%)	5.41	8.80
Greenhouse gas emissions/GDP	0.48	0.92
Primary energy source indicator	2.06	1.84
Economy focus indicator	1.65	1.43

Table 3.7: Criteria Trade-offs (weights in %).

Criteria	**Weight**	**Criteria**	**Weight**
GDP growth	21.46	Primary energy source indicator	9.28
Energy intensity	17.83	Environmental taxes/GDP	7.42
Resource productivity	11.84	Gross fixed capital formation/GDP	6.92
Unemployment rate	9.80	Greenhouse gas emissions/GDP	4.97
Current account balance/GDP	9.79	Economy focus indicator	0.69

Table 3.7 presents the estimated criteria trade-offs in the multicriteria additive model fitted to the above data. These trade-offs are proxies of the relative importance of the criteria. The indicators' trade-offs indicate that GDP growth and energy intensity are the two most important factors, followed by resource productivity, unemployment, current account balance/GDP, and the indicator involving the energy mix of the countries. These results are in

accordance with the wider socioeconomic impacts of energy efficiency that Ryan and Campbell (2012) noted, as they imply that except for increasing the value of economic activity and reducing energy intensity, additional factors such as strengthening the competitiveness of the economy, improving resources productivity, and promoting employment and the use of renewable energy, could also be part of the policy/decision making process when it comes to analyzing energy efficiency and assessing its benefits and impacts. Figure 3.4 provides further details on the sensitivity of the multicriteria energy efficiency score regarding the three selected criteria, namely GDP growth, energy intensity, and the indicator of the primary energy source in each country. In accordance with the indicators' trade-offs, the sensitivity of the global (multicriteria) efficiency score is larger for the GDP growth ratio, with countries that achieve positive GDP growth rates receiving much higher scores compared to countries in recession. Furthermore, the multicriteria score improves at the highest rate when energy intensity falls below 400 Kgoe/€1000, and renewables are used as the main energy source. Such results and these levels on the selected indicators can support policy makers in setting target goals for the benefits that energy-efficiency programs should achieve.

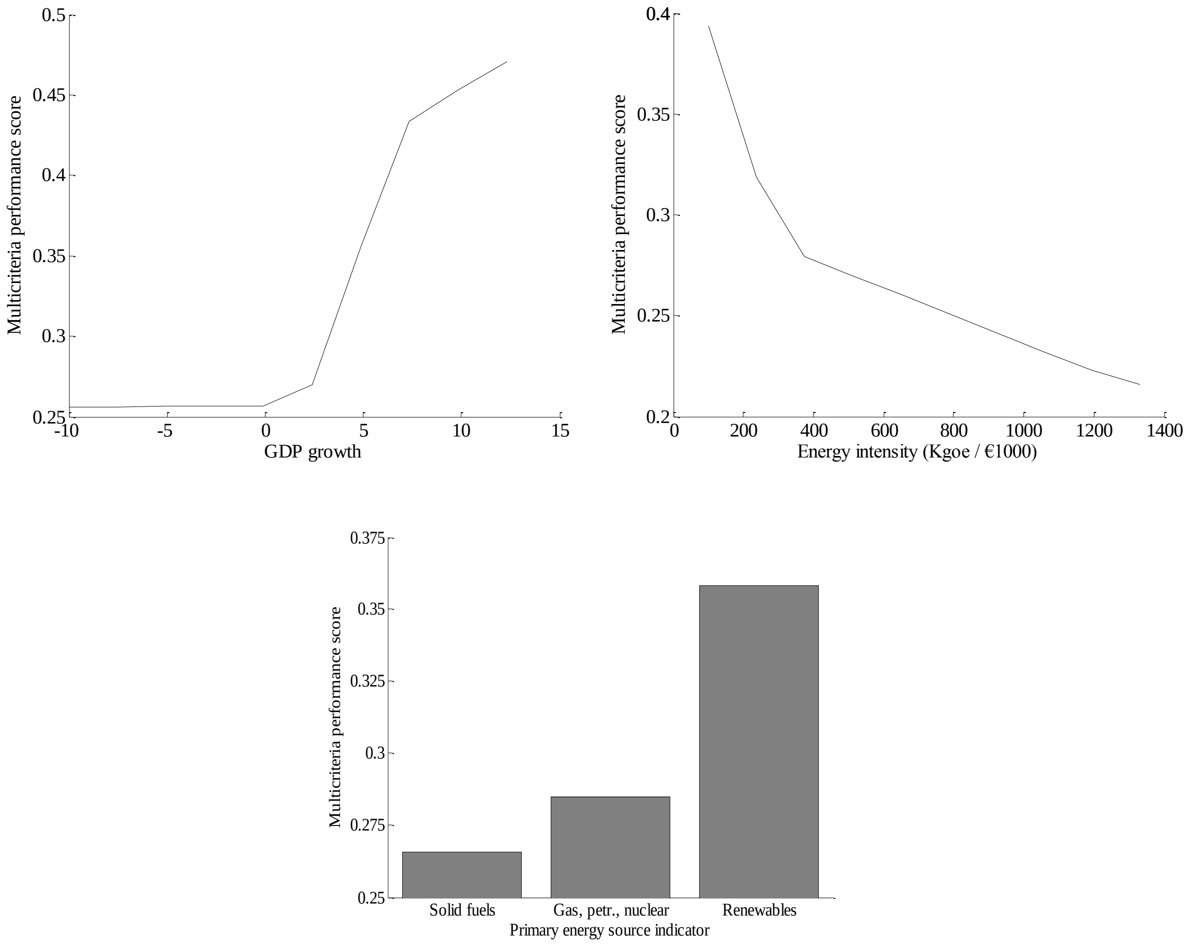


Figure 3.4: Multicriteria energy efficiency scores for three selected indicators.

The overall agreement between the efficiency classifications obtained with the DEA model (M4, CCR) and the ones of the MCDA model is 94%. In particular, 87.8% of the country-year observations classified by DEA as efficient are classified in the same group by the MCDA model, whereas the agreement level for the DEA inefficient cases is 95.4%.

Table 3.8: Extreme Average Differences between the Annual Rankings of DEA and the Multicriteria Model.

MCDA upgrades		**MCDA downgrades**	
Cyprus	7	**Poland**	-10
France	5	**Slovenia**	-6
Estonia	5	**Germany**	-5
Greece	3	**Lithuania**	-3

Table 3.8 provides a more detailed list of the countries with the largest differences in their annual rankings according to the DEA and MCDA models. In particular, Cyprus, France, Estonia, and Greece are better by the MCDA model compared to their rankings with the DEA model. For instance, Cyprus's position in the annual rankings obtained with the MCDA model improved by 7 grades (on average) compared to its ranking with the DEA model. On the other hand, the MCDA model significantly downgraded countries, such as Poland, Slovenia, Germany, and Lithuania. The downgrade for Poland is 10 grades (on average) in the annual rankings of countries. Interestingly, the group of countries significantly upgraded by the MCDA model have lower energy intensity compared to downgraded ones (310 Kgoe/€1000 vs. 344 Kgoe/€1000, on average; p-value=1.8% according to the Mann-Whitney test), lower unemployment (8.3% vs. 10.2%, p-value=1%), lower GHG emissions/GDP (0.89 vs. 0.96, p-value=4.9%), and their economy is more services-oriented. These qualities compensate for the lower GDP growth rates that the upgraded countries have achieved (2.8% on average) as opposed to the downgraded ones (3.4% on average; difference insignificant at the 10% level). Thus, the MCDA model's results introduce some refinements in the estimates obtained with DEA based solely on a frontier-based input-output framework.

3.5 Conclusions

At the first stage of this research, DEA was performed under four different modeling settings for the evaluation of energy efficiency in 26 EU countries over the period 2000–10. The CCR and BCC efficiency scores obtained by DEA showed that the scale effect is weak for the majority of the countries. The estimates of DEA also showed that the global economic crisis had a negative effect on energy efficiency. Furthermore, it was found that the effect due to the structure of the countries' economic activity appears to be stronger than the effect due to the introduction of a breakdown by their energy mix. However, the interactions and synergies among different actions, the economic and environmental trade-offs, as well as complementarity and substitutability effects which may differ from country to country should also be taken into account in policy /decision-making process.

The efficiency estimates were evaluated in a second stage through the UTADIS multicriteria method. In particular, the model estimated the energy efficiency performance considering a set of ten evaluation criteria related to energy efficiency indicators, economic growth and competitiveness indicators, environmental indicators, and two original indicators related to the primary energy source and the focus of the economy in each country. According to the results of the two-stage DEA/MCDA approach, the GDP growth and energy intensity were the two most important factors for energy efficiency improvement followed by resource productivity, unemployment, current account balance/GDP, and the indicator involving the energy mix of the countries. The results also showed that despite the considerable improvements achieved in energy intensity, there is still much to be done to improve the actual energy efficiency of EU countries.

Overall, the proposed methodology enabled the construction of an operational model that provides analysts and policy makers with evaluations of the countries' energy efficiency in a common setting for all countries. Thus, whenever a new evaluation must be performed there is no need to resort to relative sample-dependent assessments. Therefore, this approach could be also used for benchmarking purposes using country-level data. Furthermore, this modeling approach enables analysts and policy makers to consider a rich list of the impacts of energy-efficiency programs and actions, explore the underlying trade-offs, and ultimately reach more informed decisions. Of course, such a multicriteria evaluation model, which is built based on the results of a frontier technique such as DEA, needs to be periodically updated in accordance with the changes in the economic environment and the energy markets.

Taking into account the results of this study, policy makers could identify the main steps that should be followed to improve each country's energy efficiency. Furthermore, the significance of each step can be measured, leading to more informed decisions in terms of priorities given. Weighing different policy measures is a challenging task; however, the results of this study could significantly help policy makers in their decision process. For example, the observation that a services-oriented economy is more efficient than an industry-oriented one or the fact that renewable energy sources should gradually displace fossil fuels could help regulators design policies to support certain sectors of the economy or certain energy sources. Furthermore, combining MCDA with frontier techniques, as suggested in this study, enables policy makers to consider a much wider range of impacts of energy efficiency programs, instead of focusing solely on an input-output energy-economic production framework.

Future research could examine a wide range of issues. Among others, these may involve more detailed data on structural factors, the analysis of specific energy-intensive business sectors, the enrichment of the data set with countries outside the EU, and a more extensive time period, as well as the evaluation of the actions and policies implemented to improve energy efficiency at the country level.

Appendix

The multicriteria evaluation model developed with the UTADIS method is based on a sample of m observations (e.g., countries) each described over a set of n evaluation indicators. The observations are pre-classified intro classes/categories defined in an ordinal manner. For simplicity, here it will be assumed that there are only two classes, involving m_E energy-efficient countries (denoted by *E*) and m_I inefficient countries (denoted by *I*). The UTADIS method fits an additive (nonlinear) model on the given classification of the observations in the sample.

The model optimization process is simplified by setting $v'_j(x_{ij}) = w_j v_j(x_{ij})$ in (3.1), which leads to the following equivalent alternative form of the additive evaluation model:

$$V(\mathbf{x}_i) = \sum_{j=1}^{n} v'_j(x_{ij}) \tag{3.2}$$

In this form, the marginal value functions $v'_1, v'_2, \ldots, v'_n$ are scaled between zero and the trade-off constants of the criteria $w_1, w_2, \ldots, w_n$. No restrictions are imposed on the functional form of the marginal value functions, other than that they are piecewise linear functions, non-decreasing for maximization indicators (e.g., GDP growth) and non-increasing for minimization criteria (e.g., energy intensity).

The estimation of the additive model that best fits the given classification of the observations is performed through the solution of the following mathematical programming problem:

$$\begin{array}{lll}
\min & \dfrac{1}{m_E}\sum_{i\in E}\sigma_i + \dfrac{1}{m_I}\sum_{i\in I}\sigma_i & \\
\text{Subject to:} & \sum_{j=1}^{n} v'_j(x_{ij}) + \sigma_i \geq t + \delta & \forall\, i \in E \\
& \sum_{j=1}^{n} v'_j(x_{ij}) - \sigma_i \leq t - \delta & \forall\, i \in I \\
& v'_j(x_{kj}) - v'_j(x_{\ell j}) \geq 0 & \forall\, k, l \text{ with } x_{kj} \geq x_{\ell j} \\
& \sum_{j=1}^{n} v'_j(x^*_j) = 1, \;\; \sum_{j=1}^{n} v'_j(x_{*j}) = 0 & \\
& v'_j(x_{ij}),\ \sigma_i,\ t \geq 0 & \forall\, i = 1,\ldots,m,\ j = 1,\ldots,n
\end{array} \tag{3.3}$$

The objective of this formulation is to minimize the overall weighted classification error (controlling for the number of observations from each class). The non-negative variables σ define the classification error as $\sigma_i = \max\{t+\delta - V(\mathbf{x}_i), 0\}$ for the efficient cases and $\sigma_i = \max\{V(\mathbf{x}_i) - t + \delta, 0\}$ for the inefficient ones, where t is the cut-off point that distinguishes the two classes (to be estimated) and δ is a small positive constant. The first two constraints are used to define the error variables. The third set of constraints ensures that that marginal value functions are non-decreasing (assuming that all criteria are expressed in maximization form), whereas the next two equality constraints normalize the global scores in [0, 1]. The highest possible score is assigned to an ideal country defined by the best available data on all criteria ($x_1^*, \ldots, x_n^*$), whereas an anti-ideal country that comprises of the least preferred available data on all criteria ($x_{*1}, \ldots, x_{*n}$) is assigned score equal to zero.

Introducing a piecewise linear form for modeling the marginal value functions allows expressing the above optimization model in linear form, which is easy to solve even for large data sets. Detailed descriptions of the resulting linear programming formulation can be found in the work of Zopounidis and Doumpos (1999) and Doumpos and Zopounidis (2002).

CHAPTER 4

Energy Efficiency Analysis at the Industry Level

This chapter extends the analysis of energy efficiency at a much more disaggregated level such as EU industries. Firstly, the scope and aim of this research are outlined followed by a literature review about energy efficiency evaluation at the sectoral level. Then, a detailed presentation of the empirical setting is given, including a description of the data, the analysis techniques, and the obtained results. The chapter ends with the conclusions and suggestions for future research.

4.1 Introduction

Following the first stage of our analysis (chapter 3), which focused on the evaluation of energy efficiency at the country level, we extend the analysis towards adopting a more disaggregated perspective that takes into account the sectoral decomposition of the countries' economic activity. Thus, we seek to obtain energy efficiency estimates over time, while controlling for the structure of a country's economy, focusing on the main industrial sectors. Such a disaggregated approach enables not only to test the robustness of the obtained results, but most importantly to identify particular effects that specific characteristics of countries and sectors have on the efficiency performance.

The International Energy Outlook – IEO (2014) reports that global energy consumption is expected to grow by 56% between 2010 and 2040, and this growth will be due to increasing energy use in industry. This is not surprising, as the industrial sector uses more energy than any other end-use sector. In 2011, it consumed about 37% of total delivered energy at the global level, whereas the IEO (2014) predicts that industry will consume more than 50% of total delivered energy in 2040. The IEO (2014) further reports that industrial activities are also responsible for almost 40% of worldwide CO_2 emissions and are expected to increase by 46% by 2040.

As industry is generally the largest consumer of energy and the highest in energy-related CO_2 emissions, it has attracted much attention in recent years. The challenge of climate change in combination with security of supply concerns have spurred an increased interest in how different industrial sectors can reduce their energy consumption while at the same time remaining competitive in the international market place. Improving energy efficiency is considered the best way to this end. Energy efficiency contributes to improving industrial competitiveness and decoupling economic growth from resource and energy use. Therefore, finding ways to enhance industrial energy efficiency can contribute significantly to moving the world towards a more sustainable energy future.

In this context, the objective of the analysis presented in this chapter is to assess the energy efficiency performance of 10 industrial sectors across 23 EU countries. At the first stage, DEA is employed to evaluate the relative efficiency of these sectors using a comprehensive set of variables related to socioeconomic and environmental factors, including capital stock, employment, gross energy use, gross value added, and GHG emissions. Then, the Malmquist Productivity Index (MPI) is employed to assess the dynamics of the efficiency estimates over the examined period and distinguish between the effects of efficiency and technology changes. At a next stage, a cross-classified multilevel modeling is performed for the analysis of the main drivers behind the observed efficiency performance considering a number of sector and country characteristics.

Given the importance of determining the underlying drivers and causes of contemporary efficiency trends in formulating coherent and effective energy policies for the future, this work certainly contributes to the understanding of this complex interplay. In general, the results of this study could offer useful information and insight into the potential and critical policies that should be taken to promote industrial energy efficiency.

4.2 Literature Review

According to most studies, energy efficiency is considered as the best way to meet the increasing industrial energy consumption requirements and minimise environmental degradation. Many energy efficiency indicators and energy benchmarking approaches have been performed worldwide to analyse industrial energy use and energy efficiency potential (Saygin et al., 2011). In numerous studies, appropriate energy efficiency indicators have been applied to estimate energy efficiency performance in different sectors (Neelis et al., 2007; Siitonen et al., 2010; Saygin et al., 2011; Oda et al., 2012). Efficiency indicators are also used to monitor economy-wide efficiency trends and compare the efficiency performance within and outside the sector in different countries (Zhou and Ang, 2008a). Such indicators can also be used by industries to draw lessons on how to improve their reliability and flexibility. Energy benchmarking is also an important tool that has been used by many researchers to estimate the potential for sectoral energy efficiency improvement (Boyd et al., 2008; Hasanbeigi et al., 2010).

Due to its simplicity and the relatively abundant data that are required, IDA is another popular tool that is used in the analysis and modeling of industrial energy consumption. Most decomposition studies focus on a single country (Mairet and Decellas, 2009; Huntington, 2010), while those that adopt a cross-country perspective focus primarily on the manufacturing sector and heavy industries (Cahill and Gallachoir, 2012; Kim and Kim, 2012). Furthermore, IDA is now being employed to analyse how structural and sectoral energy intensity changes affect industrial energy consumption (Pardo Martínez, 2011; Cahill and Gallachoir, 2012).

Nevertheless, the most popular models for energy efficiency measurement are the parametric and non-parametric ones: more specifically, DEA and SFA, respectively. Several studies have used DEA to assess the efficiency in energy-intensive sectors (Azadeh et al., 2007; Mukherjee, 2008b; Perez-Reyes and Tovar, 2009; Oggioni et al., 2011; Blomberg et al., 2012; Riccardi et al., 2012; Sueyoshi and Goto, 2012; Broeren et al., 2014; Zhou et al., 2014). SFA has also been used in energy efficiency evaluation on industrial level (Managi et al., 2006; Farsi et al., 2007; Growitsch et al., 2009; See and Coelli, 2013; Honma and Hu, 2014a). Many studies use both SFA and DEA to estimate efficiency performance (Kashani, 2005; Azadeh et al., 2009). As discussed in chapter 2, DEA is more beneficial than SFA. Therefore, it is the DEA model that is used in this research for measuring the energy efficiency performance of industrial sectors.

4.3 Data and Methodology

4.3.1 Data

In this chapter the energy efficiency of 10 energy-intensive industries in 23 EU countries over the period 2000–09 is examined [1]. In particular, the analysis covers the sectors of construction, electricity, mining and quarrying, transport, and six sub-sectors of

[1] Cyprus, Estonia, Malta and Luxembourg are excluded due to their small size and unavailability of some data. The period of study is restricted to 2000 to 2009 because data were obtained from the World Input Output Database (WIOD) that provides environmental data for industries by 2009.

manufacturing (food and tobacco, textiles and leather, pulp and paper, coke and chemicals, non-metallic mineral and fabricated metal, as well as machinery). A description of the sectors' codes according to World Input–Output Database[2] (WIOD) is given in Table 4.1. Although, these sectors reflect different development patterns, quantities of energy use, and environmental emissions, they are among the largest and fastest-growing sectors globally. Furthermore, they are considered major contributors to countries' economic growth. It has been proved that any improvement in industrial performance can have a positive effect on a country's economy. After the Industrial Revolution, a third of the world's economic output was derived from the manufacturing industries. Therefore, the selection of the sectors that are examined was not based only on the available data related to energy consumption and environmental issues but also and mainly on their significant impact on countries' economic performance and growing power.

Table 4.1: The examined industrial sectors and their WIOD codes.

Industrial sector	**WIOD Code**
Mining and Quarrying	C
Food, Beverages and Tobacco	15t16
Textiles and Textile Products, Leather, Leather and Footwear	17-19
Pulp, Paper, Printing and Publishing	21t22
Coke, Refined Petroleum and Nuclear Fuel, Chemicals and Chemical Products, Rubber and Plastics	23-25
Other Non-Metallic Mineral, Basic Metals and Fabricated Metal	26-28
Machinery, Electrical and Optical Equipment, Transport Equipment	29-35
Electricity, Gas and Water Supply	E
Construction	F
Transport (Other Inland Transport, Other Water Transport, Other Air Transport, Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies)	60-63

The majority of studies that measure industrial energy efficiency using the DEA framework choose inputs such as energy consumption, capital, and labour (Mukherjee, 2008a; Honma and Hu, 2011; Pardo Martínez, 2011; Wu et al., 2012; see also Table 2.1). Zhou et al. (2010) used capital stock, labour force, energy consumption, GDP and CO_2 emissions to measure the carbon emissions of 18 countries for the period 1997–2004. Shi et al. (2010) considered the investment in fixed assets, energy consumption, and labour as inputs and the added value and

[2] The WIOD database is available at http://www.wiod.org. This paper uses data released in July 2014. However, not all data used in this thesis were updated until then.

volume of industrial waste gas as outputs of DEA for evaluating industrial energy efficiency in 28 Chinese regions. Furthermore, Honma and Hu (2011) measured the energy efficiency of 11 industries using labour, capital stock, and energy, among other variables as inputs, whereas gross value added as the only output. Wang et al. (2012) followed a similar approach for analysing industrial energy efficiency in 30 Chinese regions. Azadeh et al. (2007) and Wu at al. (2012), among others, used the value added to assess and optimise energy efficiency performance in energy-intensive sectors.

Some of the variables used at this stage were also used for the energy efficiency evaluation at country level. Specifically, the labor (number of employees), capital stock and energy consumption were used as inputs to DEA model in both aggregated and disaggregated analysis. However, some energy-related variables including the consumption of fossil fuels, other fuels and domestic materials were only used in energy efficiency evaluation at country level. Similar to the common inputs, the economic variable of gross value added was the common output of DEA applied at both stages of analysis. As at the first stage we adopted the traditional approach for energy efficiency evaluation focusing on economic outputs, we eliminated from the set of output variables the GHG emissions. However, the variable of GHG emissions was the undesirable output of DEA in industrial energy efficiency analysis. This is due to the fact that the industry is responsible for almost all of the increase in GHG emissions in the atmosphere. Furthermore, the variable of value added from the industry and the services sectors that provide a more detailed insight into the economic output of each country were examined as outputs of DEA only at country level analysis.

Based on the above literature and the availability of data, the gross value added and GHG emissions were the outputs, whereas the employment, real fixed capital stock, and gross energy use were the inputs in our DEA analysis (Table 4.2). Furthermore, we considered the GHG emissions as an undesirable output for obtaining unbiased results. All inputs and outputs of DEA were obtained from the WIOD, a consistent data set that enables the calculation of a consistent year-to-year time series. The strengths and weaknesses of WIOD, as well as the main guidance for its use have been analysed in detail by Timmer et al. (2015).

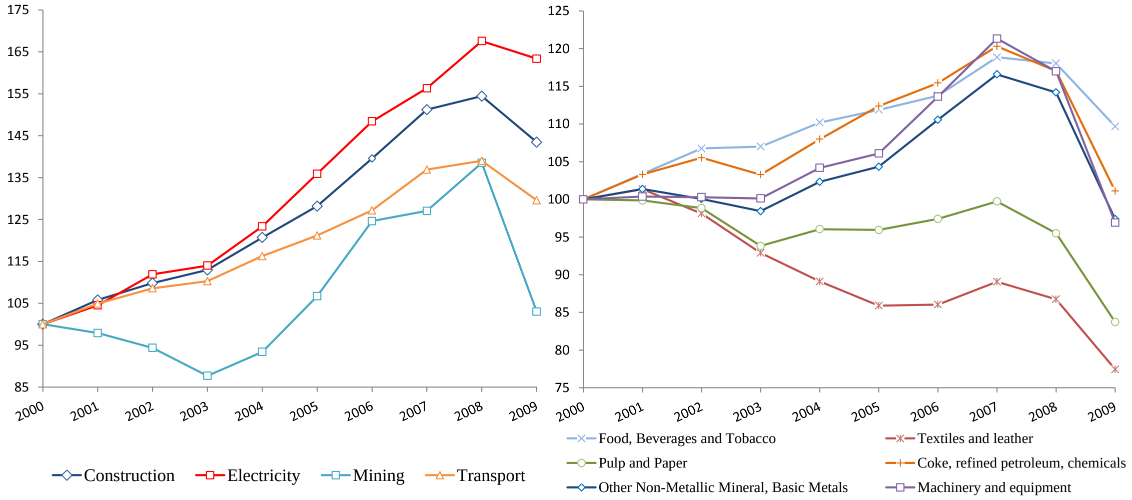
Table 4.2: Input and output variables.

Type	Variable	Unit
Outputs	GHG emissions	Tonnes
	Gross value added	Millions of euros
Inputs	Number of employees	Thousands
	Real fixed capital stock	Euro
	Gross energy use	Terajoules

Note: All inputs and outputs of DEA were obtained from the World Input-Output Database (WIOD).

Figure 4.1 presents the evolution of gross value added and gross energy use over the period of the analysis for all industrial sectors. Between 2003 and 2007, gross value added increased in all sectors, with electricity, construction and mining accounting for the highest increases within sectors. Conversely, all sectors, and especially mining, show a downward trend after 2008, and this is mainly due to the economic crisis. The period between 2000 and 2003 is relatively stable for all sectors, except mining, which experienced a noticeable decrease in gross value added. As far as the performance of sub-sectors of manufacturing is concerned, the non-metallic mineral and basic metals presented the highest gross value added values whereas the textiles the lowest ones. Furthermore, the sub-sector of non-metallic metals also experienced the sharpest decrease after 2008 compared to other manufacturing sectors. In regard to gross energy use, almost all sectors show a downward trend after 2008 with the non-metallic metals presenting again the sharpest decrease. The sector of transport exhibits the highest values whereas the textiles and leather sector the lowest ones over the 10 years of the analysis with a sharp decrease presenting after 2005. Furthermore, the sub-sector of textiles is the sector that experiences the lowest values both in gross value added and gross energy use of all sectors especially during the economic crisis.

Gross Value Added (Millions of euros)



Gross Energy Use (Terajoules)

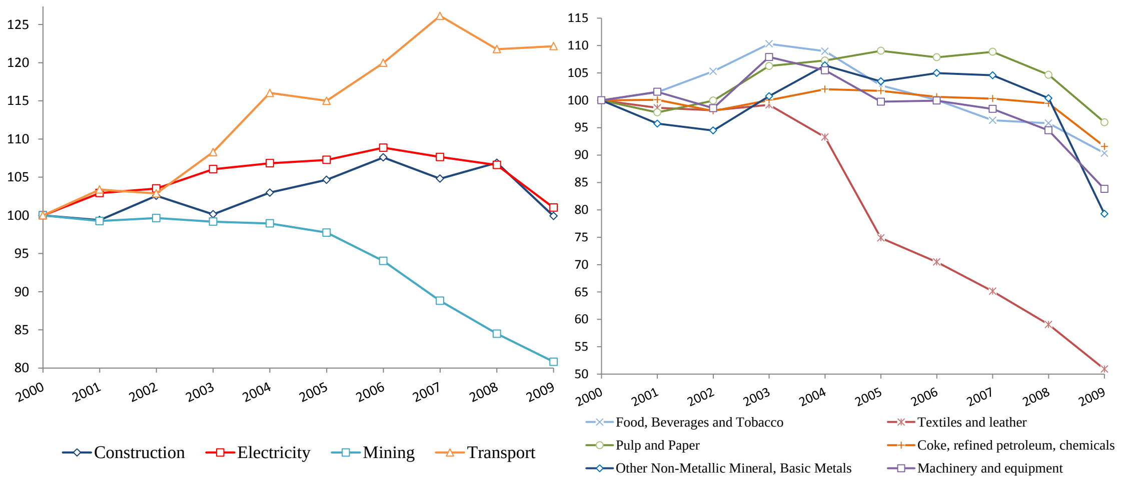


Figure 4.1: Evolution of gross value added and gross energy use over the period 2000–09 (year 2000=100) in all examined sectors.

Following the evaluation of energy efficiency performance and trends over time, a relevant question could be addressed: Which are the main drivers behind these trends? To give a clear reply, and in a way that helps policymakers to be cautious in drawing conclusions regarding policy decisions, at the second stage, the cross-classified data structure that represents a special type of hierarchical linear multilevel model (HLM) is applied. HLMs are statistical models of parameters that are used when data are organised into multiple levels. In particular, a two-level cross-classified model is performed in STATA to analyse the influence of time, sector, and country determinants on energy efficiency performance. To this end, the bootstrapped BCC efficiency scores obtained by DEA are defined as the dependent variables, whereas nine explanatory variables related to sector and country characteristics are used as inputs to the model.

Energy efficiency can be affected by, among other factors, energy prices and carbon-energy taxation (Johansson 2006). Pardo Martínez (2009) also claimed that industrial energy efficiency is mainly dependent on economic factors, such as energy prices. Most of the literature claims that energy efficiency improves as energy prices increase (Birol and Keppler, 2000; Cornillie and Fankhauser, 2004; Fisher-Vanden et al., 2006; Alyousef and Stevens, 2011; Broeren et al., 2014; Xiaoli et al., 2014). Metcalf (2008) concluded that per capita income and energy prices have a positive effect on energy efficiency performance. Walton (1981) noted that labour quality, cost of energy, and capital could also be important factors in determining energy efficiency. According to Birol and Keppler (2000) and Fisher-Vanden et al. (2006), technology development activity is another crucial factor that drives energy efficiency. Geller et al. (2006) claimed that energy efficiency improvement can be achieved through technological progress, as well as by increasing energy prices and eliminating subsidies for fossil fuels. Mukherjee (2008b) concluded that quality of labour has a positive impact on efficiency performance, whereas capital, electricity share in total energy, and reforms have no significant coefficient. By measuring energy efficiency in 85 countries over the 1971–2007 period, Stern (2012) concluded that high total factor productivity, undervalued currency, and low fossil fuels can have a positive influence on energy efficiency. He et al. (2013) claimed that low investment in R&D and labour productivity have a negative impact on the performance of the Chinese steel industry. Huang et al. (2014) indicated that an increase in per capita GDP, percentage of output value of industry, energy price, and investment of scientific and technological activities in industry could lead to industrial energy efficiency improvement. Furthermore, it has been proven that many countries impose energy and environmental taxes to encourage energy efficiency and fuel switching (Davidsdottir and Ruth, 2004; Mahmood and Marpaung, 2014). Bampatsou and Hadjiconstantinou (2009) concluded that countries can improve their efficiency index by using cleaner forms of energy, such as renewable energy resources.

Based on the above literature, the variables of the market share of the largest generator in the electricity market, the energy taxes, and electricity prices are used to assess the cross-country differences. For cross-sector differences, the contribution of a sector's gross value added to the total gross value of a country, the energy mix, the share of fossil fuels in total gross energy consumption, the real fixed capital stock to gross value added, the real fixed capital stock to number of employees, and the productivity — defined as the gross value added divided by the total hours worked by employees — are examined. A detailed description and the source of these data are provided in Table 4.3.

Table 4.3: Description of variables used at cross-classified modeling.

Variable	Description	Unit	Source
Market share of the largest generator in the electricity market (MS)	The indicator shows the market share of the largest electricity generator in each country. It is defined as the ratio of the annual net electricity production of the largest electricity generator over the total net electricity generation of the country. Net electricity production excludes the electricity used by generators for their own consumption.	Percentage of the total generation	EUROSTAT
Energy taxes (TAX)	This category includes taxes on energy production and on energy products used for both transport and stationary purposes. The most important energy products for transport purposes are petrol and diesel. Energy products for stationary use include fuel oils, natural gas, coal and electricity. Taxes on biofuels and on any other form of energy from renewable sources are included. Taxes on stocks of energy products and on Carbon dioxide (CO_2) are also included.	Percentage of GDP	EUROSTAT
Electricity prices for industrial consumers (ELECPR)	This indicator presents electricity prices charged to final consumers. Electricity prices for industrial consumers are defined as follows: Average national price in Euro per kWh without taxes applicable for the first semester of each year for medium size industrial consumers (Consumption Band Ic with annual consumption between 500 and 2000 MWh). Until 2007 the prices are referring to the status on 1st January of each year for medium size consumers (Standard Consumer le with annual consumption of 2 000 MWh).	EUR per kWh	EUROSTAT
Energy Mix given by the Simpson Index (EM)	This variable is given by the Simpson Index. This Index is equal to the sum of the squared of the arguments per sector. The arguments are the Coals (sum of HCOAL, BCOAL and COKE), Petroleum Products (sum of DIESEL, GASOLINE, JETFUEL, LFO, HFO, NAPHTA and OTHPETRO), Gases (sum of NATGAS and OTHGAS), Renewables and Wastes (sum of	-	WIOD

	WASTE, BIOGASOL, BIODIESEL, BIOGAS and OTHRENEW), Electricity and Heat (sum of ELECTR, HEATPROD, NUCLEAR, HYDRO, GEOTHERM, SOLAR, WIND and OTHSOURC) each one divided by the total energy mix (the summation of all these).		
VA/VA of Total Industries (VAIND)	Gross Value added of a specific sector/ Gross Value added of Total Industries	Percentage	WIOD
Share of fossil fuels in total gross energy consumption (FF)	Share of fossil fuels (sum of coal, petroleum and gases products) in total energy mix.	Percentage	WIOD
K_GFCF/VA (CVA)	Real fixed capital stock / Gross Value added	Euro/Millions of euro	WIOD
K_GFCF/EMPE (CEMP)	Real fixed capital stock / Number of employees	Euro/ Thousands of employees	WIOD
VA/H_EMPE (PROD)	Gross Value added/ Total hours worked by employees	Millions of euro/ Millions of hours	WIOD

4.3.2 Non-parametric Methodology

On the methodological side, an input-oriented approach is performed following a perspective that emphasises the reduction of energy consumption. This is in accordance with the philosophy that underlies all global policies established over the years, which have focused on setting targets for reductions in energy consumption at the country, sector, and firm levels. Based on this approach, the efficiency score θ_i in linear program (Eq. 2.2) represents the reduction that country i should achieve in its energy inputs to become efficient compared to other countries that use the same or less non-energy inputs (second constraint) and produce at least the same level of outputs as country i (third constraint).

In contrast to the standard setting that was employed in the previous chapter for the application of DEA, the analysis in this chapter is based on bootstrapped DEA estimates. It is well-known in the DEA literature that the two-stage analyses that use DEA efficiency scores as an input to statistical explanatory (regression) models lead to biased inferences and results. The MCDA model performed in the previous chapter is not subject to such limitations and consequently it can use the standard DEA efficiency estimates. However, such a multicriteria model cannot cope with the hierarchical structure of the data (time/sectors/countries) in the current analysis. Therefore, a multilevel regression model is developed for measuring industrial energy efficiency. In order to get unbiased results from such a model, we first obtain proper DEA efficiency estimates through the bootstrap approach proposed by Simar and Wilson (1998).

Taking into account that the efficiency measured by DEA is static, the use of DEA that incorporates the MPI (Malmquist, 1953) is proposed. Such an approach has been considered a useful tool for energy efficiency decision-making and has, therefore, been widely employed to evaluate the performance of a number of industrial sectors (Wei et al., 2007; Xue et al., 2008; He et al., 2013). As explained in section 2.3.2, the DEA-based MPI enables the quantification of changes in total factor productivity over time (Perez-Reyes and Tovar, 2009; Zhou et al., 2010).

4.3.3 Econometric Model

Given that each industrial sector and country has unique characteristics, the identification of the factors affecting energy performance is required. Therefore, at the second stage, a two-level cross-classified model that combines a number of sector and country characteristics is performed. The proposed model aims to detect the contribution and effect of country and sector characteristics in the total variation of energy efficiency as well as to identify which of these characteristics are mainly responsible for the observed energy efficiency performance. The proposed cross-classified multilevel model contains two levels. The first level is time, and the second is a combination of country and sector characteristics. Time is not uniquely nested to either a country-level or sector-level grouping of the data. Thus, a cross-classification scheme, such as the one used in this study, allows the analysis of the effects due to two different factors/contexts: (i) at the country level and (ii) at the sector level (Zaccarin and Rivellini, 2002).

Following this specification, the empty (null) model is firstly constructed to assess the relative importance of each level in the variance of energy efficiency scores. Thus, the empty model examines whether there is significant intra-class correlation (ICC) between the level and the mean of energy efficiency scores. It focuses on random effects, ignoring fixed effects. Therefore, the specification of the first level is expressed by a function of the mean value of

BCC bootstrapped efficiency scores of year t within the cross-classification of sector j and country k

$$100 \times BCC_{tjk} = \beta_{0jk} + e_{tjk} \tag{4.1}$$

where β_{0jk} is the intercept (overall mean value of BCC efficiency scores) expressing the efficiency score of sector j in country k over all years, and e_{tjk} follows a distribution with mean zero and variance σ^2. The random error (e_{tjk}) represents the variance across time.

At the second level of analysis, the intercept β_{0jk} is defined as a function of the grand mean of BCC efficiency scores (γ_{000}) for all years and the residual random effects for sector j (u_{0j0}), country k (υ_{00k}), and the sector-by-country cell (δ_{0jk}). The level 2 model is defined as follows:

$$\beta_{0jk} = \gamma_{000} + u_{0j0} + \upsilon_{00k} + \delta_{0jk} \tag{4.2}$$

By taking into account equations (4.1) and (4.2), we obtain the mixed-effect empty model (Model 1):

$$100 \times BCC_{tjk} = \gamma_{000} + u_{0j0} + \upsilon_{00k} + \delta_{0jk} + \varepsilon_{tjk} \tag{4.3}$$

where BCC efficiency scores are modelled with an overall intercept γ_{000} and an error term each for sector j and country k and the residual error term e_{tjk} for year t in the cross-classification of sector j and country k. Therefore, (4.3) implies one fixed effect (γ_{000}), two random effects $(u_{0j0}, \upsilon_{00k})$, the within-cell residual (δ_{0jk}), and the random error e_{tjk}, representing the variance across time. The sector, country, and interaction effects and the year-level residual error are each assumed to follow normal distributions with zero means and constant variances.

The above empty model can be extended with the inclusion of the explanatory variables related to sector (VAIND, EM, FF, CVA, CEMP, and PROD) and country characteristics (MS, TAX, and ELECPR):

$$\begin{aligned}100\times BCC_{tjk} &= \gamma_{000}+\gamma_{0j1}(\mathrm{MS}_{tj})+\gamma_{0j2}(\mathrm{TAX}_{tj})+\gamma_{0j3}(\mathrm{ELECPR}_{tj})\\&+\gamma_{01k}(\mathrm{VAIND}_{tjk})+\gamma_{02k}(\mathrm{EM}_{tjk})+\gamma_{03k}(\mathrm{FF}_{tjk})+\gamma_{04k}(C\,\mathrm{VA}_{tjk})\\&+\gamma_{05k}(C\,\mathrm{EMP}_{tjk})+\gamma_{06k}(\mathrm{PROD}_{tjk})+u_{0j0}+\upsilon_{00k}+\delta_{0jk}+\varepsilon_{tjk}\end{aligned} \tag{4.4}$$

This model shows that the efficiency scores obtained by the BCC model are a function of sector- and country-level covariates and their respective random errors.

4.4 Results

4.4.1 DEA and MPI Results

As explained in section 4.3.2, DEA was applied combined with the bootstrap approach of Simar and Wilson (1998) to obtain unbiased efficiency estimates, which are suitable to be used as inputs to the econometric model at the second stage of the analysis. Similarly to the analysis presented in the previous chapter, both CCR and BCC were considered. However, the energy efficiency evaluation under CCR model can be rather misleading and incorrect since there are observed differences in variables between examined countries. Thus, our analysis is focused only on BCC efficiency scores. Table 4.4 shows the countries' BCC (bootstrapped) efficiency scores averaged over all the years of our analysis for each industrial sector.

Table 4.4: Overall BCC efficiency scores (averaged over 2000–09)

by country and industrial sector.

Country	Constr.	Electr.	Mining	Transp.	Food	Textile	Pulp	Coke	Non-metal.	Mach.	AVG
AT	0.832	0.787	0.261	0.776	0.841	0.809	0.206	0.433	0.809	0.812	0.657
BE	0.840	0.428	0.268	0.487	0.802	0.693	0.674	0.480	0.476	0.696	0.584
BG	0.835	0.394	0.728	0.623	0.463	0.735	0.493	0.376	0.469	0.873	0.599
CZ	0.484	0.392	0.285	0.774	0.462	0.357	0.353	0.765	0.680	0.655	0.521
DK	0.540	0.669	0.630	0.207	0.640	0.828	0.696	0.652	0.798	0.712	0.637
FI	0.365	0.293	0.298	0.672	0.828	0.780	0.085	0.176	0.403	0.835	0.474
FR	0.650	0.787	0.323	0.722	0.850	0.823	0.577	0.517	0.822	0.875	0.695
DE	0.732	0.787	0.275	0.773	0.828	0.626	0.699	0.680	0.799	0.836	0.703
GR	0.571	0.458	0.493	0.514	0.668	0.813	0.595	0.128	0.581	0.535	0.536
HU	0.874	0.631	0.597	0.672	0.467	0.814	0.699	0.708	0.818	0.835	0.712
IE	0.835	0.816	0.721	0.565	0.844	0.827	0.697	0.677	0.389	0.808	0.718
IT	0.831	0.787	0.722	0.776	0.842	0.813	0.758	0.732	0.798	0.805	0.786
LV	0.835	0.787	0.733	0.779	0.730	0.814	0.706	0.679	0.776	0.837	0.768
LT	0.722	0.787	0.729	0.709	0.772	0.656	0.594	0.026	0.803	0.585	0.638
NL	0.855	0.709	0.724	0.402	0.601	0.618	0.534	0.253	0.798	0.469	0.596
PL	0.753	0.791	0.722	0.729	0.569	0.730	0.532	0.761	0.792	0.782	0.716
PT	0.830	0.658	0.762	0.463	0.699	0.367	0.111	0.244	0.827	0.870	0.583
RO	0.739	0.786	0.720	0.781	0.827	0.813	0.570	0.679	0.798	0.867	0.758
SK	0.831	0.651	0.337	0.776	0.728	0.770	0.135	0.264	0.277	0.787	0.556
SI	0.764	0.572	0.546	0.680	0.827	0.619	0.124	0.679	0.798	0.669	0.628
ES	0.830	0.596	0.736	0.464	0.758	0.620	0.529	0.562	0.728	0.583	0.641
SW	0.606	0.787	0.318	0.574	0.827	0.779	0.316	0.311	0.666	0.835	0.602
UK	0.826	0.724	0.721	0.774	0.834	0.525	0.697	0.687	0.741	0.537	0.707
AVG	0.738	0.656	0.550	0.639	0.726	0.706	0.495	0.499	0.689	0.743	0.644

Based on the BCC obtained results the average BCC efficiency scores ranged between 49% and 74% across all sectors. It is evident that BCC efficiency is higher in construction, food, textiles, as well as machinery. Conversely, the highest inefficiencies (more than 45%) are present in mining, pulp and coke.

The most trivial way to aggregate the sectoral results for each country is to formulate an overall country efficiency estimate as the average of the corresponding sectoral results. The corresponding results are reported in the last column of Table 4.4. To examine the relationship between the aggregate BCC efficiency scores obtained through this approach with the efficiency scores of the sectors, we used a nonparametric measure of statistical dependence. Specifically, we calculated the Spearman's rank correlation coefficient (r_s). The obtained results revealed that the efficiency results for electricity as well as pulp and coke have the highest level of correlation (above 0.6) with the averaged efficiency scores. On the other hand, the sector of machinery has the lowest correlation (0.26) whereas all the other sectors have correlations ranging between 0.3 and 0.6.

We also used the Spearman's rank correlation coefficient to measure the strength of the relationship between sectors in a country. The results showed that the efficiency of the electricity sector has a strong and positive correlation with all other sectors. This observation is not surprising, as the efficient performance of electricity market affects the efficiency of other industrial sectors. Furthermore, most of the industries (except construction and mining) were also found to be positively associated to each other (the correlations were positive in the vast majority of the cases). This is reasonable as sectors in the same country have similar behaviour regarding financing and other policy making decisions, although such patterns differ across industries.

Regarding the efficiency results at the country level, Germany, Hungary, Ireland, Italy, Latvia, Poland, Romania and United Kingdom achieved the highest BCC efficiency scores (above 70%) on average across all sectors. On the other hand, Belgium, Bulgaria, Czech Republic, Finland, Greece, Netherlands, Portugal and Slovakia presented the lowest BCC efficiency scores (below 60%). Finland is the most inefficient country (47.4%) over all years and sectors.

Comparing the BCC efficiency scores obtained from this stage (disaggregated analysis) with those from the aggregated analysis (chapter 3), it is evident that all countries except Belgium, Bulgaria, Czech Republic, Hungary, Portugal, Romania and Slovakia present lower scores under the analysis at the sectoral level. This means that almost all countries show a better energy efficiency performance when this is evaluated in a global and aggregated context. Under both evaluations (the aggregate one analysed in chapter 3 and the disaggregated assessment analysed here), Italy, Ireland, Latvia, Germany, UK, and France appear to be the most energy efficient countries whereas Czech Republic, Slovakia, Belgium, Portugal, and Greece are the most inefficient ones. On the other hand, countries such as Netherlands, Denmark, Slovenia, Sweden, Lithuania and Finland, which achieved high efficiency scores according to the country level analysis, they performed poorly at the industrial level. Furthermore, the aggregated analysis showed that Romania and Hungary are two of the most inefficient countries, whereas according to their sectors' performance they are highly efficient.

Such differences between the analysis at the country and industry levels, could be attributed to the structure of the industrial activity of the countries, which may lead to different results when it is taken into consideration. This effect is clearly stronger for some countries such as Romania and Hungary.

The relation between the BCC efficiency scores obtained by DEA under the two analysis settings (aggregated versus disaggregated), was further examined through the Spearman's rank correlation coefficient, which was found to be equal to 0.434 (p-value 0.0398). This result suggests that there is a strong correlation (significant at the 5% level) between the performance of countries as estimated through a unified (country level) and a more detailed context (industry level).

Despite the high correlation between the results, it is evident that the proposed disaggregation analysis conducted at this stage of the research can provide a more detailed view of the performance of the countries. Furthermore, as the industrial sector is one that is mainly responsible for the high level of energy consumption and GHG emissions, it would be misleading if analysis focuses solely at aggregate country data, without considering a decomposition of the industrial activity and its characteristics. The differences between the energy efficiency performance of each sector inside the same country also make clear the necessity of evaluating energy efficiency at a more disaggregated level.

Further insights can be obtained by considering scale efficiency which is defined as the ratio of the CCR to BCC efficiency scores. The scale efficiency is a measure of the extent to which a DMU (country/sector) deviates from the optimal scale. A scale efficiency score of 1 implies that the sector is operating at optimal scale or size, whereas a score below 1 indicates that the sector is either too small or too big relative to its optimal size.

Figure 4.2 reveals that scale efficiency ranges between 29% and 96%, on average, under all countries. The average scale efficiency of the sectors across all countries has been consistently higher than 70% in all sectors except pulp and coke. In particular, the sectors of construction, transport, food, textiles and machinery present a scale effect above 90% on average under all countries. Thus, these sectors were almost at the optimal size for their particular input–output mix. The remaining sectors had scale efficiency scores of less than 90% and were thus deemed as more scale inefficient. The detailed results are as follows: coke had a scale efficiency score of 29%, pulp a scale efficiency of 55% and the remaining sectors a scale efficiency between 71-90%.

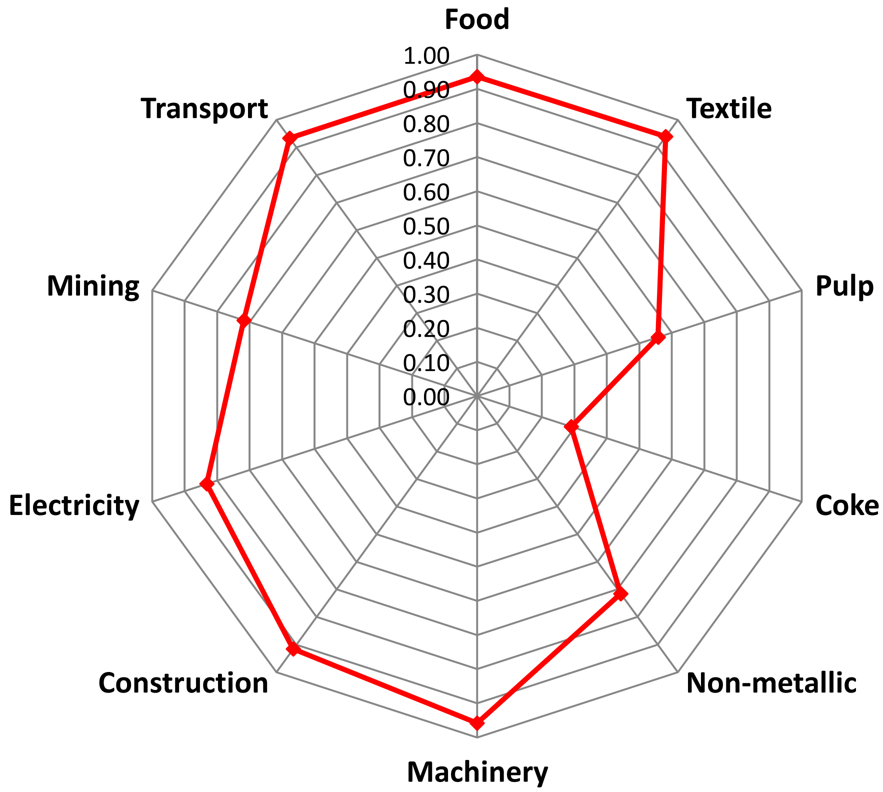


Figure 4.2: The Scale Efficiency (averaged over 2000–09 and countries) by sector.

As far as the country's scale efficiency is considered, it is evident (Figure 4.3) that Denmark, Latvia, and Ireland are the most scale efficient countries on average in all sectors (show an average scale efficiency above 90%). On the other hand, Romania, Bulgaria, Germany, France, and Poland show an average scale efficiency below 70% under all sectors, whereas Poland achieved the lowest scale efficiency (55%). Furthermore, the high scale efficiency of countries like Denmark, Finland, Slovenia, and Belgium, as opposed to their low BCC efficiency, implies that internal issues in the industrial sector and the energy markets of these countries should be carefully considered.

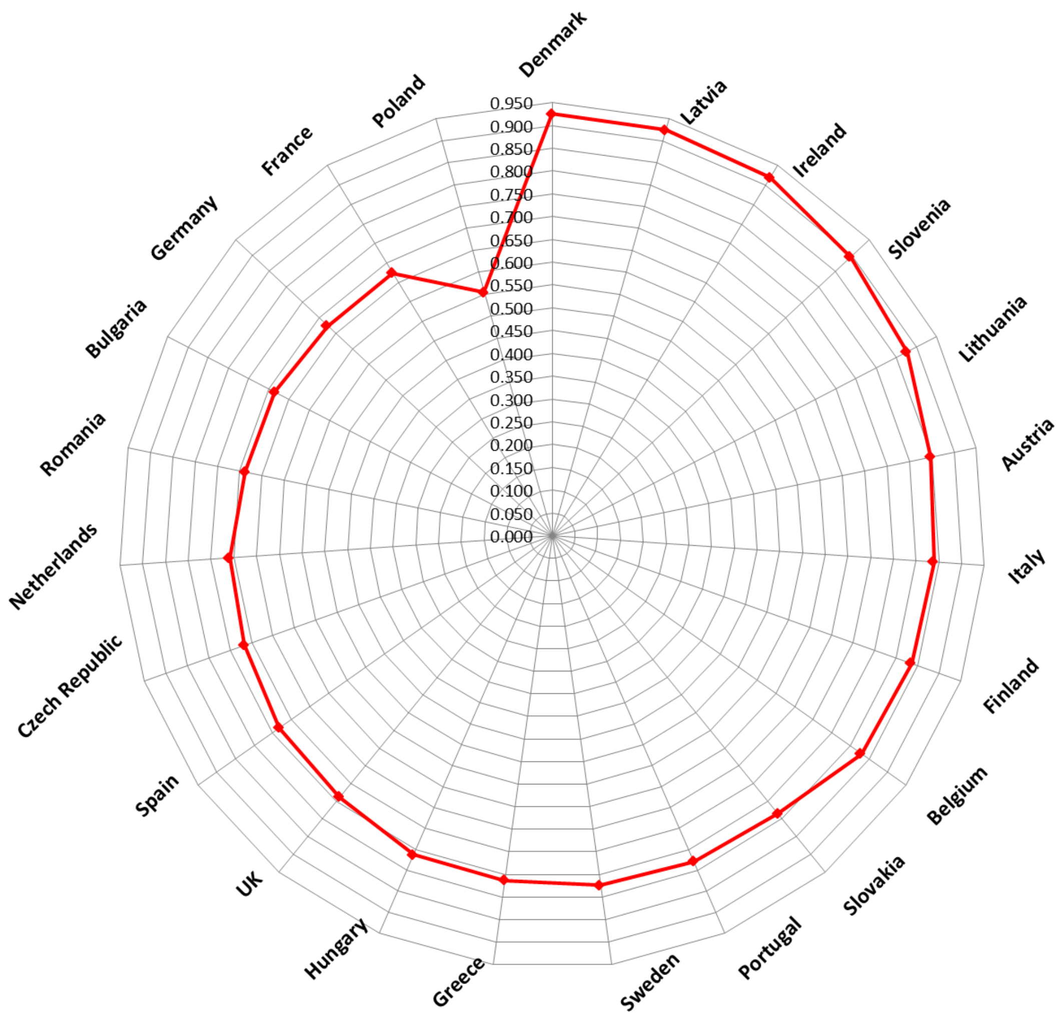


Figure 4.3: The Scale Efficiency (averaged over 2000–09 and sectors) by country.

Given the panel nature of the available data, changes in productivity growth can be calculated using the Malmquist productivity change index. This index is composed of distance functions, and is therefore superior to alternative indexes of productivity growth (such as the Törnqvist index and the Fisher Ideal index) as it is based only on quantity data. Rather than looking at the annual average over the period, we compare the sectors' performance in each year with a base year (2000 in this case) to examine the cumulative productivity change over time. Table 4.5 reports the cumulative MPI estimates (CMPI) calculated as $CMPI_t = MPI_1 \times MPI_2 \times \cdots \times MPI_t$. Values greater than one indicate productivity improvements, while values less than one imply deterioration compared to the base year 2000. Thus, if a sector has a cumulative MPI greater than one in year t this means that the sector's productivity in year t exceeded the 2000 productivity level, otherwise its productivity has decreased.

According to the CMPI estimates (Table 4.5), construction, mining, food, and coke improved their productivity throughout the period 2001-09 compared to the base year 2000. Furthermore, it is evident that the CMPI has been consistently higher than 1, from 2006 onwards, in all sectors except transport, thus indicating productivity improvements over the years. Prior to 2006 the improvements were moderate in most cases, with fluctuations from year to year. However, after 2006 most sectors present a consistent upward efficiency trend. In some sectors, this improvement was even higher than 50%. For example, the textiles sector improved its performance by 58.4% in 2009 compared to 2000. The textiles sector has been subject to a series of radical transformations over recent decades, due to a combination of technological changes, the evolution of production costs, the emergence of important international competitors, and the elimination of imports quotas after 2004[3]. Companies across the whole textile and apparel value chain place sustainable production and higher resource efficiency at the centre of their growth strategy[4]. It is worth noting that even during the economic crisis (2008-09) all sectors (except transport) improved their productivity by at least 10%. The highest improvements were achieved in mining, food, textiles, and non-metallic products (productivity increase above 30% from 2000 to 2009).

Table 4.5: Cumulative MPI for each industrial sector (averaged over all countries).

	Constr.	**Electr.**	**Mining**	**Transp.**	**Food**	**Textile**	**Pulp**	**Coke**	**Non-metal.**	**Mach.**
2001	1.077	0.965	1.007	0.964	1.050	1.009	1.014	1.052	1.032	0.982
2002	1.054	0.972	1.064	0.969	1.037	1.013	0.987	1.112	1.043	1.028
2003	1.113	0.950	1.005	0.940	1.026	0.975	0.952	1.085	1.002	0.966
2004	1.097	0.966	1.024	0.894	1.064	0.998	0.992	1.015	0.974	1.039
2005	1.061	1.001	1.062	0.911	1.112	1.170	0.999	1.001	1.000	1.045
2006	1.055	1.037	1.109	0.917	1.166	1.207	1.006	1.089	1.002	1.068
2007	1.169	1.075	1.164	0.895	1.234	1.312	1.049	1.142	1.046	1.134
2008	1.120	1.090	1.245	0.908	1.266	1.451	1.098	1.129	1.112	1.156
2009	1.204	1.104	1.306	0.862	1.310	1.584	1.160	1.193	1.312	1.182

As explained in section 2.3.2, the MPI can provide additional insights since it can be decomposed into two additional components, one measuring changes in technical efficiency (i.e., whether sectors are getting closer to the production frontier over time), and one

[3] http://ec.europa.eu/growth/sectors/fashion/textiles-clothing/eu/index_en.htm [Accessed 5 November 2015]
[4] http://www.innovationintextiles.com/energy-efficiency-for-european-textile-and-clothing-industry-discussed-in-brussels/ [Accessed 5 November 2015]

indicating changes in technology (i.e., whether the production frontier progresses over time). Tables 4.6 and 4.7 illustrate the evolution of the two corresponding main components (in cumulative terms) for all sectors over the period 2001–09 compared to their 2000 levels (which are equal to 1).

Table 4.6 presents the cumulative efficiency trends that reflect the capability of a sector in catching up with the efficient ones from 2001 to 2009. Construction, food, pulp and machinery present an improvement, at least 2%, in their efficiency over all period under examination. Furthermore, all sectors except mining, transport, coke, and non-metallic minerals, show an improving trend after 2004. However, this trend is not stable as there are fluctuations (at least ±5%). At the end of the examined period (in 2009) all sectors, with the exception of mining, improved their efficiency performance. Pulp had the highest improvement (24%), whereas the other sectors had at least a 1% increase in their efficiency performance compared to that in 2000.

Table 4.6: Cumulative efficiency change over the period 2000–09

(year 2000=1).

	Constr.	**Electr.**	**Mining**	**Transp.**	**Food**	**Textile**	**Pulp**	**Coke**	**Non-metal.**	**Mach.**
2001	1.045	0.998	0.992	0.998	1.018	1.031	1.100	0.925	1.079	1.020
2002	1.087	0.992	0.922	0.980	1.021	1.018	1.068	0.889	0.981	1.019
2003	1.072	1.003	0.921	0.993	1.028	0.994	1.107	0.985	1.018	1.027
2004	1.062	1.015	0.973	0.962	1.023	0.983	1.160	1.102	0.995	1.049
2005	1.093	1.048	1.012	0.986	1.102	1.048	1.105	1.064	1.016	1.055
2006	1.087	1.065	1.093	1.007	1.116	1.047	1.162	0.956	1.063	1.039
2007	1.120	1.052	1.069	0.997	1.120	1.028	1.043	0.956	1.096	1.039
2008	1.085	1.080	1.097	1.022	1.153	1.043	1.054	1.028	0.965	1.036
2009	1.094	1.080	0.936	1.013	1.139	1.106	1.241	1.062	1.026	1.065

According to the technology change results (Table 4.7), the best-practice frontiers in mining, food, and coke improved by more than 2% over the period 2001–09. All sectors, except transport, had an upward trend (improvement) in technology change after 2005. In particular, all sectors except construction, electricity, and transport had a consistent upward trend in technology improvement (above 4%), whereas mining, textiles, coke, and non-metallic minerals achieved at least a 10% improvement. It is also observed that even during the economic crisis (in 2009), the best-practice frontier improved by more than 7% in all sectors except transport, with the improvement being much stronger in mining, textiles, and coke (more than 50%). Of all sectors, coke achieved the highest improvement in 2009. Actually, this sector had the most consistent improvement throughout the examined time period.

Table 4.7: Cumulative technology change over the period 2000–09

(year 2000=1).

	Constr.	**Electr.**	**Mining**	**Transp.**	**Food**	**Textile**	**Pulp**	**Coke**	**Non-metal.**	**Mach.**
2001	1.037	0.970	1.045	0.976	1.037	0.984	0.964	1.372	0.968	0.968
2002	0.979	0.988	1.225	1.004	1.029	1.006	0.995	1.577	1.089	1.020
2003	1.055	0.961	1.181	0.972	1.020	0.998	0.972	1.581	1.018	0.959
2004	1.055	0.971	1.153	0.970	1.067	1.041	0.994	1.481	1.025	1.018
2005	0.999	0.980	1.167	0.973	1.040	1.158	1.091	1.543	1.042	1.022
2006	1.004	1.006	1.159	0.968	1.080	1.211	1.106	2.020	1.004	1.065
2007	1.086	1.059	1.262	0.961	1.145	1.352	1.325	2.390	1.023	1.133
2008	1.081	1.053	1.351	0.961	1.146	1.486	1.426	2.659	1.255	1.164
2009	1.161	1.077	1.703	0.946	1.207	1.552	1.432	3.125	1.421	1.162

Taking into account the above results trends regarding the changes in the efficiency and technology components of the MPI, it is evident that the effects due to efficiency and technology change differ among sectors and periods. It is evident that the technology (best-practice frontier) improvements have been stronger than the efficiency change component, during the period under examination. Therefore, we conclude that technology is mainly responsible for the improvement in performance of almost all sectors. This effect is stronger in mining, transport, pulp, coke, and machinery. Conversely, textile appears to have been driven primarily by efficiency change (in almost all years). Construction, electricity, food, and non-metallic minerals showed a mixed behaviour, with the efficiency and technology change factors contributing differently in separate periods.

4.4.2 Multilevel Regression Results

At the second stage of our analysis, we used the two-level cross-classified model to analyse the factors behind the observed energy efficiency trends. The bootstrapped BCC efficiency scores obtained by DEA were used as the dependent variable whereas the country and sector characteristics as the independent variables. Table 4.8 reports the descriptive statistics for all variables, as well as their pairwise Pearson correlation coefficients. The sample consists of 2.300 observations from ten industrial sectors in 23 EU countries over the period 2000–09.

Table 4.8: Descriptive statistics and Pearson correlation coefficients.

	Variable	Mean	St.dev.	1	2	3	4	5	6	7	8	9
1	**BCC**	0.644	0.205									
2	**MS**	53.874	24.428	-0.093								
3	**TAX**	1.939	0.393	0.009*	-0.339							
4	**ELECPR**	0.068	0.020	0.035*	-0.041*	-0.289						
5	**VAIND**	0.033	0.024	0.201	-0.024*	0.048	-0.017*					
6	**EM**	0.471	0.206	-0.004*	0.045	-0.024*	0.005*	0.448				
7	**FF**	0.709	0.202	0.049	-0.014*	-0.042	0.054	0.354	0.484			
8	**CVA**	2.014	1.626	-0.096	0.075	-0.061	0.045	-0.221	0.059	-0.105		
9	**CEMP**	178.563	362.472	0.004*	-0.046	-0.038*	0.073	-0.136	0.079	-0.005*	0.523	
10	**PROD**	44.006	108.388	0.000*	-0.065	-0.022*	0.096	-0.026*	0.152	0.086	0.083	0.728

Note: * insignificant correlation at the 5% level.

It is obvious that the variables are not highly correlated either positively or negatively. There is only a strong positive relationship between PROD and CEMP. Moreover, the relationships between FF and EM, between CEMP and CVA are also positive but moderate. Furthermore, the dependent variable is correlated positively with all independent variables, except the MS, EM and CVA. VAIND presents the highest correlation with BCC efficiency scores (0.201), followed by the variables of the MS (|-0.093|) and CVA (|-0.096|) in absolute terms.

Table 4.9 shows the variance decomposition estimates at the sector (u_{0j0}) and country levels (υ_{00k}), the interaction between sector and country levels (δ_{0jk}) and the time effect (e_{tjk}), for both the empty (Model 1) and the random intercept model (Model 2). It also illustrates the ICC, which is the percentage of each level's variance to total variance.

Table 4.9: Variance decomposition and fixed effects estimates for the empty and the random intercept model.

	Model 1: Empty Model	**Model 2: Random Intercept Model**
Variance decomposition		
Sector-level, u_{0j0}	74.461	63.774
Country-level, υ_{00k}	43.021	48.069
Sector x Country-level, δ_{0jk}	243.360	236.002
Time-level, e_{tjk}	60.750	58.505
Percentage of total variance		
Between sectors	17.66%	15.69%
Between countries	10.20%	11.83%
Between sectors & countries	57.72%	58.08%
Across time	14.41%	14.40%
Fixed effects		
Intercept	64.404 (0.000)	76.981 (0.000)
Sector variables		
VAIND		159.280 (0.000)
EM		-1.705 (0.680)
FF		-12.377 (0.000)
CVA		-0.881 (0.018)
CEMP		0.005 (0.113)
PROD		0.009 (0.097)
Country variables		
MS		-0.053 (0.036)
TAX		-1.405 (0.126)
ELECPR		-31.646 (0.009)

Note: p-values in parentheses. A positive coefficient corresponds to variables that contribute in increasing energy efficiency.

Model 1 provides a view of the relative importance of each level for the variance of efficiency scores. From the variance decomposition estimates, it is obvious that the sector/country interaction effect is the most stronger one, accounting for 57.72% of the total variance in energy efficiency. This significant effect justifies the application of the two-level cross-classified model at this stage. The sector level, which accounts for 17.66% of the observed variance in energy efficiency scores, seems to also play an important role. The effects of the country and time levels, which account for 10.20% and 14.41%, respectively, also influence efficiency performance but to a much lesser extent.

As far as the variance decomposition estimates of the random intercept model (Model 2) are concerned, the conclusions are similar to those under Model 1. Thus, the combination of country and sector levels accounts for the highest variance and almost to the same proportion as in case of Model 1 (58.08%). The explanatory power of the time level in Model 2 (14.40%) is also similar to its effect in Model 1 (14.41%). On the other hand, the sector characteristics are now responsible for a smaller proportion (15.69%), whereas the country level now accounts for a slightly higher proportion (11.83%) on energy efficiency variance.

Table 4.9 also shows the fixed-effects estimates for all explanatory variables (country and sector characteristics). Specifically, VAIND, FF, and ELECPR are statistically significant at the 1% level, CVA and MS significant at 5%, and PROD at 10% level. However, the EM, and to a lesser extent, the CEMP and TAX are not significant.

Looking more closely the results for the above variables, it is evident that the sector characteristics related to VAIND, CEMP, and PROD have a positive impact on energy efficiency performance. Pardo Martínez (2011) and He et al. (2013) also concluded that a higher value of VAIND is associated positively with energy efficiency. Our finding that labour quality (as described by CEMP) has a positive effect on the efficient use of energy is in accordance with similar results reported by Subrahmanya (2006), Mukherjee (2008a), and Pardo Martínez (2011). However, according to our results this effect is not statistically significant. Furthermore, the result regarding the positive impact of PROD on energy efficiency is in accordance with similar conclusions reported in other studies. For example, Subrahmanya (2006) and He et al. (2013) observed that the sectors or countries that exhibit higher labour productivity have higher energy efficiency performance. Conversely, Pardo Martínez (2009) noted that changes in labour intensity should not necessarily mean higher or lower energy efficiency.

The remaining sector variables (EM, FF, and CVA) have a negative effect on energy efficiency. In particular, the negative coefficient of EM implies that using a diversified set of energy sources tends to improve energy efficiency. However, its effect does not seem to be significant. FF, on the other hand, has a significant negative impact on efficiency. This is well in line with a number of studies (Geller et al., 2006; Pardo Martínez, 2011; Stern, 2012; Bampatsou et al., 2013), in which a shift from lower-end use to higher-end use efficiency fuels has been proven to have a positive influence on energy efficiency. Furthermore, we observe that CVA has a negative contribution to energy efficiency. This variable expresses the capital output ratio and more specifically the productivity of capital inputs. Based on the Harrod-Domar model, the rate of growth in an economy can be increased by reducing this ratio. If the value of CVA is high, this means that an economy needs a lot of capital for production and it does not get as much value of output for the same amount of capital. Thus, its energy efficiency performance is poor. This is in line with the observation that energy efficiency is negatively affected by increases in CVA. Yuan et al. (2009) concluded that the larger is the growth rate of output per capital (the opposite rate of CVA), the larger is that of energy intensity. This also proves that a decrease in CVA results to energy efficiency improvements.

Regarding the country variables, they all have a negative coefficient. In particular, ELECPR and MS are statistically significant, whereas TAX does not have a significant effect on energy efficiency. These results imply that the higher the price of electricity, the lower the energy efficiency. Undoubtedly, energy efficiency depends on the price of energy. Although most literature claims that higher energy prices are the principal determinant of gains in energy efficiency (Birol and Keppler, 2000; Cornillie and Fankhauser, 2004; Metcalf, 2008; Alyousef and Stevens, 2011; Broeren et al., 2014; Xiaoli et al., 2014), our results contrast with the above findings, as we observed that a higher energy price has a negative impact on energy efficiency. This is somewhat surprising, but it possibly reflects the negative effect that high electricity prices have on economic development. Without a strong economy, the demand for energy decreases, thereby leading to lower investment and slower energy efficiency development.

The above argument is supported by a number of policy studies and reports. For instance, a recent study by ECOFYS[5] analysed the effect of an electricity price increase on the prices and production of the most relevant upstream and down-stream sectors such as the steel, aluminium, copper, paper, chemical and textile industry. The analysis showed that if electricity price increases are passed on to product prices, this would lead to a significant decline in demand and production in most sectors, thus leading to losses and therefore business failures and shut-downs. For instance, in sectors such as the paper industry and non-ferrous metal industry, the study estimates an average product price increase of 5% due to electricity prices increasing, which in turn is expected to lead to production decrease by 11-18%.

Such results are in accordance with current experiences and opinions from industry experts. For instance, Rolf Kuby, the chief of the Brussels bureau of WirtschaftsVereinigung Metalle

[5] http://www.ecofys.com/files/files/ecofys-fraunhoferisi-2015-electricity-costs-of-energy-intensive-industries.pdf

federation, noted that the EU's energy efficiency bill would push electricity prices up and could bring their businesses close to closure[6]. The unilateral energy and climate costs would make investment in metals impossible leading to lower competitiveness of European companies. Therefore, he proposed that all should strive for lower energy prices by fostering innovation, lower market entrance barriers for new technologies and financing facilities.

The European Competitiveness Report (2014) has also highlighted the potential negative impacts of high energy prices for the competitive performance of the EU economy. The report shows that between 2008 and 2012, industrial electricity prices increased in most EU Member States. However, a wide variation in electricity prices was observed for industry between different EU countries. The report notes the importance of the generation mix of countries in explaining the different absolute levels and dynamics of electricity prices (thus supporting the analysis setting in this analysis which considers variables related to energy mix production). For example, Cyprus and Malta present high electricity prices because their electricity generation is largely based on petroleum products that are characterized by high energy and supply costs. On the other hand, the low electricity prices in Denmark can be explained by the renewables boom that imposes a negligible cost in electricity generation. On the basis of the reports' results it is emphasized that "Caution is needed in using prices as a policy instrument to induce energy savings: the increase of energy prices created a real burden that most European firms were not able to fully compensate for" (factsheet of Chapter 6).

Other studies have examined the connections between energy prices with parallel mechanisms and policy actions that have been implemented during the past decade in Europe. For instance, Robinson (2015) focuses on the EU ETS, which has affected several components of electricity prices. The author argues that by introducing mandatory targets for renewable energy and policies to encourage energy efficiency, the EU reduced the demand for emission allowances in the ETS, thus discouraging innovation and investment in technologies that were not receiving government support outside the energy market. Second, by allocating too many permits, the EU created an excess supply of them, which contributed to lower prices both for CO_2 allowances and for electricity. Furthermore, the EU ETS mechanism was not designed to deal with an economic recession. The crisis that started in 2008 has lowered even further the demand for energy and emission allowances. Robinson notes that "in the longer term there is little, if any, confidence that future emission allowance prices will be high enough, or stable enough, to drive low-carbon investment".

[6] http://www.euractiv.com/specialreport-energy-efficient-b/industry-eus-energy-efficiency-b-interview-513184

Except for policy and industry reports, our results on the role of electricity prices share similarities with results reported in a number of past research publications. For instance, Jaraite and Di Maria (2012) concluded that carbon price has a negative effect on the efficiency performance of public power plants. Lindmark et al. (2011) and Geller at al. (2006) also noted that energy efficiency improvements result from cutting all types of costs, including energy costs. Wu (2012) found that energy price has a positive effect on the reduction of energy intensity but this effect is not statistically significant. Furthermore, it has been shown that efficiency improvement lags behind price increases because it takes time to replace technology. Thus, if prices remain high for only a short period, or if prices are expected to decrease again, the motivation to invest in energy efficiency will probably decrease. Conversely, Abeelen et al. (2013) argued that there is no clear relationship between energy prices and energy efficiency. They noted that, despite the high prices, no increase in energy savings was observed, while in a later period that was characterised by relative constant prices, the savings increased. According to them, the large time gap between the increase in energy prices and investments in energy saving projects, the large fluctuations in prices over years and the uncertainty concerning future prices as well as the low share of energy costs in most sectors may explain why the energy price should not be considered a key driver for energy efficiency.

The negative and significant coefficient of MS shows that competition in the electricity production market can have a positive effect on a country's energy efficiency. This effect is also well in line with the reported negative influence of high electricity prices. Carbon/energy taxes and energy efficiency improvement have been studied in depth in recent years in regard to their potential adverse impacts on the economy. Based on our analysis, although energy taxes contribute negatively on energy efficiency, they are not a key variable for improving energy efficiency. Davidsdottir and Ruth (2004) claimed that an increase in energy taxes can gradually improve energy efficiency but not on a permanent basis. Contrary to the usual assumption that higher energy taxes can promote more energy-efficient technologies, we find that higher taxes lead to lower energy efficiency performance. Possibly, as in the case of the price of electricity, an increase in energy taxes has a negative effect on the economy of a country and, as a result, on energy-efficient technologies as well. Mahmood and Marpaung (2014) found that the imposed energy taxes indeed contribute to GDP decline and thus energy efficiency cannot be promoted due to economic restrictions.

4.5 Conclusions

In this chapter, the energy efficiency performance of 10 industrial sectors across 23 EU countries over the 2000–09 period was evaluated. At the first stage, DEA was performed for the estimation of the relative energy efficiency. A number of economic and environmental factors were employed to this end. According to the obtained results, construction, transport, food, textiles, and machinery are almost at the optimal size for their particular input–output mix as the scale effect is weaker (higher scale efficiency on average across all countries) in these sectors. Conversely, pulp and coke are the most inefficient sectors. Thus, energy efficiency strategies applied to pulp and coke could be more effective as there is more room for considerable improvement in these sectors. Energy efficiency measures, such as subsidies and incentives for energy-efficient technologies, loan guarantees, minimum building and equipment efficiency standards could be applied for improving energy efficiency. Regarding the countries' energy efficiency performance, it is worth mentioning that although Denmark, Finland, Slovenia and Belgium present low efficiency scores, they present high scale efficiency as well. In this regard, their low efficiency scores can be attributed not to scale size effect but to internal energy-related policies at the country level in connection to their economic outputs.

At a next stage, the DEA-based MPI approach was used to examine the efficiency trends over time and distinguish between efficiency change and technology change. The evaluation and decomposition of MPI reveal that the improvements due to efficiency change have been modest at best, whereas improvements due to changes in the best practices (the technology factor) have been significant in most sectors. The growth rates (improvements) in technology exceed those in efficiency change in all sectors and periods. Based on the corresponding results, transport is the only sector that has not improved its productivity performance from 2000 to 2009. This observation is in line with that reported by IEA (2010), according to which transport was the sector that received the least energy efficiency policy action across all countries. The inefficiency of the transport sector in comparison with its increasing energy consumption is the main contributor to the sector's decline in productivity (MPI) over the period 2000–09. However, since mid-2009, numerous measures have been developed to improve energy efficiency in transport and, more specifically, to promote environmentally friendly forms of transportation. To this end, the Directive on the Promotion of Clean and Energy Efficient Road Transport Vehicles has also been developed.

Understanding the determinants that have the highest explanatory power in efficiency performance is also essential for the development of the appropriate policy-making initiatives and actions. The results from the two-level cross-classified model could be helpful towards this direction. Many studies have also analysed the reasons for the changes in industrial energy efficiency (e.g. Birol and Keppler, 2000; Cornillie and Fankhauser, 2004; Metcalf, 2008; Alyousef and Stevens, 2011; Stern, 2012; Broeren et al., 2014; Xiaoli et al., 2014). Not surprisingly, we found that the combination of sector and country levels is the most relevant in explaining the energy efficiency variance. Moreover, we concluded that a large proportion of energy efficiency variance is due to the sector characteristics. This suggests that policymakers should take into account the intrinsic sector characteristics when formulating energy efficiency measures. However, they should not ignore the importance of country characteristics in energy efficiency performance. This was evident by the results of the empty model, which indeed showed that the country level effect is strong. According to the results of the econometric analysis, policymakers should turn their attention to strengthening the private sector’s contribution to the overall economy, and at a lesser extent, promoting productivity gains. Measures such as promoting the gradual displacement of fossil fuels should also be part of the policy-/decision-making when it comes to improving industrial energy efficiency. The results also show that opening up the electricity market by creating a more competitive environment might contribute to energy efficiency improvement. A more competitive market provides more choices to consumers, promotes fairer prices, as well as a cleaner energy supply and energy. It is worth noting that in September 2007, the European Commission launched its third legislative package to liberalise energy markets, and since March 2011, it has been transposed into national law. During the period 2000–09, Latvia and Greece were both characterised by a complete monopoly, with more than 90% of their electricity being generated by the largest (sole) generator. Although, all EU countries have gradually opened energy production over the examined period, four EU Member States (Belgium, Ireland, France, and Slovakia) have remained mostly oligopolistic as the shares of the largest producers were above 80%. In accordance with the electricity market opening, the policies designed to reduce electricity prices could also have a significant impact on energy efficiency improvement.

The information gained through this study could support policy formulation and provide a sound basis for informed decisions related to energy efficiency in industry. However, there is a wide range of issues that could be explored in future research. Among others, these may involve the enrichment of the data set with a more comprehensive categorization of the industrial sectors, a more extensive time period (up-to-date data), and the examination of more country and sector characteristics that could explain the industrial energy efficiency.

CHAPTER 5

Conclusions and Recommendations

This chapter concludes the thesis, first summarizing the main findings and contributions of the obtained results, discussing their policy implications, analyzing the limitations of the analysis, and finally suggesting future research directions.

5.1 Summary of the Main Findings and Contributions

Today, the major policy interest is riveted on the end-use energy-efficiency improvements as an effective approach for the reduction of GHG emissions and other pollutants as well as energy use. In pursuing these goals, governments and the energy sector have undergone several major changes during the last decades. They continue to face new challenges and opportunities including, among others, the increase in oil and gas prices, the extending use of renewable energy sources, the introduction and development of emissions markets, the increasing customer awareness on pollution related issues and energy efficiency.

This rapidly evolving framework affects the operation, performance and efficiency of all economic sectors as well as the countries' policy choices. Therefore, the tools that facilitate the monitoring of the current status and trends in energy efficiency at the country and sectoral level are of major interest to all stakeholders (e.g., policy makers, governments, manager of firms). Although, the existing literature is indeed very rich and especially on the country level (e.g., analysis of energy consumption, production and efficiency), there is a lack on the development of an integrated methodology suitable for the evaluation of energy efficiency at both the country and sectoral level on the basis of up to date data.

The goal of this thesis was the assessment of energy efficiency at both an aggregated and a more disaggregated base. In particular, its objective was twofold: to develop and implement a holistic methodology for energy efficiency measurement in EU countries and industries as well as to determine the factors that have the highest explanatory power in efficiency performance. The proposed approach considers energy efficiency in a multidimensional context, taking into account the multiple perspectives of the problem including, among others, financial and economic data, environmental factors, as well as country and sector characteristics. Specifically, at the first stage, an operations research approach based on DEA tools was implemented to analyse the dynamics of the energy efficiency trends. The MPI was also performed to distinguish between the effects of efficiency and technology changes. At a next stage, given the importance of understanding the key drivers behind energy efficiency, the research was extended to specify the factors that affect energy efficiency performance using the MCDA and multilevel methodology.

This work makes a significant contribution to energy related literature and especially to energy planning. MCDA and DEA have received considerable attention in the OR/MS literature. However, despite having much in common, the two fields have developed almost entirely independently to each other (Mavrotas and Trifillis, 2006). Furthermore, there has been almost no attempt to combine both methods in a unified context for energy efficiency measurement. It is only in the last decades that the formal analogies existing between DEA and MCDA have been considered in the area of performance evaluation. Specifically, the replacement of DMUs with alternatives, outputs with maximization criteria and inputs with minimization criteria have led some authors to use DEA as a tool for MCDA. Thus, this study contributes to the literature by adopting a two-stage approach, based on DEA and MCDA, for the evaluation of country's energy efficiency performance. The combination of these approaches is considered to be a useful tool for quantifying and measuring energy efficiency as it provides the advantages of both methods while addressing their limitations. In particular, the adopted two-stage approach focused on building a multicriteria model that allows the evaluation of all alternatives (countries) on the grounds of their DEA efficiency classification (i.e., DEA and MCDA are used in combination instead of mixing ideas from both fields to introduce a new evaluation technique). Thus, this approach enables all policy makers and stakeholders involved in the policy-making process to consider a much wider range of impacts of energy efficiency programs, instead of focusing solely on an input-output energy-economic production framework. According to the results of this stage of the analysis, policy makers should turn their attention on the GDP growth and energy intensity as these are the two most important factors for energy efficiency improvement. Furthermore, they should promote various initiatives to develop a more diversified and service oriented economy that would use more the renewable energy sources.

At the second stage of the analysis, a multilevel model was applied to estimate the relative importance of time, country, and industry related factors on industrial energy efficiency. As the main target of all energy efficiency policy design and implementation is the identification of energy efficiency drivers, the obtained findings can help policymakers in formulating coherent and effective energy policies for energy intensive sectors. The empirical results showed that there is room for considerable improvement in sectors such as pulp and coke. It was also found that technology changes were mainly responsible for the high energy efficiency performance in most sectors whereas some countries need to address internal issues for improving their energy efficiency. The strengthening of the private sector's contribution to the overall economy and productivity as well as the gradual displacement of fossil fuels and opening up of the electricity market to more competition should be also carefully considered for promoting and strengthening energy efficiency. The identification of the factors behind energy efficiency at the sectoral level could also assist policy makers in evaluating the current energy efficiency policies towards these factors and creating a mix of strategies that will address the existing problems.

Taking into account the challenges lying ahead for improving energy efficiency, the results and conclusions of this work led to a better understanding of issues which are of vital concern and importance to governments and energy intensive sectors. Specifically, this thesis delivers important inputs to the field of policy learning that can be used to improve future policies for energy efficiency as well as to support innovation and facilitate technology change for sustainable energy use.

To sum up, the key research milestones of the thesis include:

- The use of a unifying methodology for assessing energy efficiency in a multidimensional context.
- The implementation of an input-oriented DEA setting for assessing the efficiency performance of EU countries and industries under different scenarios.
- The development of a two-stage DEA/MCDA approach that could be used for benchmark comparisons across countries without requiring the use of DEA every time the energy efficiency performance of a single country needs to be assessed. This approach could provide analysts and policy makers with evaluations of energy efficiency in absolute terms and enable them to consider a rich list of the impacts of energy efficiency programs and actions as well as explore the underlying trade-offs.
- The analysis of the dynamics of energy efficiency over time, identifying productivity differences and estimating the effect of efficiency and technology change on energy efficiency performance.
- The development of a multilevel framework that considers a number of intrinsic sector and country characteristics for highlighting the drivers behind the energy efficiency performance of energy intensive sectors.

Overall, the findings and conclusions of this thesis are of major importance as they can provide helpful guidance for regulators in designing policies for energy efficiency improvement at the country and sectoral level. In particular, these can enable policy makers and other decision makers to: (1) measure energy efficiency performance, (2) gain an understanding of the main factors influencing energy efficiency, (3) evaluate current energy efficiency programs and policies towards the main explanatory factors, (4) compare the performance and benefit from lessons learned by other countries and industries.

5.2 Limitations and Future Directions

The findings from our theoretical and empirical analysis come along with some limitations that have been explained in the previous chapters (chapter 3 and 4). Accordingly, suggestions for future research have been also proposed to address these issues as well as to suggest alternative avenues that could be considered in the future. Here we discuss what we consider to be the most important ones.

One of the main limitations of this study relates to data used in the analysis. Our dataset was limited to 26 EU countries over the period 2000-10 and 23 EU countries over the period 2000-09 for energy efficiency evaluation on country and industry level, respectively. Future work should be enriched by including data for countries outside the EU, developing and developed ones. Many developing countries have experienced rapid growth in energy consumption in recent years. This growth has been stronger for non-OECD countries and especially in Asia with the highest total demand coming from China and India alone. Thus, the consideration of these countries should be high up on the energy efficiency research agenda. It would be interesting to analyse the energy efficiency in developing and transition economies as these are also characterised by rapid population expansion and a structural change toward more energy-intensive industries. The analysis could also include major economies, such as the G8 countries[1] that comprise some two-thirds of the global economy and around 70% of global energy consumption. The performance of five key developing countries (China, Indian, Brazil, Mexico, and South Africa) should also be considered in energy efficiency analysis because of their high energy intensive character. The focus on countries, such as Japan, Canada and U.S.A, where major energy and environmental issues took place would allow the analysis to shed some light on the factors that have a significant effect on energy efficiency and how the country's energy map changed because of these. For example, the 2011 earthquake and tsunami in Japan led the country to close all 50 of its

[1] Canada, France, Germany, Italy, Japan, Russia, United Kingdom, United States.

nuclear plants and take initiatives to lower energy consumption and dependence on nuclear power through the promotion of energy efficiency and alternative energy sources, such as renewables.

A more extensive time period that includes the most up to date data should also be examined. The framework developed in this doctoral thesis has wider applications than globally comparing energy efficiency across countries and industries. Local administrative regions (e.g., municipalities) and firms could also use it as a tool to compare their energy efficiency performance to that of other similar units. Thus, energy efficiency analysis at a much more disaggregated level should be conducted. For example, the performance of energy related fields should also be examined, as the performance of each field could affect the industrial energy efficiency as a whole.

Another extension could be the consideration of more detailed data on socio-economic and environmental factors. In particular, the characteristics and prices of commodities (e.g. energy prices, fuel prices), the trade openness, the financial development and green investments could offer an in-depth investigation of the drivers and causes of energy efficiency. The EU emissions trading system (EU ETS), a cornerstone of the EU's policy to combat climate change and reduce GHG emissions, should also be taken into consideration. EU ETS acts as a major driver of investment in clean technologies and low-carbon solutions and thus it could play a major towards improving energy efficiency. Therefore, it would be interesting to investigate how such systems contribute to energy efficiency performance of industries and countries as well.

It would be also worthwhile to examine the relationship between energy efficiency and energy security. In particular, this relationship should be examined not only in terms of energy supply but in a broader base that includes economic, technological, environmental, social, cultural, and geopolitical perspectives. The significant of energy security is highlighted by the fact that nowadays energy security is higher in the agenda of energy firms and governments than ever before. Thus, the main characteristics of energy security including the diversification of supply, diversification of fuel types and industrial globalization, should be considered as possible energy efficiency drivers too.

A further extension of this research would be the application of energy efficiency evaluation methods for estimating the performance of the implementation of new technologies for improved energy management systems. For instance, smart grid technologies, which are primarily linked to electricity generation, storage, transmission, and distribution, can promote end-use energy efficiency through mechanisms such as demand response, dynamic pricing, and a multitude of energy-efficiency programs (Paget et al., 2011). However, a context should be set that could quantify the results obtained from the application of these technologies mainly in regards to energy efficiency. This framework could be used as a starting place for the engagement of all multiple stakeholders (including consumers, service providers, suppliers, and regulators) in shaping energy efficiency policies. Furthermore, the contribution of the smart grid capabilities to resolve energy-efficiency concerns should be examined so that countries can develop future directions or roadmaps for energy efficiency. This could also confirm the statement that national policy supporting energy efficiency should be considered along with national policy supporting smart grids.

On the methodological point of view, the application of other evaluation methods such as SFA and IDA for energy efficiency assessment would be an important contribution. The construction of energy efficiency indicators or the comparison of our results with those obtained by using existing energy efficiency indicators could represent valuable tools for interesting further developments of the current work.

Although there have been a considerable number of energy efficient technological improvements throughout the world since the late 1970s, the consumption of energy has not been reduced at anywhere near the same level. Thus, future research should investigate some of the market barriers that impede the diffusion of energy efficient technologies. Innovations such as smart grid systems as well as distribution and corporate investments in energy-efficient technologies are factors that need to be addressed when energy efficiency is measured. The structure and role of industrial energy programs such as energy audit programs and long-term agreements are some of the most common drivers of energy efficiency in industry (Thollander and Dotzauer, 2010). More work for identifying and analyzing these drivers is required as this offers a more detailed insight into the actions and policies that should be implemented for energy efficiency improvement. To increase the efficacy of the proposed framework through this research and make it operational, a user-friendly web based interface could be also developed in the future.

References

Abbott, M., 2006. The productivity and efficiency of the Australian electricity supply industry. Energy Economics 28 (40), 444–454.

Abdelaziz, E.A., Saidur, R., Mekhilef, S., 2011. A review on energy saving strategies in industrial sector. Renewable and Sustainable Energy Reviews 15, 150-168.

Abeelen, C., Harmsen, R., Worrell, E., 2013. Implementation of energy efficiency projects by Dutch industry. Energy Policy 63, 408–418.

Adler, N., Friedman, L., Sinuany-Stern, Z., 2002. Review of ranking methods in the data envelopment analysis context. European Journal of Operational Research 140, 249–265.

Afgan, N.H., Pilavachi, P.A., Carvalho, M.G., 2007. Multi-criteria evaluation of natural gas resources. Energy Policy 35, 704–13.

Aigner, D.J., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. Journal of Econometrics 6, 21–37.

Alyousef, Y., Stevens, P., 2011. The cost of domestic energy prices to Saudi Arabia. Energy Policy 39, 6900–6905.

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy 32 (9), 1131–1139.

Ang, B.W., 2006. Monitoring changes in economy-wide energy efficiency: from energy–GDP ratio to composite efficiency index. Energy Policy 34 (5), 574–582.

Ang, B.W., Mu, A.R., Zhou, P., 2010. Accounting frameworks for tracking energy efficiency trends. Energy Economics 32 (5), 1209–1219.

Ang, B.W., Zhang, F.Q., 1999. Inter-regional comparisons of energy-related CO_2 emissions using the decomposition technique. Energy 24, 297–305.

Ang, B.W., Zhang, F.Q., 2000. A survey of index decomposition analysis in energy and environmental studies. Energy 25 (12), 1149–1176.

Arcelus, F.G., Arocena, P., 2000. Convergence and productive efficiency in fourteen OECD countries: a non-parametric frontier approach. International Journal of Production Economics 66, 105–117.

Asia Pacific Energy Research Centre (APERC), 2001. Energy efficiency indicators-a study of energy efficiency indicators in APEC economies. Tokyo.

Azadeh, A., Amalnick, M.S., Ghaderi, S.F., Asadzadeh, S.M. 2007. An integrated DEA PCA numerical taxonomy approach for energy efficiency assessment and consumption optimization in energy intensive manufacturing sectors. Energy Policy 35, 3792–3806.

Azadeh, A., Ghaderi, S.F., Omrani, H., Eivazy, H., 2009. An integrated DEA–COLS–SFA algorithm for optimization and policymaking of electricity distribution units. Energy Policy 37, 2605–2618.

Bampatsou, C., Hadjiconstantinou, G., 2009. The use of the DEA method for simultaneous analysis of the interrelationships among economic growth, environmental pollution and energy consumption. International Journal of Economic Sciences and Applied Research 2, 65–86.

Bampatsou, C., Papadopoulos, S., Zervas, E., 2013. Technical efficiency of economic systems of EU-15 countries based on energy consumption. Energy Policy 55, 426–434.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 30, 1078–1092.

Barros, C.P., 2008. Efficiency analysis of hydroelectric generating plants: a case study for Portugal. Energy Economics 30, 59–75.

Barros, C.P., Peypoch, N., 2008. Technical efficiency of thermoelectric power plants. Energy Economics 30, 3118–3127.

Bauer, T.N., Morrison, E.W., Callister, R.R., 1998. Organizational socialization: A review and directions for future research. In G. R. Ferris (Ed.), Research in Personnel and Human Resource Management 16, 149 –214. Greenwich, CT: JAI Press.

Begic, F., Afgan, N.H., 2007. Sustainability assessment tool for the decision making in selection of energy system—Bosnian case. Energy 32, 1979–1985.

Bian, Y., Yang, F., 2010. Resource and environmental efficiency analysis of provinces in China: a DEA approach based on Shannon’s entropy. Energy Policy 38, 1909–1917.

Birol, F., Keppler, J.H., 2000. Prices, technology development and the rebound effect. Energy Policy 28, 457–469.

Bleischwitz, R., Andersen, L.M., 2009. Informational barriers to energy efficiency - theory and European policies. Bruges European economic research papers. College of Europe: Bruges.

Blomberg, J., Henriksson, E., Lundmark, R., 2012. Energy efficiency and policy in Swedish pulp and paper mills: A data envelopment analysis approach. Energy Policy 42, 569–579.

Bouyssou, D., 1999. Using DEA as a tool for MCDM: some remarks. Journal of the Operational Research Society 50, 974–978.

Boyd, G.A., 2005. A statistical model for measuring the efficiency gap between average and best practice energy use: the ENERGY STAR industrial energy performance indicator. Journal of Industrial Ecology 9 (3), 51–66.

Boyd, G., Dutrow, E., Tunnessen, W., 2008. The evolution of the ENERGY STAR® energy performance indicator for benchmarking industrial plant manufacturing energy use. Journal of Cleaner Production 16, 709–715.

Brännlund, R., Ghalwash, T., Nordström, J., 2007. Increased energy efficiency and the rebound effect: effects on consumption and emissions. Energy Economics 29 (1), 1-17.

Broeren, M.L.M., Saygin, D., Patel, M.K., 2014. Forecasting global developments in the basic chemical industry for environmental policy analysis. Energy Policy 64, 273-287.

Buchholz, T., Rametsteiner, E., Volk, T.A., Luzadis, V.A., 2009. Multi criteria analysis for bioenergy systems assessments. Energy Policy 37, 484–95.

Buck, J., Young, D., 2007. The potential for energy efficiency gains in the Canadian commercial building sector: a stochastic frontier study. Energy 32, 1769–1780.

Buildings Performance Institute Europe (BPIE), 2011. Europe's buildings under the microscope - A country by-country review of the energy performance of buildings. Brussels: Building Performance Institute Europe.

Cahill, C.J., Gallachoir, B.P., 2012. Combining physical and economic output data to analyse energy and CO2 emissions trends in industry. Energy Policy 49, 422–429.

Casler, S., Rose, A., 1998. Carbon dioxide emissions in the US economy: a structural decomposition analysis. Environmental and Resource Economics 11, 349–363.

Ceylan, D., Gunay, E.N.O., 2010. Energy efficiency trends and policies: Cross-country comparison in Europe. Presented at International Conference of Economic Modelling (ECOMOD), Istanbul.

Chang, T.P., Hu, J.L., 2010. Total-factor energy productivity growth, technical progress, and efficiency change: an empirical study of China. Appl Energy 87, 3262–3270.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429–44.

Chedid, R., Mezher, T., Jarrouche, C., 1999. A fuzzy programming approach to energy resource allocation. International Journal of Energy Research 23, 303–17.

Chien, T., Hu, J.L., 2007. Renewable energy and macroeconomic efficiency of OECD and non-OECD economies. Energy Policy 35, 3606–3615.

Christopher, W.F., 1993. Three steps for improving productivity/quality measurement and performance. In: Handbook for productivity measurement and improvement, 6-2, Portland, Oregon: Productivity Press.

Coelli T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. An introduction to efficiency and productivity analysis. Second Edition. New York, NY: Springer.

Cook, W.D., Seiford, L.M., 2009. European Journal of Operational Research 192, 1–17.

Cooper, W.W., Seiford, L.M., Tone, K., 2006. Introduction to to data envelopment analysis and its uses with DEA-solver software and references. New York: Springer.

Cornillie, J., Fankhauser, S., 2004. The energy intensity of transition countries. Energy Economics 26, 283–295.

Cui, Q., Kuang, H., Wu, C., Li, Y., 2014. The changing trend and influencing factors of energy efficiency: The case of nine countries. Energy 64, 1026–1034.

Cui, Q., Li, Y., 2014. The evaluation of transportation energy efficiency: An application of three-stage virtual frontier DEA. Transportation Research Part D: Transport and Environment 29, 1-11.

Davidsdottir, B., Ruth, M., 2004. Capital vintage and climate change policies: the case of US pulp and paper. Environmental Science & Policy 7, 221–233.

Davis, L., 2012. Evaluating the slow adoption of energy efficient investment: Are renters less likely to have energy efficient appliances? In D. Fullerton and C. Wolfram (eds.). The design and Implementation of U.S. Climate Policy. University of Chicago Press.

DeCanio, S. J., 1998. The efficiency gap: bureaucratic and organisational barriers to profitable energy saving investments. Energy Policy 26 (5), 441-54.

de la Rue du Can, S., Sathaye, J., Price, L., McNeil, M., 2010. Energy efficiency indicators methodology booklet. Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley, CA (US).

Diakoulaki, D., Antunes, C.H., Martins, A.G., 2005. MCDA and Energy Planning. Multiple Criteria Decision Analysis: State of the Art Surveys VII, 859-890.

Diakoulaki, D., Mandaraka, M., 2007. Decomposition analysis for assessing the progress in decoupling industrial growth from CO_2 emissions in the EU manufacturing sector. Energy Economics 29, 636–664.

Diakoulaki, D., Zopounidis, C., Mavrotas, G., Doumpos, M., 1999. The use of a preference disaggregation method in energy analysis and policy making. Energy 24, 157–166.

Doumpos, M., Zopounidis, C., 2002. Multicriteria decision aid classification methods. Dordecht: Kluwer Academic Publishers.

Doyle, J., 1995. Multiattribute choice for the lazy decision maker: Let the alternatives decide!. Organizational Behavior and Human Decision Processes 62, 87–100.

Dyer, C.H., Hammond, G.P., Jones, C.I., McKenna, R.C., 2008. Enabling technologies for industrial energy demand management. Energy Policy 36, 4434–4443.

Efron, B., 1979. Bootstrap methods: another look at the jackknife.Annals of Statistics 9, 1-26.

Efron, B., Tibshirani, R.J., 1993. An introduction to the bootstrap. Chapman and Hall, London.

Emerson, J.W., Hsu, A., Levy, M.A., de Sherbinin, A., Mara, V., Esty, D.C., Jaiteh, M., 2012. Environmental performance index and pilot trend environmental performance index. New Haven: Yale Center for Environmental Law and Policy.

Energy Efficiency and Conservation Authority of New Zealand (EECA), 2006. Energy Efficiency and Renewable Energy in New Zealand, Year Four Report: March 2001 to 2005.

Energy Information Administration (EIA), 1995. Measuring energy efficiency in the United States' economy: A beginning. DOE/EIA-0555(95)/2 US Energy Information Administration,Washington, D.C., United States.

Energy Information Administration (EIA), 2014. International Energy Outlook 2014. Washington, D.C., United States.

Estache, A., de la Fé, B.T., Trujillo, L., 2004. Sources of efficiency gains in port reform: a DEA decomposition of a Malmquist TFP index for Mexico. Utilities Policy 12 (4), 221–230.

Estache, A., Tovar, B., Trujillo, L., 2007. Are African electricity distribution companies efficient?. Evidence from southern African countries (Report No. 07/13). London, UK: Department of Economics, City University London.

European Competitiveness Report, 2014. Helping firms grow. Publications Office of the European Union. Luxembourg.

European Union (EU), 2009. EU action against climate change. Retrieved May 3, 2009, from Climate Action: http://ec.europa.eu/climateaction/eu_action/index_en.htm

Fang, H., Wu, J., Zeng, C., 2009. Comparative study on efficiency performance of listed coal mining companies in China and the US. Energy Policy 37, 5140–5148.

Färe, R., Grosskopf, S., Hernandez-Sancho, F., 2004. Environmental performance: an index number approach. Resource and Energy Economics 26, 343–52.

Färe, R., Grosskopf, S., Lindgren, B., Roos, P., 1992. Productivity change in Swedish pharmacies 1980-1989: A nonparametric Malmquist approach, Journal of Productivity Analysis 3, 85-102.

Farsi, M., Filippini, M., Kuenzle, M., 2007. Cost efficiency in the Swiss gas distribution sector. Energy Economics 29, 64–78.

Feijoo, M.L., Franco, J.F., Hernandez, J.M., 2002. Global warming and the energy efficiency of Spanish industry. Energy Economics 24, 405–23.

Filippini, M., Hunt, L.C., 2011. Energy demand and energy efficiency in the OECD countries: a stochastic demand frontier approach. The Energy Journal 32, 59–80.

Fisher-Vanden, K., Jefferson, G.H., Jingkui, M., Jianyi, X., 2006. Technology development and energy productivity in China. Energy Economics 28, 690–705.

Fleiter, T., Worrell, E., Eichhammer, W., 2011. Barriers to energy efficiency in industrial bottom-up energy demand models. Renewable and Sustainable Energy Review 15, 3009-3111.

Fried, H.O., Lovell, C.A.K., Schmidt, S.S., 1993. The measurement of productive efficiency: Techniques and applications. Oxford University Press, New York, Oxford.

Frondel, M., Schmidt, C.M., 2002. The capital-energy controversy: An artifact of cost shares? The Energy Journal 23 (3), 53–79.

Geller, H., Harrington, P., Rosenfeld, A. H., Tanishima, S., Unander, F., 2006. Policies for increasing energy efficiency: Thirty years of experience in OECD countries. Energy Policy 34, 556-573.

Giannakis, D., Jamasb, T., Pollitt, M., 2005. Benchmarking and incentive regulation of quality of service: an application to the UK electricity distribution networks. Energy Policy 33, 2256-2271.

Gillingham, K., Palmer, K., 2014. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. Review of Environmental Economics and Policy 8 (1), 18-38.

Global Energy Assessment (GEA), 2012. Toward a sustainable future. International Institute for Applied Systems Analysis, Vienna, Austria and Cambridge University Press, Cambridge, UK and New York, NY, USA.

Goumas, M., Lygerou, V., 2000. An extension of the PROMETHEE method for decision making in fuzzy environment: Ranking of alternative energy exploitation projects. European Journal of Operational Research 123, 606–613.

Greening, L.A., Bernow, S., 2004. Design of coordinated energy and environmental policies: Use of multi-criteria decision-making. Energy Policy 32, 721–735.

Greer, M.R., 2008. Nothing focuses the mind on productivity quite like the fear of liquidation: Changes in airline productivity in the United States, 2000-2004. Transportation Research Part A, 42, 414-426.

Growitsch, C., Jamasb, T., Pollitt, M., 2009. Quality of service, efficiency and scale in network industries: an analysis of European electricity distribution. Applied Economics 41 (20), 2555-2570.

Halkos, G., Tzeremes, N., 2013. Renewable energy consumption and economic efficiency: Evidence from European countries. MPRA Paper No. 44136.

Hasanbeigi, A., Price, L., Lu, H., Lan, W., 2010. Analysis of energy-efficiency opportunities for the cement industry in Shandong Province, China: A case study of 16 cement plants. Energy 35 (8), 3461–3473.

Hattori, T., Jamasb, T., Pollit, M.G., 2003. The performance of UK and Japanese electricity distribution system 1985–1998: a comparative efficiency analysis. DAE Working Paper WP 0212, Department of Applied Economics, University of Cambridge.

Haydt, G., Leal, V, Dias, L., 2014. A multi-objective approach for developing national energy efficiency plans. Energy Policy 67, 16–27.

He, F., Zhang, Q., Lei, J., Fu, W., Xu, X., 2013. Energy efficiency and productivity change of China's iron and steel industry: Accounting for undesirable outputs. Energy Policy 54, 204–213.

Hirst, E., Brown, M., 1990. Closing the efficiency gap: barriers to the efficient use of energy. Resources, Conservation and Recycling 3, 267-81.

Hoekstra, R., van den Bergh, J.C.J.M., 2003. Comparing structural and index decomposition analysis. Energy Economics 25 (1), 39–64.

Holm, S.O., Englund, G., 2009. Increased ecoefficiency and gross rebound effect: Evidence from USA and six European countries 1960–2002. Ecological Economics 68, 879 – 887.

Honma, S., Hu, J.L., 2008. Total-factor energy efficiency of regions in Japan. Energy Policy 36, 821–33.

Honma, S., Hu, J.L., 2011. Industry-level total-factor energy efficiency in developed countries. Energy Policy 36 (2), 821-833.

Honma, S., Hu, J.L., 2014a. A panel data parametric frontier technique for measuring total factor energy efficiency: an application to Japanese regions. Energy 78, 732–739.

Honma, H., Hu, J.L. 2014b. Industry-level total-factor energy efficiency in developed countries: A Japan-centered analysis. Applied Energy 119, 67–78.

Hu, J.L., Kao, C.H., 2007. Efficient energy-saving targets for APEC economies. Energy Policy 35, 373–82.

Hu, J.L., Wang, S.C., 2006. Total-factor energy efficiency of regions in China. Energy Policy 34, 3206–3217.

Huang, T., Onishi, A., Shi, F., Morisugi, M., Cherry, M.L., 2014. Regional characteristics of industrial energy efficiency in China: application of stochastic frontier analysis method. Frontiers of Environmental Science & Engineering, 1-16.

Huntington, H.G., 1994. Been top down so long its look like up to me. Energy Policy 22 (10), 833–839.

Huntington, H.G., 2010. Structural change and U.S. energy use: recent patterns. Energy Journal 31, 25–39.

International Chamber of Commerce (ICC), 2014. Enabling frameworks to scale up investments in energy efficiency. No. 213/101.

International Energy Agency (IEA), 1997. Indicators of energy use and efficiency. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2004. Oil Crises and Climate Challenges: 30 Years of Energy Use in IEA Countries. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2007. Tracking Industrial Energy Efficiency and CO_2 Emissions. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2008. Energy Efficiency Requirements in building codes, energy efficiency policies for new buildings. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2009a. Towards a more energy efficient future: Applying indicators to enhance energy policy. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2009b. Implementing energy efficiency policies - Are IEA member countries on track? OECD/IEA, Paris, France.

International Energy Agency (IEA), 2010. Transport energy efficiency: Implementation of IEA recommendations since 2009 and next steps. Paris, France.

International Energy Agency (IEA), 2011. Energy efficiency policy and carbon pricing. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2013. Visualising the "Hidden" fuel of energy efficiency. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2014a. Energy efficiency market report 2014. OECD/IEA, Paris, France.

International Energy Agency (IEA), 2014b. Energy efficiency indicators: fundamentals on statistics. OECD/IEA, Paris, France.

International Energy Outlook (IEO), 2014. World petroleum and other liquid fuels. U. S. Energy Information Administration. Washington, DC 20585.

Jaffe, A.B., Stavins, R.N., 1994. The energy-efficiency gap - What does it mean? Energy Policy 22, 804-810.

Jamasb, T., Newbery, D., Pollitt, M., 2006. Core indicators for determinants and performance of electricity sector in developing countries. International Journal of Regulation and Governance 6(1), 43-78.

Jamasb, T., Pollitt, M., Triebs, T., 2008. Productivity and efficiency of US gas transmission companies: a European regulatory perspective. Energy Policy 36 (9), 3398–3412.

Jaraite, J., Di Maria, C., 2012. Efficiency, productivity and environmental policy: A case study of power generation in the EU. Energy Economics 34, 1557–1568.

Javid, R., Nejat, A., Hayhoe, K., 2014. Selection of CO_2 mitigation strategies for road transportation in the United States using a multi-criteria approach. Renewable and Sustainable Energy Reviews 38, 960–972.

Johansson, B., 2006. Climate policy instruments and industry—effects and potential responses in the Swedish context. Energy Policy 34, 2344–2360.

Jovanovic, M., Afgan, N., Radovanovic, P., Stevanovic, V., 2009. Sustainable development of the Belgrade energy system. Energy 34, 532–9.

Kablan, M.M., 2004. Decision support for energy conservation promotion: an analytic hierarchy process approach. Energy Policy 32, 1151–1158.

Kao, K., Hung, H.T., 2005. Data envelopment analysis with common weights: The compromise solution approach. Journal of the Operational Research Society 56 (10), 1196-1203.

Kashani, H.A., 2005. Regulation and efficiency: an empirical analysis of the United Kingdom continental shelf petroleum industry. Energy Policy 33, 915–925.

Kavrakoglu, I., Kiziltan, G., 1983. Multiobjective strategies in power systems planning. European Journal of Operational Research 12, 159–170.

Kim, K., Kim, Y., 2012. International comparison of industrial CO2 emission trends and the energy efficiency paradox utilizing production-based decomposition. Energy Economics 34, 1724–1741.

Krüger, J.J., 2012. A Monte Carlo study of old and new frontier methods for efficiency measurement. European Journal of Operational Research 222, 137–148.

Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis. Cambridge: Cambridge University Press.

Lahdelma, R., Salminen, P., 2006. Stochastic multicriteria acceptability analysis using the data envelopment model. European Journal of Operational Research 170 (1), 241–252.

Lanfang, C., Jingwan, L., 2009. Modeling undesirable factors in the measurement of energy efficiency in China. IEEE, Red Hook, NY: International Conference on Management and Service Science.

Lin, S.J., Lu, I.J., Lewis, C., 2006. Identifying key factors and strategies for reducing industrial CO_2 emissions from a non-Kyoto protocol member's (Taiwan) perspective. Energy Policy 34, 1499–1507.

Linares, P., Labandeira, X., 2010. Energy efficiency: economics and policy. Journal of Economic Surveys 24 (3), 573–592.

Lindmark, M., Bergquist, A.K., Andersson, L.F., 2011. Energy transition, carbon dioxide reduction and output growth in the Swedish pulp and paper industry: 1973-2006. Energy Policy 39, 5449-5456.

Loken, E., 2007. Use of multicriteria decision analysis methods for energy planning problems. Renewable and Sustainable Energy Reviews 11, 1584–1595.

Lovins, A.B., 2004. Energy efficiency: taxonomic overview. Encyclopedia of Energy 2, 383–401.

Lozano, S., Gutiérrez, E., 2008. Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO_2 emissions. Ecological Econ 66, 687-699.

Lu, C.C., Chiu, Y.H., Shyu, M.K., Lee, J.H., 2013. Measuring CO2 emission efficiency in OECD countries: Application of the hybrid efficiency model. Economic Modelling 32, 130–35.

Mahmood, A., Marpaung, C.O.P., 2014. Carbon pricing and energy efficiency improvement -- why to miss the interaction for developing economies? An illustrative CGE based application to the Pakistan case. Energy Policy 67, 87–103.

Mairet, N., Decellas, F., 2009. Determinants of energy demand in the French service sector: a decomposition analysis. Energy Policy 37, 2733–2744.

Malmquist, S., 1953. Index number and indifferences surfaces. Trabajos de Estadistica 4, 209–2042.

Managi, S., Jin, D., Grigalunas, T.A., 2006. Stochastic frontier analysis of total factor productivity in the offshore oil and gas industry. Ecological Economics 60, 204–215.

Mandal, S.K., 2010. Do undesirable output and environmental regulation matter in energy efficiency analysis?. Evidence from Indian cement industry. Energy Policy 38, 6076–6083.

Mandal, S.K., Madheswaran, S., 2011. Energy use efficiency of Indian cement companies: a data envelopment analysis. Energy Efficiency 4, 57–73.

Mavrotas, G., Trifillis, P., 2006. Multicriteria decision analysis with minimum information: combining DEA with MAVT. Computers and Operations Research 33, 2083–2098.

Meeusen, W., van den Broeck, J., 1977. Efficiency estimation from Cobb–Douglas production functions with composed error. International Economic Review 18, 435–444.

Metcalf, G.E., 2008. An empirical analysis of energy intensity and its determinants at the state level. The Energy Journal 29 (3), 1–25.

Metcalf, G.E., Hassett K.A., 1999. Measuring the energy savings from home improvement investments: Evidence from monthly billing data. Review of Economics and Statistics 81 (3), 516-528.

Miller, R.E., Blair, P.D., 2009. Input–output analysis: Foundations and extensions (2nd edition). Cambridge University Press, New York.

Mukherjee, K., 2008a. Energy use efficiency in the Indian manufacturing sector: An interstate analysis. Energy Policy 36, 662-672.

Mukherjee, K., 2008b. Energy use efficiency in U.S. manufacturing: A nonparametric analysis. Energy Economics 30, 76–96.

Mukherjee, K., 2010. Measuring energy efficiency in the context of an emerging economy: the case of Indian manufacturing. European Journal of Operational Research 201, 933–941.

Munda, G., Saisana, M., 2007. Methodological considerations on regional sustainability assessment based on multicriteria and sensitivity analysis. Reg Stud 45(2), 261–276.

Munksgaard, J., Pedersen, K.A.,Wien, M., 2000. Impact of household consumption on CO_2 emissions. Energy Economics 22, 423–440.

Natural Resources Canada (NRC), 2006. Energy Efficiency Trends in Canada: 1990 to 2004.

Neelis, M., Ramirez-Ramirez, A., Patel, M., Farla, J., Boonekamp, P., Blok, K., 2007. Energy efficiency developments in the Dutch energy-intensive manufacturing industry, 1980–2003. Energy Policy 35, 6112–6131.

Neumayer, E., 2003. Weak versus strong sustainability: exploring the limits of two opposing paradigms. 2nd ed. Cheltenham: Edward Elgar.

Neves, L.P., Dias, L.C., Antunes, C.H., Martins, A.G., 2009. Structuring an MCDA model using SSM: A case study in energy efficiency. European Journal of Operational Research 199, 834–845.

Oda, J., Akimoto, K., Tomoda, T., Nagashima, M., Wada, K., Sano, F., 2012. International comparisons of energy efficiency in power, steel and cement industries. Energy Policy 44, 118-129.

Odeck, J., 2009. Statistical precision of DEA and Malmquist indices: A bootstrap application to Norwegian grain producers. Omega 37 (5), 1007–1017.

ODYSSEE, 2009. Retrieved http://www.odyssee-indicators.org/overview/overview.php

Office of Energy Efficiency, 2002. Energy efficiency trends in Canada 1990–2000. Natural Resources Canada, Ottawa. Office of Energy Efficiency, Ottawa.

Oggioni, G., Riccardi, R., Toninelli, R., 2011. Eco-efficiency of the world cement industry: A data envelopment analysis. Energy Policy 39, 2842–2854.

Oikonomou, V., Becchis, F., Steg, L., Russolillo, D., 2009. Energy saving and energy efficiency concepts for policy making. Energy Policy 37 (11), 4787–4796.

Paget, M., Seacrest, T., Widergren, S., Balducci, P., Orrell, A., Bloyd, C., 2011. Using smart grids to enhance use of energy-efficiency and renewable-energy technologies. Munich Personal RePEc Archive, Paper No. 58877.

Painuly, J.P., Lee, M., Park, H., Noh, J. 2003. Promoting energy efficiency financing and ESCOs in developing countries: mechanisms and barriers. Journal of Cleaner Production 11, 659-665.

Pardo Martínez, C.I., 2009. Energy efficiency developments in the manufacturing industries of Germany and Colombia, 1998–2005. Energy for Sustainable Development 13, 189–201.

Pardo Martínez, C.I., 2011. Energy efficiency development in German and Colombian non-energy-intensive sectors: a non-parametric analysis. Energy Efficiency 4, 115–131.

Pardo Martínez, C.I., Silveira, S., 2012. Analysis of energy use and CO_2 emission in service industries: Evidence from Sweden. Renewable and Sustainable Energy Reviews 16 (7), 5285–5294.

Patterson, M.G., 1996. What is energy efficiency? Concepts, issues and methodological issues. Energy Policy 24 (5), 377–390.

Perez-Reyes, R., Tovar, B., 2009. Measuring efficiency and productivity change (PTF) in the Peruvian electricity distribution companies after reforms. Energy Policy 37, 2249-2261.

Phylipsen, G.J.M., Blok, K., Bode, J.W., 2002. Industrial energy efficiency in the climate change debate: comparing the US and major developing countries. Energy for Sustainable Development 6(4), 30-44.

Piesse, J., Thirtle, C., 2000. A Stochastic Frontier Approach to firm level efficiency, technological change, and productivity during the early transition in Hungary. Journal of Comparative Economics 28, 473–501.

Pohekar, S.D., Ramachandran, M., 2004. Application of multi-criteria decision making to sustainable energy planning—A review. Renewable and Sustainable Energy Reviews 8, 365–381.

Pombo, C., Taborda, R., 2006. Performance and efficiency in Colombia's power distribution system. Energy Economics 28, 339–369.

Qin, X.S., Huang, G.H., Chakma, A., Nie, X.H., Lin, Q.G., 2008. A MCDM-based expert system for climate-change impact assessment and adaptation planning—a case study for the Georgia Basin, Canada. Expert Systems with Applications 34, 2164–2179.

Ramanathan, R., 2005. Estimating energy consumption of transport modes in India using DEA and application to energy and environmental policy. Journal of the Operational Research Society 56 (6), 732-737.

Ramli, N.A., Munisamy, S., 2013. Modeling undesirable factors in efficiency measurement using Data Envelopment Analysis: A review. Journal of Sustainability Science and Management 8 (1), 126-135.

Ramos-Real, F.J., Tovar, B., Iootty, M., Almeida de, E.F., Pinto Jr., H.Q., 2009. The evolution and main determinants of productivity in Brazilian electricity distribution 1998‐2005: an empirical analysis. Energy Economics 31, 298‐305.

Riccardi, R., Oggioni, G., Toninelli, R., 2012. Efficiency analysis of world cement industry in presence of undesirable output: Application of data envelopment analysis and directional distance function. Energy Policy 44, 140–152.

Robinson, D., 2015. The Scissors Effect: How structural trends and government intervention are damaging major European electricity companies and affecting consumers. The Oxford Institute for Energy Studies, OIES Paper EL14.

Rohdin, P., Thollander P., 2006. Barriers to and driving forces for energy efficiency in the non-energy intensive manufacturing industry in Sweden. Energy 31 (12), 1836–1844.

Rose, A., Casler, S., 1996. Input–output structural decomposition analysis: a critical appraisal. Economic Systems Research 8, 33–62.

Ryan, L., Campbell, N., 2012. Spreading the net: The multiple benefits of energy efficiency improvements. IEA Energy Papers, ©OECD/IEA.

Sadjadi, S.J., Omrani, H., 2008. Data envelopment analysis with uncertain data: an application for Iranian electricity distribution companies. Energy Policy 36, 4247–4254.

Sardianou, E., 2008. Barriers to industrial energy efficiency investments in Greece. Journal of Cleaner Production 16 (13), 1416-23.

Saygin, D., Worrell, E., Patel, M.K., Gielen, D.J., 2011. Benchmarking the energy use of energy-intensive industries in industrialized and in developing countries. Energy 36, 6661-6673.

Schipper, L., 1997. Indicators of energy use and human activity: Linking energy use and human activity. International Energy Agency (IEA), Paris.

Schulz, V., Stehfest, H., 1984. Regional energy supply optimization with multiple objectives. European Journal of Operational Research 17, 302–312.

See, K.F., Coelli, T., 2013. Estimating and decomposing productivity growth of the electricity generation industry in Malaysia: A stochastic frontier analysis. Energy Policy 62, 207–214.

Seiford, L.M., Thrall, R.M., 1990. Recent developments in DEA: the mathematical programming approach to frontier analysis. Journal of Econometrics 46, 7–38.

Shi, G.M., Bi, J., Wang, J.N., 2010. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Policy 38, 6172–6179.

Shi, H., Peng, S. Z., Liu, Y., Zhhong, P., 2008. Barriers to the implementation of cleaner production in Chinese SMEs: government, industry and expert stakeholders' perspectives. Journal of Cleaner Production 16, 842-52.

Siitonen, S., Tuomaala, M., Ahtila, P., 2010. Variables affecting energy efficiency and CO_2 emissions in the steel industry. Energy Policy 38, 2477-2485.

Simar, L., Wilson, P.W., 1998. Sensitivity Analysis of Efficiency Scores: how to Bootstrap in Nonparametric Frontier Models. Management Science 44 (1), 49-61.

Simar, L., Wilson, P.W., 2000. Statistical inference in nonparametric frontier models: The state of the art. Journal of Productivity Analysis 13, 49–78.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics 136, 31–64.

Sinuany-Stern, Z., Mehrez, A., Hadad, Y., 2000. An AHP/DEA methodology for ranking decision making units. International Transactions in Operational Research 7, 109–124.

Sioshansi, F., 2013. Energy efficiency: Towards the end of demand growth. Amsterdam: Elsevier Science/AP.

Siskos, J., Hubert, Ph., 1983. Multicriteria analysis of the impacts of energy alternatives: A survey and a new comparative approach. European Journal of Operational Research 13, 278–299.

Smith, K., Moore, E., 2010. Behavioral economics and benefit cost analysis. environmental and resource economics 46 (2), 217-234.

Sorrell, S., Dimitropoulos, J., Sommerville, M., 2009. Empirical estimates of the direct rebound effect: a review. Energy Policy 37, 1356–1371.

Sorrell, S., O'Malley, E., Schleich, J., Scott, S., 2004. The economics of energy efficiency - Barriers to cost-effective investment. Edward Elgar, Cheltenham.

Stern, D.I., 2012. Modeling international trends in energy efficiency. Energy Economics 34, 2200–2208.

Streimikiene, D., Balezentis, T., 2013. Multi-objective ranking of climate change mitigation policies and measures in Lithuania. Renewable and Sustainable Energy Reviews 18, 144–153.

Su B., Ang, B.W., 2012. Structural decomposition analysis applied to energy and emissions: Some methodological developments. Energy Economics 34 (1), 177–188.

Subrahmanya, M.H.B., 2006. Labour productivity, energy intensity and economic performance in small enterprises: A study of brick enterprises cluster in India. Energy Conversion and Management 47, 763–777.

Sueyoshi, T., Goto, M., 2011. DEA approach for unified efficiency measurement: assessment of Japanese fossil fuel power generation. Energy Economics 33, 292–303.

Sueyoshi, T., Goto, M., 2012. Efficiency-based rank assessment for electric power industry: A combined use of Data Envelopment Analysis (DEA) and DEA Discriminant Analysis (DA). Energy Economics 34 (3), 634-644.

Sumanth, D.J., 1998. Total productivity management: A systemic and quantitative approach to compete in quality, price, and time. Boca Raton, Florida: St. Lucie Press.

Tao, F., Li, L., Xia, X.H., 2012. Industry efficiency and total factor productivity growth under resources and environmental constraint in China. The Scientific World Journal, 1-10.

Thakur, T., Deshmukh, S.G., Kaushik, S.G., 2006. Efficiency evaluation of the state owned electric utilities in India. Energy Policy 34, 2788–2804.

Thollander, P., Dotzauer, E., 2010. An energy efficiency program for Swedish industrial small- and medium-sized enterprises. Journal of Cleaner Production 18 (13), 1339-1346.

Thollander, P., Palm, J., 2012. Improving energy efficiency in industrial energy systems: An interdisciplinary perspective on barriers, energy audits, energy management, policies, and programs. Springer, London.

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J., 2015. An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. Review of International Economics.

van Biesebroeck, J., 2007. Robustness of productivity estimates. Journal of Industrial Economics 55, 529–569.

van Soest, D.P., Bulte, E.H., 2001. Does the energy-efficiency paradox exist? Technological progress and uncertainty. Environmental and Resource Economics 18 (1), 101–112.

Vaninsky, A., 2006. Efficiency of electric power generation in the United States: analysis and forecast based on data envelopment analysis. Energy Economics 28 (3), 326–338.

Vlahinić-Dizdarević, N., Sěgota, A., 2012. Total-factor energy efficiency in the EU countries. Proceedings of Rijeka School of Economics 30(2), 247–265.

Vlontzos, G., Niavis, S., Manos, B., 2014. A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. Renewable and Sustainable Energy Reviews 40, 91-96.

Wade, S.H., 2002. Measuring change in energy efficiency for the annual energy outlook 2002. Energy Information Administration, Washington, United States.

Walton, A.L., 1981. Variations in the substitutability of energy and non energy inputs: the case of the Middle Atlantic region. Journal of Regional Science 21, 411–420.

Wang, C., Chen, J., Zou, J., 2005. Decomposition of energy-related CO_2 emission in China: 1957–2000. Energy 30, 73–83.

Wang, J.H., Ngan, H.W., Engriwan, W.K., Lo, L., 2007. Performance based regulation of the electricity supply industry in Hong Kong: an empirical efficiency analysis approach. Energy Policy 35, 609–615.

Wang, J.J., Jing, Y.Y., Zhang, C.F., Zhao, J.H., 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews 13, 2263–2278.

Wang, J.J, Zhang, C.F, Jing, Y.Y, Zheng, G.Z., 2008. Using the fuzzy multi-criteria model to select the optimal cool storage system for air conditioning. Energy and Buildings 40, 2059-2066.

Wang, Q.W., Zhou, D.Q., 2008. An empirical study on the change of total factor energy efficiency in China. Systems Engineering.26 (7), 74–80.

Wang, Z.H., Zeng, H.L., Wei, Y.M., Zhang, Y.X., 2012. Regional total factor energy efficiency: An empirical analysis of industrial sector in China. Applied Energy 97, 115–123.

Watanabe, M., Tanaka, K., 2007. Efficiency analysis of Chinese industry: A directional distance function approach. Energy Policy 35, 6323–6331.

Wei, C., Ni, J., Shen, M., 2009. Empirical Analysis of Provincial Energy Efficiency in China. China & World Economy 17, 88 – 103.

Wei, C., Ni, J., Sheng, M., 2011. China’s energy inefficiency: A cross-country comparison. The Social Science Journal 48, 478–88.

Wei, Y.M., Liao, H., Fan, Y., 2007. An empirical analysis of energy efficiency in China’s iron and steel sector. Energy 32, 2262–2270.

World Energy Council (WEC), 2010. Energy efficiency: A recipe for success. London.

World Energy Council (WEC), 2013. World energy perspective: Energy efficiency policies - What works and what does not. London.

Wright, J.A., Loosemore, H.A., Fermani, R., 2002. Optimization of building thermal design and control by multi-criterion genetic algorithm. Energy and Buildings 34, 959–72.

Wu, F., Fan, L.W., Zhou, P., Zhou, D.Q., 2012. Industrial energy efficiency with CO_2 emissions in China: A nonparametric analysis. Energy Policy 49, 164–172.

Wu, L., Kaneko, S., Matsuoka, S., 2005. Driving forces behind the stagnancy of China's energy related CO_2 emissions from 1996 to 1999: the relative importance of structural change, intensity change and scale change. Energy Policy 33, 319–335.

Wu, Y., 2012. Energy intensity and its determinants in China’s regional economies. Energy Policy 41, 703–711.

Xiaoli, Z., Rui, Y., Qian, M., 2014. China's total factor energy efficiency of provincial industrial sectors. Energy 65, 52–61.

Xue, X., Shen, Q., Wang, Y., Lu, J., 2008. Measuring the productivity of the construction industry in China by using DEA-based Malmquist Productivity Indices. Journal of Construction Engineering and Management 134 (1), 64–71.

Yedla, S., Shrestha, R.M., 2003. Multi-criteria approach for the selection of alternative options for environmentally sustainable transport system in Delhi. Transportation Research Part A Policy and Practice 37, 717–729.

Yeh, T.L., Chen, T.Y., Lai, P.Y., 2010. A comparative study of energy utilization efficiency between Taiwan and China. Energy Policy 38, 2386–2394.

Yörük, B.K., Zaim, O., 2005. Productivity growth in OECD countries: A comparison with Malmquist indices. Journal of Comparative Economics 33, 401-420.

Yu, J., 2010. Energy efficiency and household behaviour in OECD countries (DRAFT).

Yuan, C., Liu, S., Wu, J., 2009. Research on energy-saving effect of technological progress based on Cobb–Douglas production function. Energy Policy 37, 2842–2846.

Zaccarin, S., Rivellini, G., 2002. Multilevel analysis in social research: An application of a cross-classified model. Statistical Methods and Applications 11 (1), 95-108.

Zhang, X.P., Cheng, X.M., Yuan, J.H., Gao, X.J., 2011. Total-factor energy efficiency in developing countries. Energy Policy 39, 644–50.

Zhao, X., Ma, C., Hong, D., 2010. Why did China's energy intensity increase during 1998–2006: Decomposition and policy analysis. Energy Policy 38, 1379–1388.

Zhou G., Chung W., Zhang Y. 2014. Measuring energy efficiency performance of China's transport sector: A data envelopment analysis approach. Expert Systems with Applications 41 (2), 709–722.

Zhou, P., Ang, B.W., 2008a. Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy 36 (8), 2911–2916.

Zhou, P., Ang, B.W., 2008b. Decomposition of aggregate CO_2 emissions: A production-theoretical approach. Energy Economics 30 (8), 1054–1067.

Zhou, P., Ang, B.W., Han, J.Y., 2010. Total factor carbon emission performance: a Malmquist index analysis. Energy Economics 32, 194–201.

Zhou, P., Ang, B.W., Poh, K.L., 2006. Decision analysis in energy and environmental modeling: An update, Energy, 31, 2604–2622.

Zhou, P., Ang, B.W., Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. European Journal of Operational Research 189, 1–18.

Zhou, P., Ang, B.W., Zhou, D.Q., 2012. Measuring economy-wide energy efficiency performance: A parametric frontier approach. Applied Energy 90, 196–200.

Zopounidis, C. Doumpos, M., 1999. A multicriteria decision aid methodology for sorting decision problems: The case of financial distress. Computational Economics 14, 197–218.