UNIVERSIDADE CATÓLICA PORTUGUESA

Energy transition in Europe: A stochastic frontier approach

Marcelo Filipe Tavares Dias

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Marcelo Filipe Tavares Dias

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Prof. Dr. Leonardo Costa
Prof. Dra. Alexandra Leitão

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Abstract

This dissertation aims to address for energy transition movement in Europe, by evaluating each country's ability to decouple economic growth from GHG emissions. A Stochastic frontier model was deployed to allow us to estimate technical efficiencies and TFP growth for 25 European countries between 2005 and 2019. The model included the ratio between gross domestic product and greenhouse gas emissions as output, time, human capital, total energy consumption *per* worker as inputs and a set of environmental variables. No country in the data was fully efficient in the period in analysis, however, France, Portugal and Sweden reached that status in specific years. Estimations suggested that solid fossil fuel consumption, a bad business environment, country´s economic complexity and demand for heating building have a negative impact on technical efficiency. Contrarily, the remaining environmental variables as population index, the share of energy consumed coming from clean energy sources, and energy dependence impact positively technical efficiency scores. A decomposition analysis was also performed, and it was possible to observe a positive technical change, representing an upward movement of the production frontier with time that contributed partially to a negative technical efficiency change by increasing the country´s relative distance from the frontier, outweighing the positive change in technical change leading to an overall negative TFP change. Total factor accumulation also contributed negatively to decoupling growth. Consequently, output growth was significantly explained by positive random shocks.

Keywords: Stochastic frontier analysis, climate change, technical efficiency, environmental variables, total factor productivity.

Number of words: 9955.

Resumo

A dissertação tem como objetivo abordar a transição energética na Europa, avaliando a capacidade dos países para desvincular o seu crescimento das emissões de gases de efeito de estufa. Neste sentido, foi aplicado um modelo de fronteira estocástica para estimar as eficiências técnicas e o crescimento da produtividade dos fatores para 25 países europeus entre 2005 e 2019. O modelo inclui o rácio entre o produto interno bruto e as emissões de gases de efeito de estufa como output, assim como um conjunto de variáveis ambientais. Nenhum país foi totalmente eficiente durante o período contemplado, no entanto, França, Portugal e Suécia atingiram esse *status* em determinados anos. As estimações do modelo sugerem que o consumo de combustíveis fósseis sólidos, um ambiente empresarial desfavorável, a complexidade económica do país e a procura por aquecimento de edifícios têm um impacto negativo na eficiência técnica. As restantes variáveis ambientais como o índice de população, a percentagem de energia consumida proveniente de fontes de energia limpa e a dependência energética impactam positivamente os resultados de eficiência técnica dos países. Realizou-se ainda uma análise de decomposição onde foi possível observar uma variação técnica positiva, que contribui parcialmente para uma variação da eficiência técnica negativa, aumentando a distância relativa de cada país em relação à fronteira e resultando numa variação do crescimento total da produtividade dos fatores negativa. A acumulação de fatores impactou também negativamente o crescimento do *output* pelo que este é consequentemente explicado por choques aleatórios positivos.

Palavras-chave: Fronteira estocástica, alterações climáticas, eficiência técnica, variáveis ambientais, produtividade total dos fatores.

Número de palavras: 9955.

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1. Introduction

The current environmental problem of human-based climate change arises with the first industrial revolution, being the result of decades of economic growth based on fossil fuels (coal, oil, and natural gas). According to the United Nations (UN) Intergovernmental Panel on Climate Change (IPCC) report, published in 2022 (Langsdorf *et al.*, 2022), the energy sector is considered a major responsible for Greenhouse Gas (GHG) emissions, through energy production and consumption.[1] In this context, it is very important for the EU to make an energy transition, switching from a fossil-fuel-based economy to clean sources of energy production and consumption. This transition must address public goods, externalities, and market failures, so a central role in the process is given to government policies.

Why do some countries have higher levels of eco-efficiency[2] than others? Who are the leaders and the followers in this transition? To answer these research questions, a Stochastic Frontier Analysis (SFA) model is estimated for the EU 25 countries[3] in the period 2005-2019. Following Hadri *et al.* (2003) paper, it is based on Battese and Coelli (1995) time-varying inefficiency model. A wide range of environmental variables is incorporated, to have a clearer view of why different countries present different eco-efficiency levels. Finally, a productivity analysis is performed, and growth rates are decomposed according to Kumbhakar and Lovell (2000).

[1] For Manuel *et al.* (2017), "energy is central to efforts to mitigate climate change, as close to 85% of greenhouse gas emissions in the EU [European Union] are energy related." (Manuel *et al.*, 2017, p.3).

[2] According to World Business Council For Sustainable Development (WBCSD): "Eco-efficiency is achieved by the delivery of competitively priced goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the Earth's estimated carrying capacity"(World Business Council For Sustainable Development, n/a, p.3).

[3] Malta and Luxembourg are not considered due to their small dimensions (less than 1 million habitants) and insufficient data associated.

According to Mauna Loa Database (US Department of Commerce, 2005) the CO_2 concentration has increased from 327 parts *per* million (ppm hereafter) in 1972 to almost 420 ppm nowadays.

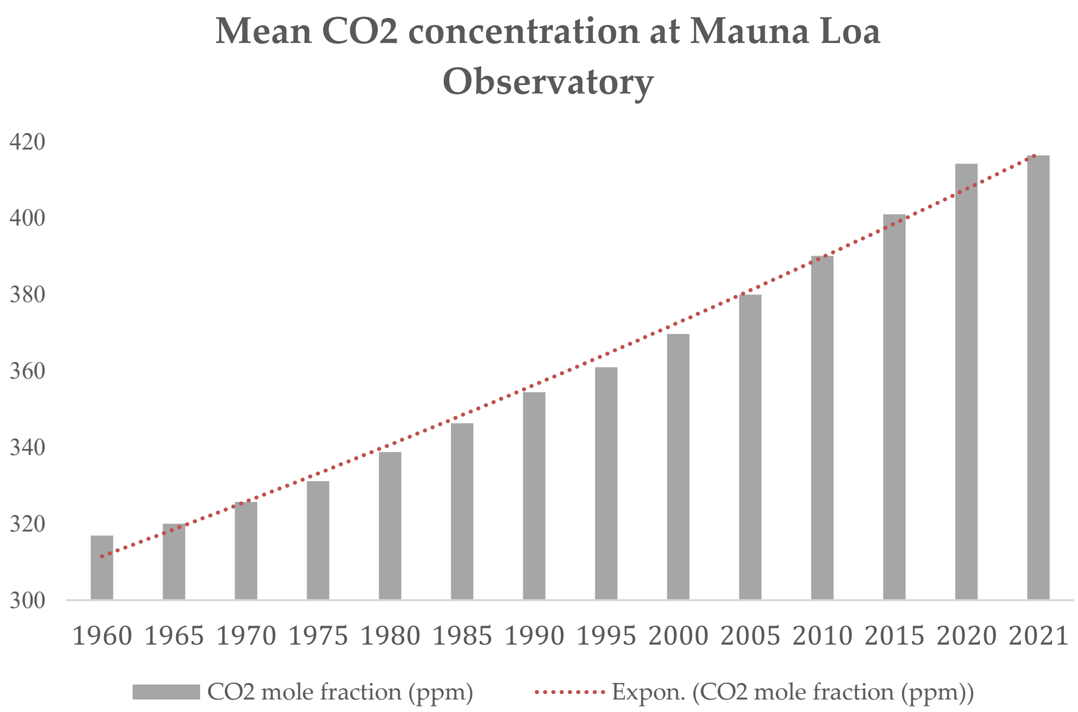

Figure 1 - Annual mean CO_2 concentration at Mauna Loa Observatory.
Source: US Department of Commerce (2005)

The main drivers were the use of fossil fuels as an energy source for many economic sectors that are responsible for a great share of GHG emissions, such as electricity and heat production (25%), agriculture, forestry and other land use (24%), industry (21%), transportation (14%), buildings (6%) and others (10%) according to IPCC (2014). This huge increase in CO_2 emissions and concentration in the atmosphere is known to affect dramatically life on Earth in many aspects, namely biodiversity, soil productivity, a safe climate, and productive oceans. The awareness of all the negative consequences associated made climate change emerge from the scientific community to the world political agenda in the 1970s. In 1972, at the UN Conference on the Human Environment in Stockholm, the sustainability topic started to be discussed. The 1992 UN Conference on Environment and Development in Rio (Earth Summit) followed, and the UN

Framework Convention on Climate Change was signed with the following main goal: "The ultimate objective of the Convention is to stabilize greenhouse gas concentrations at a level that would prevent dangerous anthropogenic (human-induced) interference with the climate system" (United Nations Climate Change, n.d.b). In this context, the 1997 COP 3, in Kyoto, and the 2015 COP 21, in Paris, represented a significant milestone since from these conferences emerged two important international agreements.

Kyoto Protocol's main objective was to commit countries to reduce their emissions by an average of 5% below the 1990 level, between 2008 and 2012. However, it was determined that only developed countries (Annex 1 parties) were forced to achieve those emissions targets while developing countries like China (non-Annex 1 countries) were not. Another key element of the Kyoto Protocol was the establishment of flexible market mechanisms: International Emissions Trading, Clean Development Mechanisms (CDM) and Joint Implementation (JI). This protocol was not well succeeded from the beginning, with the United States (US) dropping the agreement in 2001, a decision justified by the fears of a potential increase in China's trade competitiveness compared to the US since China was not required to meet emissions reductions.

In COP 21, the Paris Agreement no longer distinguished between developed and developing countries and so, it was the first universal "legally binding international treaty on climate change" (United Nations Climate Change, n.d.a), whose primary goal was to "limit global warming to well below 2, preferably to 1.5 degrees Celsius, compared to pre-industrial levels". In the COP26, in Glasgow, the EU, which has always been the most committed part, announced its plan to reduce emissions by 55% in 2030 compared to 1990 levels.

The IPCC reports have also given a huge contribution to the way we nowadays face global warming. The Physical Science Basis Working group 1, published by the IPCC (Masson-Delmotte *et al.*, 2021), gives us the most recent insights about the current status of this global movement and concluded that not to exceed the 1,5ºC increase in global average temperature, CO_2 emissions need to be cut by 45% compared to 2010 levels until 2030, reaching carbon neutrality by 2050.

Energy transition in the EU and its speed is a complex system addressed in this dissertation. The 2020 climate & energy package was established by EU leaders in 2007 and had three main targets: i) a 20% cut in GHG emissions (vs 1990 levels); ii) a 20% of EU energy from renewable sources; iii) and finally a 20% improvement in energy efficiency. This package was very successful mainly due to the effective implementation of the European Emissions Trading System, which finally transformed carbon into a commodity with a price that is supposed to be equal to its negative social impact (European Commission, n.d.a). The successfulness of the first package has stimulated the EU to set, in 2014, more ambitious targets for 2030. In the 2030 climate & energy framework: i) 40% or more cuts in GHG emissions (vs 1990 levels); ii) 27% or more share of renewable energy; and iii) 27% or more improvement in energy efficiency (European Commission, n.d.b). Meanwhile, the European Green Deal was adopted in 2019 with the clear ambition of transforming Europe "into a modern, resource-efficient and competitive economy" (European Commission, n.d.d), ensuring climate neutrality in 2050 and economic growth decoupled from resource use, with Europe becoming the first carbon neutral continent around the world. Also, the EU´s climate ambition for 2030 was increased to 55% compared to the 40% of the 2030 climate & energy framework package, in a clear effort to be aligned with 2050 goals of climate neutrality.

Climate change is a very difficult problem to fix given its nature. It constitutes a global crisis that requires a world mobilization of resources to fight this intergenerational problem. Also, GHG emissions are deeply embodied in modern economic activities, while at the same time, they represent the core of climate change. In addition, this is a slow-moving crisis, where consequences are only starting to be observed. Lobbying forces present in such a powerful sector like energy, also contribute to the delay in reaction to this climate change crisis. All these adversities constitute a great motivation for this thesis. A deep investigation and research in energy transition is required to allow to apply more accurate and efficient measures available to tackle the biggest challenge of this century.

To the best of our knowledge, this thesis will be the first study to address environmental efficiency specifically in EU25 countries using the SFA method, estimating a frontier, developing a decomposition analysis for the specific countries, and incorporating context/environmental variables into the analysis to explain differences in efficiencies across countries. This model is much used in studies that focus on energy efficiency, disregarding the environmental efficiency perspective. Understanding why some countries in the EU25 are performing better than others in this transition will be a powerful inside to develop country-specific paths to achieve the desired energy transition.

The dissertation unfolds as follows. After this introductory Chapter 1, Chapter 2 provides a literature review, summarizing the literature that studies energy and environmental efficiency and the existing methods on productivity and efficiency analysis. Chapter 3 describes the data, the stochastic frontier model used in the empirical analysis, the decomposition of TFP change and growth, and the estimated model. The results are discussed in Chapter 4 and concluding remarks are presented in Chapter 5.

Chapter 2
2. Literature review

2.1. Previous literature on energy transition

This chapter addresses the previous literature on the factors determining the energy transition, the methods of productivity and efficiency analysis, and the variables chosen in the empirical analysis as outputs, inputs, and environmental variables when it comes to environmental efficiency and energy transition. It supports the specification of the empirical model and its variables in this dissertation.

2.2 Factors determining the energy transition

To make coherent and correct decisions, policymakers need to have a clear view of the key factors that play a role in the subject. Bourcet (2020) reviews all the past literature on those key factors related to the deployment of renewable energy. The review concluded that the 3 main determinants of energy transition and renewable energy are economic, energy-related, and environment-related factors, although regulatory, political, and demographic factors also have an influence. However, the author concluded from the literature that there is still little consensus on the effective impact of each one of those factors. The factors considered by at least 5 authors[4] are (+ means positive impact, - negative impact, and NC means no consensus):

[4] The paper only considered factors mentioned by at least 5 from the 45 authors reviewed by the author. A full description of each author/paper and variables used is available on Bourcet (2020) paper appendix.

1. Economic factors: Income (+, - or NC); Fossil fuel prices (+ or NC); Local financial sector (+ or NC); Energy/electricity price (+, - or NC); International flows (NC);

2. Energy factors: Energy/electricity consumption (+, - or NC); Energy security (- or NC); Fossil fuel production (NC);

3. Environmental factors: CO_2 emissions (+, - or NC);

4. Regulatory factors: Renewables support policies (+ or NC); Kyoto Protocol (+ or NC);

5. Political factors: Institutional quality (+ or NC); Government left ideology (+ or NC);

6. Demographic factors: population size (+, - or NC).

In the pursuit of understanding the key determinant factors influencing carbon dioxide emission *per* capita in 42 European countries, Apostu *et al.* (2022) identified empirically the statistical significance of several factors such as GDP *per* capita, trade openness, globalization index, and renewable energy consumption as a share of energy consumption. They concluded that the first two factors were not statistically significant even at the 10% level of significance, while the remaining two were significant to determine the carbon dioxide emissions *per* capita.

Chang *et al.* (2009) and Marques & Fuinhas (2011) papers are both focused on an empirical approach that investigates specifically the impact of the price of fossil fuels in the energy transition. Chang *et al.* (2009) paper used panel data from 1997 to 2006 for each OECD country and concluded that the consumer price index has a significant positive correlation with the supply of renewable energy in countries with high economic growth and no significant relationship in countries with low economic growth. The authors were able to identify it by using a panel threshold regression on the GDP growth rate. However, Marques and Fuinhas used panel data for 24 European countries from 1990 to 2006 and conclude that the income and prices of fossil-based fuels were not significant in renewable energy supply in the period under analysis. This finding according to the authors suggested that "it was not the market that encouraged renewables" (Marques & Fuinhas, 2011, p.1607).

2.3. Methods used in productivity and efficiency analysis

The two most popular methods used in productivity and efficiency analysis, in general, and in energy and environmental productivity and efficiency analysis, in particular, are Data Envelopment Analysis (DEA), which is non-parametric, and Stochastic Frontier Analysis (SFA), which is parametric.

The SFA method was first addressed by Aigner *et al.* (1977) and Meeusen & van Den Broeck (1977). However, this primitive model only enabled to find group average efficiency scores. Throughout time the model has evolved in order to allow to estimate efficiency scores for each unit of analysis (Jondrow *et al.* 1982). Kumbhakar & Lovell, (2003) provide an extensive overview on stochastic frontier models.

The DEA approach, instead, was first introduced by Charnes *et al.* (1978). However, as in the SFA literature, throughout time, the DEA method has been developed and reinterpreted by many authors.

Lampe & Hilgers (2015) paper analyzes DEA and SFA articles between 1978 and 2012 by conducting a bibliometric analysis. The paper concluded that Greene (2005a) was the SFA paper with the higher average number of citations *per* year while Banker *et al.* (1984) was the leader in this ranking metric for DEA models, proving the importance of these two papers in current productivity and efficiency analysis studies.

Compared to DEA, SFA has more statistical power. As a stochastic model, it allows to differentiate inefficiency from noise since it has the capacity to allow random shocks and measure the error, being inefficiency manageable and noise exogenous. The DEA non-parametric model use a deterministic frontier, and so this model is not able to give such precision because there are no assumptions made regarding the distribution of the error term, and then, noise cannot be distinguished from inefficiency. Furthermore, the model is more sensitive to outliers. This constitutes the major advantage of SFA compared to DEA. Adding more, SFA has also the nice feature of being useful to evaluate in detail which key determinants affect both the stochastic frontier and the efficiency scores (Cullinane *et al.*, 2006). Another important distinction is that DEA does not directly address changes over time of technology, as it relies on cross-sectional data. To do so, it needs to be complemented with a Malmquist Index analysis. As opposed, panel versions of SFA allow for time variance, being more useful for many research purposes and improving statistical properties.

Again, the bibliometric analysis of the DEA and SFA paper conducted by Lampe and Hilgers (2015) reached the conclusion that SFA is the method that is more adopted in economic research while DEA is more frequently used in operations research. Accordingly, and based on the comparison presented above, this thesis will adopt SFA as the method to estimate environmental efficiency and energy transition in Europe.

2.4. Methods used in environmental and energy efficiency analysis

2.4.1 DEA and SFA addressing energy and environmental productivity and efficiency analysis - models and variables

One of the most cited attempts to analyze energy efficiency is presented by Filippini & Hunt (2012). In this paper, the authors' purpose was to estimate, using a SFA model and panel data, relative (in)efficiency scores for each U.S. states from 1995 to 2007. In order to have a model that does not suffer from “unobserved variables bias”, the study used the Mundlak version of the Random Effects Model (REM hereafter) suggested by Pitt & Lee (1981), solving the problem related with both REM and the True Random Effects Model (TREM hereafter) suggested by Greene (2005a,b) that suffer from this econometric problem. In the model, aggregate energy consumption is used as output, and real income, population, average household size, the share of detached houses, time dummy variables, and both cooling and heating degree days as inputs. The authors concluded that policymakers should adopt an approach that uses economic, climate, and other factors to measure energy efficiency and take more accurate policy measures, as we will do further in this dissertation.

Jin and Kim (2019) paper used panel data, SFA analysis and a Cobb-Douglas production function to identify and compare energy efficiency in both economic and ecological perspectives across 21 emerging economies from 1995 to 2016, as opposed to the paper discussed above that focused only on energy efficiency. To estimate the frontier, the True Fixed Effect Model (TFEM hereafter) was used to reflect specific differences in this group of heterogeneous countries. The authors used capital, labor, and Economic Complexity Index (ECI hereafter) as inputs. They identified that economic efficiency often comes at the cost of ecological efficiency in countries like Mexico. The study concluded also that ecological and economic outputs are both impacted by technological factors and the economic structure. The results obtained showed that the higher ECI the less carbon is emitted to the atmosphere and the higher the output generated.

In a similar work, Sun *et al.* (2019) writes about GHG emissions and energy efficiency at the meso level, including 26 sectors of economic activity in China, in the period between 2000 to 2016. A SFA approach and the TREM suggested by Greene (2005b) were deployed to evaluate the key determinants of efficiency. The key determinants selected were labor, capital, and energy use and the outputs were CO2 equivalent emissions and the value of production by sector. In addition to these inputs, the papers also selected a set of variables related to the environment such as the Chinese National emissions trading scheme, the annual price of carbon emissions transaction, the ratio of total purchased electricity to total energy consumption, the ratio of annual average electricity price to annual coal price, and technical capacity (sales/labor) to explain differences in technical efficiency between countries. The model to be developed will also use a set of context or environmental variables to explain why some countries are leading the environmental efficiency race, while others are left behind. Similarly to Filippini & Hunt (2012), Sun *et al.* (2019) concluded that energy and greenhouse gases (GHG) emissions intensity differ from the energy and GHG emissions efficiency respectively. The model estimations also proved that changes in electricity use and the price of electricity relative to coal significantly impact environmental efficiency.

Martínez & Silveira (2013) analyzed energy and CO2 efficiency in Sweden's manufacturing industries from 1993 to 2008, identifying and comparing both types of efficiencies across industries. In this way, it was demonstrated that it is "possible to achieve economic growth and sustainable development through steady advancement towards low-carbon energy" (Martínez and Silveira, 2013, p.130). This paper uses as inputs the capital stock of industries, the employment level of industries, the fossil fuel and electricity consumption, and the investments for every manufacturing industry while carbon emissions and energy intensity were introduced as dependent variables. Like Sun *et al.* (2019), the model also incorporates context or environmental variables. Energy prices and CO2 emissions tax were the environmental variables chosen as they were expected by the authors to impact countries technical efficiency. The SFA econometric model specification followed Battese and Coelli (1995). The decomposition analysis showed, first, that it is possible to grow in output and at the same time improve energy and CO2 intensity indicators, contributing to sustainable development growth. The authors concluded the analysis of their results by stating that energy prices, investments, and electricity consumption are significant and reduce the energy and CO2 intensities, proving that Sweden by acting accordingly has been able to promote effective and proper policies to move the economy towards energy transition.

Contrarily, the paper written by Menegaki (2013) used the DEA method and the Malmquist Index to calculate Total Factor Productivity (TFP), using panel data 31 European countries, in the period 1997 to 2010. The paper focused specifically on the relationship between economic growth and renewable energy sources deployment to benchmark European countries and aggregate them with peers according to their renewable energy deployment performance. To proceed with this analysis, GDP *per* capita was used as output, while GHG emissions together with the percentage of renewable energy sources in gross inland production, final energy consumption, labor and capital were included as inputs.

2.4.2 DEA and SFA addressing environmental (only) productivity and efficiency analysis - models and variables

Even if there are not many papers dedicated to studying environmental efficiency using SFA compared to those focusing on energy efficiency from a purely economic perspective, there are still some journal articles available in this field.

Zofío & Prieto (2001) is a seminal paper quantifying the environmental efficiency score, and the low and upper limits of undesirable output necessary to keep the production in OECD country's manufacturing industry, from an output perspective, in two different years: 1990 and 1995. DEA was the method used to estimate those efficiency scores for each industry based on labor and capital as inputs that were used to produce a certain amount of desirable output which is the value of manufacture production while minimizing the amount of undesirable output.

Papers committed to estimating environmental productivity and efficiency at the macro level are more closely related to the purpose of the thesis and will be more scrutinized throughout this literature review.

First Vaninsky (2010) investigated the environmental performance of all U.S. states from 1990 to 2007. To develop this work SFA was used, by applying a translog estimation equation that models the CO2 emissions frontier. CO2 emissions are dependent on GDP, energy consumption, and state population with all variables being expressed in ratios to the total US values, allowing for comparability between each state (example: $\frac{GDP_{California}}{GDP_{US}}$). To perform these estimations Vaninsky (2010) used the Maximum Likelihood Random-Effects Time-Varying inefficiency effects model proposed by Battese and Coelli (1995), as Pardo Martínez & Silveira (2013) did. The results showed a drop in environmental efficiency between 2007 and 2000, that according to the author was caused by an "insufficient reduction in the rate of growth of CO2 emissions needed to offset the (low) rates of growth of GDP, population, and energy consumption" (Vaninsky, 2010, p.25). The author believes that such findings and the model used can be applied to design strategic regulation and used as criteria for a cap-and-trade regulatory system.

Herrala & Goel (2012) conducted an SFA for 170 countries of the world between 1997 and 2007, to measure carbon efficiency and establish comparisons between countries and continents regarding their environmental performance. The authors were able to conclude that the highest efficiency levels were observed in Africa and Europe, with China being the most ecologically inefficient country. Their model is built on a function that uses GDP and population as explanatory variables to estimate the carbon dioxide frontier and efficiency scores.

Menegaki (2013) (presented above) and Robaina-Alves *et al.* (2015) (below) papers have in common the geographical scope of analysis. These two papers dedicated their research to study specifically European countries, as it is the aim of this thesis, and so comparing results with these previous works will be interesting in the sense that will allow to understand if the results are or not aligned with the literature.

Of all the above-mentioned papers, the paper by Robaina-Alves *et al.* (2015), follows more closely our research purpose by using a new frontier approach to address ecological efficiency in European countries in two different time periods: 2000 to 2004, and 2005 to 2011. The authors adopted a maximum entropy approach, based on Jaynes (1957a,b), combining information both from DEA and from the error structure of SFA. According to the authors, this approach allows for overcoming the shortcomings of both DEA and SFA methods. Renewable and fossil fuel (non-renewable) energy consumption have been identified as statistically significant variables to explain country differences in ecological efficiency. Capital and labor were the two remaining inputs used in the model that had GDP relative to GHG emissions as the desired output. The results showed a significant change in the list of countries that were the best and the worst performers in terms of economic and environmental efficiency, from the first period (before de Kyoto Protocol) to the second (after the Kyoto Protocol).

In the second period analysis, the best performer group was constituted by Portugal, Slovakia, Hungary, and Ireland while the worst countries were Bulgaria, Italy, Romania, and Denmark. However, it was also possible to identify a great effort from countries to converge to the efficiency frontier after the ratification of the Kyoto Protocol. The author's suggestions for future research (detailed analysis of the estimated parameters; decomposition analysis to identify relevant factors) are aligned with the purpose of our research.

Moutinho & Madaleno (2021) considering the same outputs and inputs of Robaina-Alves *et al.* (2015), used a log-linear Translog production function, to evaluate both economic and environmental efficiency for 22 Asian and 22 African countries for a period ranging from 2005 to 2018. The TREM model proposed by Greene was used for being the most efficient according to the authors by allowing a country´s inefficiency to change year by year, but the authors adopted four more different models to compare results: TREM, TFEM, ML random-effects time-varying inefficiency effects model suggested by Battese and Coelli (1995), and the approach suggested by Kumbhakar *et al.* (1991) where the errors follow a half normal distribution. The results showed that labor and renewable energy share increase the environmental efficiency while capital decreases this efficiency.

From the literature presented above, we conclude that, as inputs, the following ones were used: labor force, physical capital, GDP, and total energy consumption. Moreover, other authors (Filippini & Hunt, 2012; Pardo Martínez & Silveira, 2013) contributed by using fossil fuel electricity consumption, heating and cooling degree days as independent variables and energy price, energy tax, and CO2 tax as environmental variables. From all the literature presented above, these were the variables that are likely to be a good fit for our model to be estimated either in terms of input or environmental variables. In terms of output, the ratio GDP/CO2 used by Moutinho & Madaleno (2021) and Robaina-Alves *et* *al.*, (2015) seems to be a good proxy for energy transition and ecological efficiency.

This thesis will address environmental efficiency using a stochastic frontier analysis, and a decomposition analysis will be deployed for EU25 countries for the first time to have a clearer view of why some countries are performing better than others in this energy transition movement. The work to be developed will follow a method very similar to the one used in Aguiar *et al.* (2017) being however adapted to the research question in cause.

Chapter 3
3. Empirical model

3.1 Hadri *et al.* (2003) extension of Battese and Coelli (1995) model

The stochastic frontier model used to answer the research questions presented in Chapter 1 is based on the model of Battese and Coelli (1995) extended by Hadri *et al.* (2003). The extension by Hadri *et al.* (2003) solves the problem of heteroskedasticity present in the error terms.

The Battese and Coelli model is as follows:

$$y_{it} = X_{it}\beta + v_{it} - u_{it} \tag{1}$$

$$u_{it} = z_{it}\delta + w_{it} \tag{2}$$

where

- y_{it} denotes the output for the i-*th* sample decision making unit (DMU hereafter) $(i = 1,2, \dots, N)$ at time t $(t = 1,2, \dots, T)$.
- X_{it} corresponds to a $k \times 1$ vector of inputs associated with the i-*th* DMU at time t.
- β corresponds to a $k \times 1$ vector of unknown parameters to be estimated.
- v_{it} is assumed to be an error term independent and identically distributed $N(0, \sigma_v^2)$.
- u_{it} is a non-negative error term associated with technical efficiency of production. This error term is assumed to be independent and identically distributed and truncated at zero $N(z_{it}\delta, \sigma_u^2)$.

- z_{it} corresponds to a $m \times 1$ vector environmental variables associated with the i-*th* DMU at time t.
- δ corresponds to a $m \times 1$ vector of unknown parameters to be estimated.
- w_{it} is a random variable defined by the truncation of the normal distribution, with zero mean and variance σ_w^2.

The stochastic production frontier presented in (1) is usually or a Cobb-Douglas production function or a Flexible Functional Form (FFF) such as the translog production function. This frontier is characterized by having two error terms: i) an idiosyncratic error term (v_{it}); and ii) a technical inefficiency error term (u_{it}). The latter is a one-sided error term and represents the fact of some DMUs being operating bellow the stochastic production frontier, due to technical inefficiency. Moreover, Battese and Coelli (1995) assume that this one-sided error term (u_{it}) is a function of a set of environmental variables (z_{it}), which are expected to explain differences in technical inefficiency across countries in the time horizon analyzed.

Hadri *et al.* (2003) extended the Battese and Coelli model (1995), deriving a new model that allows to estimate technical efficiency in the presence of heteroskedastic error terms. In Battese and Coelli model (1995), a heteroskedastic one-sided error term (u_{it}) is the source of inconsistent technical inefficiency estimates. A heteroskedastic two-sided error term (v_{it}) allows to compute consistent slope parameters. However, the constant will be downward biased. That is, relative DMU´s technical efficiency ranking position is not affected, only the magnitude of the scores is impacted. To solve these problems, Hadri *et al.* (2003) add to Battese and Coelli model (1995) the following equations:

$$\sigma_{uit} = \exp(U_{it}\gamma) \tag{3}$$

When the one-sided error term (u_{it}) is heteroskedastic, where U_{it} corresponds to a vector of explanatory variables related to characteristics of DMU management, meaning that these variables should correspond to managerial variables, and γ is a vector of unknown parameters that should include a constant term.[5] And:

$$\sigma_{vit} = \exp(V_{it}\alpha) \quad (4)$$

Where the two-sided error term (v_{it}) is heteroskedastic, where V_{it} is a vector of explanatory variables related with the scale of the DMU, and α is a vector of unknown parameters to be estimated that should include a constant term.[6]

Hadri *et al.* (2003) present the corrections to implement in technical inefficiency in the 3 possible cases:

1. The one-sided error term (u_{it}) is heteroskedastic;
2. The two-sided error term (v_{it}) is heteroskedastic; and
3. Both error terms (u_{it} and v_{it}) are heteroskedastic.

Commonly to all the 3 cases, the density function remains the same. Only the standard deviations are replaced by their new expressions.

Finally, the empirical model specified in (1), (2), (3), and (4) is estimated applying the maximum likelihood method. Time- and DMU -specific technical efficiency is computed as proposed by Jondrow *et al.* (1982):

$$TE_{it} = \frac{y_{it}}{\exp(X_{it}\beta + v_{it})} = \frac{\exp(X_{it}\beta + v_{it} - u_{it})}{\exp(X_{it}\beta + v_{it})} = \exp(-u_{it}) \quad (5)$$

Technical inefficiency bias from heteroskedasticity is corrected using (3) and (4).[7]

3.2 Data and sample

A set of panel data on 25 EU countries (France, Spain, Italy, Sweden, Portugal, Denmark, Lithuania, Ireland, Cyprus, Romania, Latvia, Croatia, Austria, Germany, Greece, Slovakia, Slovenia, Hungary, Netherlands, Belgium, Bulgaria, Estonia, Poland, Finland, Czech Republic) was used for the time period between

[5] The standard deviation of the homoscedastic one-sided error term can be written as $\sigma_{uit} = exp(\gamma_0)$.
[6] The standard deviation of the homoscedastic two-sided error term can be written as $\sigma_{vit} = \exp(\alpha_0)$.
[7] A complete description of empirical technical efficiency correction is available on Hadri *et al.* (2003).

2005 and 2019. This panel data was collected from multiple data sources such as Eurostat, Penn Data WT, World Bank, Statista and European Environment Agency (EEA hereafter).

The output variable used in the model is the real gross domestic product (GDP) *per* unit of greenhouse gas emissions (GHG emissions hereafter), with GDP from Eurostat measured in chain linked volumes (2015 million euros) and GHG emissions from EEA measured in CO2 equivalent. Thus, the dependent variable is obtained by dividing real GDP by the GHG emissions and represents each country ability to decouple economic growth from GHG emissions.

Two inputs were considered. The first is human capital *per* worker (*h*). The human capital variable from Penn Data WT is computed following Barro and Lee (2013), using average years of schooling and rates of return for completing specific years of education. The first input variable is computed by dividing the human capital by the labor force from Eurostat. The second is total energy consumption *per* worker (*e*). Total final energy consumption data is collected from Eurostat and measured in million tonnes of oil equivalent. The second input variable is computed by dividing the total energy consumption by the labor force from Eurostat.

In addition to output and input variables, the model also considers environmental variables. The latter represent specific country characteristics expected to impact technical efficiency and total factor productivity change. The following dimensions were covered with those environmental variables: demography, institutions, economic structure, and energy deployment status.

The demography dimension is represented in the model with the population index (pop_index). This variable is from Eurostat and corresponds to the total population. It is a scale variable that will allow the model to take in account the size of each country.

The institutions dimension is included in the variable time to resolve insolvency (measured in years), with data being collected from the World Bank database. It is assumed that the more time a country takes to resolve insolvency (insolvency), the less attractive is its business environment. Consequently, the levels of investment and technological progress in the country are expected to be affected by the business environment.

The economic dimension shows up in the model both with the Economic complexity index (ECI hereafter) and the Oil Price (Oil_Price) variables. Economic complexity index data proposed by Hidalgo & Hausmann (2009) was collected from Harvard Atlas of Economic Index. This variable reflects the industrial structure of each country. Countries with higher economic complexity are expected to be economically stronger and more resilient when compared to country with lower ECI. Oil Price from Statista is the annual Brent Crude Oil Price in U.S dollars *per* barrel. The global economy is today very much fossil fuel based. Changes in oil prices are expected to have a direct impact on the global economy and on the energy mix used by countries.

Finally, the energy deployment status dimension. Renewable energy share (RES hereafter), Fossil Fuel Inland consumption (FF_Inland_Cons hereafter), Heating degree days (heat_days hereafter) and Energy Dependence (Ene_Dep hereafter) illustrate the energy deployment status. The data for all these variables is collected from Eurostat. RES represents the share of renewable sources as a percentage of gross final energy consumption. This variable allows to understand the deployment of clean energy sources from each country in each year, providing a good proxy of the energy mix used. FF_Inland_Cons measure the thousands of tonnes of inland consumption of solid fossil fuels. The higher FF_Inland_Cons in a country, the greater the production of GHG emissions, which are known to be the cause of global warming and climate change, and the lower is expected to be the environmental performance of the country. The variable heat_days is used as proxy for energy demand to heat a building. It is the number of heating days in a year, which is computed taking into account the outside air temperature. Finally, the variable Ene_Dep represents the percentage of energy consumed in a country, in a given year, that is imported. This variable is used in the model as a proxy for energy security.

For the reasons above mentioned, the sample covers 25 countries of the EU 27 in a time horizon between 2005 and 2019. The observations start in 2005, which corresponds to the year when the Kyoto Protocol entered into force. On 16th February 2005, 55 countries representing 55 percent of global GHG emissions ratified the agreement. Data goes only until 2019 for two main reasons:

a) Data was absent on key variables such as GHG emissions and human capital for 2020 and 2021;

b) By not considering 2020 and 2021 we excluded the Covid-19 pandemic shock from it.

3.3 Estimated model

In this research we adopt a translog production function specification for the stochastic production frontier:

$$lny_{it} = \beta_0 + \beta_h \ln(h_{it}) + \beta_e \ln(e_{it}) + \beta_t t + \frac{1}{2}[\beta_{hh}(\ln(h_{it}))^2 + \beta_{kk}(\ln(e_{it}))^2 + \beta_{tt}t^2] + \beta_{he}\ln(h_{it})\ln(e_{it}) + v_{it} - u_{it} \quad (6)$$

where

- y is the ratio of GDP *per* unit of GHG emissions.
- h is the index of human capital *per* worker.
- e is the total final energy consumption *per* worker.
- t is the year of observation.

The translog function was adopted instead of the Cobb Douglas because it is a flexible functional form that allows factors of production to be substitute or complementary, and elasticities of substitution to be country and time specific.

Technical inefficiency depends on environmental variables according to the following equation:

$$u_{it} = \delta_0 + \delta_1 FF\_Inland\_Cons_{it} + \delta_2 RES_{it} + \delta_3 Pop\_Index_{it} + \delta_4 Insolvency_{it} + \delta_5 ECI_{it} + \delta_6 Heat\_Days_{it} + \delta_7 Ene\_Dep_{it} + \delta_8 Oil\_Price_t + \delta_9 t + w_{it} \quad (7)$$

In both equations (6) and (7) the variable time (t) is considered. This is in line with Battese and Coelli (1995) model, where the time variable in the first equation represents technical change, while in the second equation represents the change in technical inefficiency.

As mentioned before, the estimated model is based on Hadri *et al*. (2003) extended version of the Battese and Coelli (1995) model, to correct for potential bias and inconsistency in technical inefficiency estimates caused by the heteroskedasticity of both error terms. The Bartlett's test for equal variances was performed for both error terms and the results (Appendix 1) showed that the hypothesis of both u and v being heteroskedastic cannot be rejected at the 5% level of significance. Then, the standard estimates of technical efficiency would be downward biased and inconsistent. To solve this problem, the solution proposed by Hadri *et al*. (2003) to correct technical efficiency estimates was adopted. The standard deviation of the one-sided error term u is assumed to be:

$$\sigma_{uit} = \exp\left(\gamma_0 + \gamma_1 \ln\left(e_{it}\right)\right) \quad (8)$$

where e represents as in equation (6) total final energy consumption *per* unit of labor. In the one-sided error term u, the heteroskedasticity is usually connected with factors under the countries' control, representing managerial characteristics. The logarithm of final energy consumption *per* worker was the managerial variable chosen because it was considered a variable that fits well the condition presented before. Countries can decide on technology that decreases the energy needs and can even constrain the energy use as we saw from several countries in Europe after de war in Ukraine. The standard deviation of the two-sided error term v is assumed to be:

$$\sigma_{vit} = \exp\left(\alpha_0 + \alpha_1 \ln\left(L\_CO2_{it}\right)\right) \quad (9)$$

where L_CO2 represents the logarithm of the amount of labor *per* unit of GHG emissions. This variable was chosen as a scale variable, because v is known to be potentially affected by "size-related heteroskedasticity" (Hadri *et al.*, 2003, p. 208) and it was considered that the best variable to measure country scale in our model of eco-efficiency was the amount of labor *per* emission.

In the time dimension, also cointegration tests were applied to understand if residuals were stationary. At a 5% significance level, tests rejected the stationarity of residuals and so we proceed with the model (see Appendix 2).

3.4 Productivity change and decomposition

$$T\Delta = \beta_t + \beta_{tt} t \quad (10)$$

$$TE\Delta = \overline{\Delta \mathrm{T} E_t} \quad (11)$$

$$\varepsilon_h = \beta_h + \beta_{hh} \ln(h_{it}) + \beta_{he} \ln(e_{it}) \quad (12)$$

$$\varepsilon_e = \beta_e + \beta_{ee} \ln(e_{it}) + \beta_{he} \ln(h_{it}) \quad (13)$$

$$\varepsilon = (\beta_h + \beta_e) + (\beta_{hh} + \beta_{he}) \ln(h_{it}) + (\beta_{kk} + \beta_{he}) \ln(e_{it}) \quad (14)$$

$$S\Delta = (\varepsilon - 1)\left[\left(\frac{\varepsilon_h}{\varepsilon}\right) \dot{h} + \left(\frac{\varepsilon_e}{\varepsilon}\right) \dot{e}\right] \quad (15)$$

Equation (10) goes in line with Battese and Coelli (1995) model. It shows that technical change varies only throughout time, due to Hicks-neutral technological change. TΔ > 0 implies that the production frontier shifts upwards, meaning technological progress. TΔ = 0 implies that the frontier does not change with time. TΔ < 0 implies that the production frontier shifts downwards, meaning a technological regress.

Equation (11) shows how technical efficiencies change in time. TEΔ > 0 implies that the country technical efficiency is increasing in time, moving it in the direction of the production frontier. TEΔ = 0 implies that the country technical efficiency does not change in time, keeping the same distance of it to the production frontier. TEΔ < 0 means that the country technical efficiency is decreasing in time, moving it away from the production frontier.

Equations (12), (13) and (14) represent, respectively, the output partial elasticity with respect to human capital *per* worker, the output partial elasticity with respect to total energy consumption *per* worker, and the scale elasticity. According to Hadri *et al*. (2003), and due to the correction and modeling of standard deviations presented above in equation (8) and (9), the following terms should be added to inputs elasticities (12):

$$exp[2\alpha_0 + 2\alpha_1 L\_CO2]\alpha_1 \text{ (16)}$$

This change is justified by the fact that the variance of the error term v, in the heteroskedasticity case, depend indirectly on human capital through L_CO2. In addition, the following terms should be added to (13):

$$\sigma_{uit}^2\gamma_1 - \gamma_1\left(\sigma_{uit} + \frac{Z_{it}\delta}{\sigma_{uit}}\right)\frac{\phi\left(\frac{Z_{it}\delta - \sigma_{uit}^2}{\sigma_{uit}}\right)}{\Phi\left(\frac{Z_{it}\delta - \sigma_{uit}^2}{\sigma_{uit}}\right)} + \gamma_1\frac{Z_{it}\delta}{\sigma_{uit}}\frac{\phi\left(\frac{Z_{it}\delta}{\sigma_{uit}}\right)}{\Phi\left(\frac{Z_{it}\delta}{\sigma_{uit}}\right)} \text{ (17)}$$

This change is justified by the fact that that variance of the error term u, in the is a function of *e*. The derivation of this additional terms is present in Hadri *et al.* (2003) paper.

The last equation (15) yields the scale change effect over time for each country. In the case of constant returns to scale, $\varepsilon = 1$ and the scale change effect does not impact Total Factor Productivity (TFP) change. However, as we can observe from the equation, if $\varepsilon < 1$ returns to scale are decreasing and TFP change is negatively affected, while if $\varepsilon > 1$, returns to scale are increasing and TFP change is positively affected.

Finally, the random shocks component corresponds to a residual component and is computed by subtracting the growth rate of both inputs (human capital and energy consumption *per* worker) and the growth rate of TFP from the growth rate of GDP *per* unit of GHG.

Chapter 4
4. Empirical results

4.1 Stochastic production frontier estimates

Table 1 presented bellow shows the maximum likelihood estimates of the model specified. Except for the square term for *ln(e)* and the interaction term *ln(h)* * *ln(e)*, all frontier estimated parameters are statistically significant at 1 percent level of significance.

The sample mean partial elasticity of GDP *per* unit of GHG emissions with respect to human capital *per* unit of labor (total energy consumption *per* unit of labor) is 4,453 (1,753). Therefore, the elasticity of scale at the sample mean is 6,206, denoting increasing returns to scale.

Technical change depends on both β_t and β_{tt} (see equation (6), Chapter 3). The positive value β_t more than compensates for the negative value of β_{tt}. Technical change or technological progress was on average 0,408% every year between 2005 and 2019.

Finally, Allen partial elasticities of substitutions between human capital and energy consumption *per* unit of labor is approximately 1,284% (see Appendix 3). These values suggest that human capital *per* worker and total energy consumption *per* worker are strong substitutes in GHG emissions decoupling from GDP.

Number of observations	375	Observations per country:	Minimum = 15
Number of countries	25		Maximum = 15
Number of Years	15		Average = 15
		Prob > chi2 = 0.0000	
Log likelihood = 92.8816		Wald chi2(7) = 1428.41	

ln y		Coefficients	Standard Error	z	P > |z|	95% Confidence Interval Lower	Upper
Frontier							
ln(h)	β_h	8,408702	0,8189698	10,270	0,000	6,80355	10,01385
ln(e)	β_e	1,897869	0,6735549	2,820	0,005	0,5777254	3,218012
t	β_t	0,5591312	0,0598781	9,340	0,000	0,4417723	0,6764901
*ln(h) * ln(h)*	β_{hh}	-4,192845	0,3621089	-11,580	0,000	-4,902566	-3,483125
*ln(e) * ln(e)*	β_{ee}	-0,3093949	0,2180381	-1,420	0,156	-0,7367416	0,1179519
t^2	β_{tt}	-0,1512867	0,0382841	-3,950	0,000	-0,2263221	-0,0762513
*ln(h) * ln(e)*	β_{he}	0,2376711	0,4362778	0,540	0,586	-0,6174177	1,09276
Const.	β_0	-4,992852	0,6957209	-7,180	0,000	-6,35644	-3,629264
u							
FF_Inland_Cons	δ_1	0,3530629	0,030649	11,520	0,000	0,2929919	0,4131339
RES	δ_2	-0,4554356	0,0612848	-7,430	0,000	-0,5755516	-0,3353197
Pop_Index	δ_3	-0,7453204	0,0694839	-10,730	0,000	-0,8815063	-0,6091345
Insolv_days	δ_4	0,0987421	0,0334401	2,950	0,003	0,0332008	0,1642835
ECI	δ_5	0,1484057	0,0492712	3,010	0,003	0,051836	0,2449754
Heat_day	δ_6	0,3082239	0,091626	3,360	0,001	0,1286403	0,4878075
Ene_Dep	δ_7	-0,3198331	0,0592104	-5,400	0,000	-0,4358833	-0,2037829
t	δ_8	0,327091	0,0442252	7,400	0,000	0,2404112	0,4137708
Const.	δ_0	0,4229612	0,1392689	3,040	0,002	0,1499992	0,6959232
Usigma							
LN_EneC_pw		3,270992	0,6216008	5,260	0,000	2,052677	4,489308
Const.		-6,157969	0,6666343	-9,240	0,000	-7,464548	-4,85139
Vsigma							
LN_LCO2		-3,449665	2,604707	-1,320	0,185	-8,554797	1,655467
Const.		-2,080623	2,562582	-0,810	0,417	-7,10319	2,941945
	σ_u	0,2590413				0,246996	0,2710865
	σ_v	0,064946				0,0633125	0,0665795
	$\lambda = \frac{\sigma_u}{\sigma_v}$	3,988564346				3,901220138	4,071621145

Table 1 – Estimates of Stochastic Frontier Time-Varying Inefficiency Model.
Source: own work

4.2 Technical inefficiency estimates

Regarding the environmental variables that explain technical inefficiency, all parameters are statistically significant at 1% level of significance. Starting with the demography dimension, the scale variable population index has a negative coefficient. $\delta_3 < 0$ yields that the more populated is the country the less technically inefficient they tend to be, *ceteris paribus*, indicating a positive size effect.

Concerning the institutional dimension, $\delta_4 > 0$, which confirms our expectation for this variable described in Chapter 3. The higher the number of years to resolve insolvency, the less attractive is the business environment, negatively impacting private investment levels, technological progress (productivity) and, in our cases, the growth on decoupling of GDP from GHG emissions. Hall and Jones (1999) identified that social infrastructure (institutions and government policies) explain partially both capital and human capital (with the last one being one of the inputs of our model), and consequently the capacity of countries to generate output. To develop and deploy clean energy sources, huge investment amounts and technological progress is needed.

In the economic dimension, contrarily to Jin and Kim (2019) where ECI was not statistically significant to explain energy and carbon efficiency, the ECI coefficient was positive and significant. $\delta_5 > 0$ means, *ceteris paribus*, that an increase in its complexity index increases a country technical inefficiency. Industrialized countries are the ones that emit the largest amount of GHG emissions. This justification was inclusively the one used in the Kyoto Protocol (see Chapter 1) to force only developed and industrialized countries to comply with GHG emissions reduction targets (Annex 1 vs non-Annex 1 countries).

In the energy deployment status dimension, from table 1 presented above, we can observe that $\delta_1 > 0$. This estimation results yields that an increase in solid fossil fuel consumption is expected to increase, *ceteris paribus*, the country technical inefficiency by moving it away from the stochastic production frontier[8].

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[8] According to Eurostat (n.d.), solid fossil fuels include hard coal, brown coal and coal products. This type of fossil fuels is known to be the most aggressive one to the environment according to Martins *et al.* (2019), since it is responsible for releasing a huge amount of carbon dioxide emissions to the atmosphere.

In turn, $\delta_2 < 0$ indicates that an increase in the share of gross energy consumed coming from renewable energy sources is expected to decrease, *ceteris paribus*, country technical inefficiency. This result goes perfectly in line with the work developed by Robaina-Alves *et al.* (2015) on eco-efficiency in European countries. The paper concluded that "countries who bet on renewable energy efficiently, gradually substituting fossil energy, have a greater potential to move closer to the efficiency frontier" (Robaina-Alves *et al.*, 2015, p. 568). The heating degree days coefficient, $\delta_6 > 0$, indicates that the higher is the demand for energy to heat buildings the greater is expected to be, *ceteris paribus*, technical inefficiency. Pardo Martínez and Silveira (2013) supported the idea that heating degree days can be used as a proxy of energy demand by proving that elasticity of energy demand with respect to heating degree days was around 0,4. By increasing the total energy used by a country, we are increasing the pressure to use more fossil fuels in order to have enough supply to meet the increasing demand. Energy dependence closes energy deployment status dimension variables. $\delta_7 < 0$ yields that an increase in the share of energy imports is expected to decrease, *ceteris paribus*, country technical inefficiency. This result shows that countries that depend more on external energy supply, by being less abundant on this resource, will need to use it more efficiently.

Finally, the time coefficient is also positive and significant. $\delta_8 > 0$ shows that countries are moving away from the frontier in time, meaning that technical inefficiency increases with time in the period between 2005 and 2019. This empirical evidence is closely related to the verified upward movement in the stochastic production frontier (technical change > 0) during the period, which leads to an increase in time, to the distance of countries to the frontier.

4.3 Technical efficiency and returns to scale

Table 2 presents both technical efficiency and returns to scale for each country. The values are obtained using the time mean in the period for each country in the sample.

Ranking based on average tecnichal efficiency and returns to scale (2005-2019)

Rank	*Country*	*TE*	*Rank*	*Country*	*RTS*
1	France	0,99	1	Cyprus	7,43
2	Spain	0,97	2	Estonia	7,36
3	Italy	0,94	3	Slovenia	7,09
4	Sweden	0,94	4	Latvia	7,02
5	Portugal	0,93	5	Lithuania	6,87
6	Denmark	0,88	6	Croatia	6,70
7	Lithuania	0,85	7	Denmark	6,61
8	Ireland	0,84	8	Ireland	6,60
9	Cyprus	0,84	9	Slovakia	6,60
10	Romania	0,84	10	Bulgaria	6,39
11	Latvia	0,81	11	Czech Republic	6,25
12	Croatia	0,73	12	Hungary	6,25
13	Austria	0,64	13	Greece	6,16
14	Germany	0,63	14	Portugal	6,05
15	Greece	0,61	15	Austria	5,95
16	Slovakia	0,57	16	Belgium	5,92
17	Slovenia	0,57	17	Netherlands	5,90
18	Hungary	0,57	18	Romania	5,86
19	Netherlands	0,48	19	Sweden	5,83
20	Belgium	0,46	20	Finland	5,78
21	Bulgaria	0,42	21	Poland	5,54
22	Estonia	0,37	22	Spain	5,34
23	Poland	0,36	23	Italy	5,25
24	Finland	0,35	24	France	5,22
25	Czech Republic	0,28	25	Germany	5,19
Mean		0,67	Mean		6,21

Table 2 - Average technical efficiencies and returns to scale by country.
Source: own work.

No country has been fully efficient in the overall period. However, France has been fully efficient between 2005-2011, 2014-2015, 2018-2019. Portugal has also achieved that status between 2012 and 2014 and Sweden between 2018 and 2019.

With 0,99 technical efficiency, France has been the most technically efficient country in the 15 years' period considered. The country depends hugely on natural gas, the fossil fuel that emits less greenhouse gases and is one of the countries that is able to generate more output in Europe.

The top-5 countries include also (in this order) Spain, Italy, Sweden and Portugal. Except for Sweden all these 3 countries (Spain, Italy and Portugal) high level of technical efficiency may be explained by their lower demand for energy to heat buildings when compared to the EU average and by their energy dependence values being well above the EU average. The latter means that these countries import an important share of the energy they use, which puts pressure on increasing efficiency. Portugal is the second country with lower energy demand for heating, presenting 1212 heating degree days compared to average of 2908. Portugal and Sweden have in common a high share of energy coming from renewable energy sources. This a key determinant to allow these two countries to be present in the top 5, with Sweden being from the 25 countries analyzed, the one that has higher value of energy coming from renewable energy sources (49%).

Czech Republic is by far the worst performer country in the sample, with a technical efficiency of 0,28. This undesirable position may be explained as follows: i) solid fossil fuel consumption *per* worker well above the average (10,86 vs average of 3,35); ii) unfavorable business environment resulting from weak institutions with an average of 4,15 years to resolve insolvency vs a European average of 2 years; iii) high levels of energy demand to heat buildings; iv) low energy dependence with the country importing approximately 30% of energy consumed against an average of 53%. Surprisingly, Germany occupies the 14th position, nearby the middle of the table, mainly for two reasons: i) it is the country with the highest economic complexity index (most industrialized one);

ii) it is the 5th country with the highest level of solid fossil fuel inland consumption (6,45 thousands of tones *per* worker vs an average of 3,35).

Looking now to returns to scale, naturally, we expect to see countries with low levels of both human capital *per* worker and energy consumption *per* worker to be top of the table. The evidence follows our expectations. The six countries with lower human capital *per* unit of labor are the same (even in ranking position) of countries with higher returns to scale. In the same way, the 5 countries with higher human capital *per* worker levels are the ones with lower returns to scale. Concerning energy consumption *per* worker this tendency is less obvious, which makes sense since the human capital *per* worker variable is the input that weights more in total returns to scale (average human capital *per* worker elasticity of 4,453 vs energy consumption elasticity *per* worker of 1,753), Estonia, Slovenia and Cyprus are the 3 countries with higher returns to scale (7,43, 7,36 and 7,09 respectively) and the 3 countries with lowest returns to scale are Italy, France and Germany (5,25, 5,22 and 5,19 respectively). We can also observe the presence of Portugal in the middle of the table, and this is justified mainly by two reasons: high levels of human capital *per* worker (8th country with the highest level) and low levels of energy consumption *per* worker (4th country with the lowest level of energy consumption).

It is also important to notice that all countries present significant increasing returns to scale in terms of decoupling production from emissions (level of production *per* unit of GHG emission).

4.4 Total factor productivity change – Decomposition analysis

Variable	*Compound Average Annual % Rate*
GDP/GHG growth	3,047
a) Total factor accumulation	-0,166
a.1) Human capital per worker accumulation	-0,082
a.2) Energy consumption per worker accumulation	-0,085
b) Change in TFP	-0,244
b.1) Technical change	0,408
b.2) Technical efficiency change	-0,648
b.3) Scale economies change	-0,004
c) Random shocks	3,457

Table 3 - Average decomposition analysis.
Source: own source.

Table 3 presents a decomposition analysis of growth in the output GDP *per* unit of GHG emissions, following Kumbhakar and Lovell (2000).[9]

Growth in the output (GDP *per* unit of GHG emissions) is explained here as the sum of total factor accumulation, TFP change, and a random shocks component obtained residually. The random shocks component is the part of growth not explained by the model.

Starting with input accumulation, both human capital and energy consumption *per* worker are very similar in magnitude and sign. Both inputs accumulation explains an annual degrowth of -0,166% in the output.

TFP change has 3 components: i) technical change; ii) technical efficiency change; and iii) scale economies change. Technical change has a positive annual

[9] The reader can find each country specific decomposition in the Appendix 8.

value of 0,408%, which indicates that there has been important technological progress moving the production frontier upward. This technological progress represents huge financial efforts and political actions taken by the EU to accelerate the energy transition from a fossil fuel-based economy to an economy that is expected to be based on clean sources of energy, for example, by investing in technology to develop and deploy renewable energy sources [10]. This technological progress is helping the EU economy in accelerating the process of decoupling economic growth from GHG emissions, which has been the case. This result is consistent with Wang and Su (2020) work (for a similar time period analysis), that proved that developed countries coming from a stable-weak decoupling state tended to a stronger decoupling state between economic growth and CO2 emissions. Also, Diakoulaki and Mandaraka (2007) found evidence of relevant progress in economic growth and CO2 emissions decoupling for EU manufacturing industries. However, even though there was a significant decoupling effort, there was no significant decoupling acceleration in the Post Kyoto Protocol. These results help to understand that this technological progress trend was already taking place before our period of analysis. However, the pace of decoupling seems to have improved since Kyoto Protocol effectively entered into force, corresponding to our time horizon analysis (2005-2019).

In opposite direction, technical efficiency change has been negative and outweighing technical change progress, with an annual value of -0.648%. This negative change may be partially explained by the upward movement of the stochastic production frontier, which automatically increases countries' distance to the frontier. Change in scale effects has been negative, but with a small impact.

The random shocks component has a positive and important impact. It incorporates external shock that the model does not explain. For example, the 2008 Global Financial Crisis, which hit Europe's economic performance,

[10] Some of the political actions and commitments were already discussed in Chapter 1.

particularly from 2010 onwards, interrupted the steady rise in global emissions (Steckel *et al.*, 2015). In other words, a random negative shock to the economy turned out to be a positive random shock in decoupling GDP from GHG emissions. Also, in this period, several policies were implemented by the EU (see Chapter 1) to reduce GHG emissions and fight climate change, which helped the decoupling of economic growth from GHG emissions.

Chapter 5
5. Conclusion

Throughout this dissertation, we attempted to give an answer on why some European countries are more advanced than others in the energy transition and/or in decoupling growth from GHG emissions. This led us to estimate a stochastic frontier for GDP *per* unit of GHG emissions and to benchmark countries in regard to: 1) Technical efficiency; 2) Returns to scale; 3) Impact of specific environmental variables on technical efficiency; 4) TFP changes, including technical change, technical efficiency and returns to scale change components; 5) Contribution of TFP change, total factor accumulation and random shocks in decoupling growth from GHG emissions. The Stochastic Frontier Analysis (SFA) empirical model followed Hadri *et al.* (2003) extension of Battese and Coelli (1995) time-varying inefficiency model for 25 EU countries between 2005-2019. Productivity growth rates were decomposed based on Kumbhakar and Lovell (2000) decomposition. The model allows to perform a productivity and efficiency analysis in the countries considered and to compare them.

Technical efficiency results are estimated for each country in each year for the time period between 2005 and 2019. The evidence shows that no country in the data was fully efficient throughout the period. However, France, Portugal, and Sweden were able to achieve this status recently. Both inputs human capital *per* worker and total energy consumption *per* worker (*h* and *e* respectively) present positive elasticities, however, human capital elasticity is the most significant one showing the importance of this variable in the decoupling process. Consequently, countries with lower levels of human capital elasticity were the ones with higher returns to scale, as expected.

All the specific environmental variables included in the model proved to a significant impact on technical efficiency, at 5% level of significance. Solid fossil fuel consumption (FF_Inland_Cons), a bad business environment (Insolvency), the country´s economic complexity (ECI), demand for heating buildings (Heat_day), and time (t) have shown to have a negative impact on technical efficiency, while the share of energy consumed coming from clean energy sources (RES), population (Pop_Index), and energy dependence (Ene_Dep) have shown to have a positive impact on technical efficiency.

Growth of GDP *per* unit of GHG emissions was decomposed in TFP change, factors accumulation, and a random shocks component obtained residually. TFP change was also decomposed into 3 components: technical change, technical efficiency change, and scale efficiency change.

From the three components of TFP change, only technical change is positive, meaning that the frontier is moving upward with time. The positive technical change partially contributes to the negative technical efficiency change. Apart from the random shocks, the latter component is the one that affects the most the decoupling of GDP growth from GHG emissions. The changes in returns to scale are nearly insignificant. Putting the three components together, TFP change has a negative contribution in explaining the decoupling of GDP growth from GHG emissions. Total factor accumulation contributes also negatively to the decoupling of GDP growth from GHG emissions in both factors considered, human capital *per* worker and total energy consumption *per* worker. Consequently, random shocks are significantly positive, which is probably related to the financial crisis and political reforms implemented at the EU level in order to deal with climate change issues.

The analysis has also limitations. A single frontier was adopted, assuming no technological gaps existed between countries in the data[11]. However, a model that allows to overcome this limitation would represent an important improvement. Also, Russia - Ukraine war was not addressed, due to data limitations. This war is expected to have an impact on the EU energy transition, and addressing it, once data is available, would be of great value.

[11] As we are studying only EU countries, we expect them to be more homogenous compared to a sample with countries with different development levels (for example, OECD vs non-OECD countries).

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Appendix

Appendix 1: Synthesis of literature review

Paper	Methodology	Output	Input
Jin and Kim, (2019)	TFEM (Greene, 2005a)	Energy consumption in kilotones of oil equivalent Carbon emissions in kilotones	Capital (Gross Fixed Capital Formation) GDP in constant 2010 USD as a proxy of growth Labor (Derived from World Development Indicators) Economic Complexity Index *
Herrala & Goel, (2012)	Not specified	Carbon emissions in kilotones	GDP in constant 2007 USD Population as a proxy of labor Land area as a proxy of travels needs inside the country
Moutinho & Madaleno, (2021)	TREM (Greene, 2005a) TFEM (Greene, 2005b) ML random-effects time-varying inefficiency effects model (Battese and Coelli, 1995)	GDP/ CO2 (GDP at constant prices of 2010) (GHG emissions in CO2 equivalent)	Share of final energy consumption of fossil fuels** Share of renewable energy consumption Capital per capita Labor per capita
Robaina-Alves et al., (2015)	Entropy approach. Combines DEA and SFA	GDP/ CO2 (GDP at constant prices of 2000) (GHG emissions in CO2 equivalent)	Fossil fuel consumption** in th tonnes of oil equivalent Renewable energy consumption in TOE Capital Labor as total employment
Pardo Martínez & Silveira, (2013)	ML random-effects time-varying efficiency decay model (Battese and Coelli, 1992) ML random-effects time-varying inefficiency effects model (Battese and Coelli, 1995)	CO2/Y (Carbon emissions intenisty) E/Y (Energy intensity) (E as energy measured in final energy consumption in tj) (Y as gross production in euros)	CO2 emissions in tonnes Capital stock of industries Labor as employment level per industry Fossil fuels consumption in terajoules Electricity consumption in terajoules Investments measured in euros Energy prices measured in euros Energy tax and C02 tax measured in euros- EV***
Vaninsky, (2010)	ML random-effects time-varying inefficiency effects model (Battese and Coelli, 1995)	State CO2 emission	State GDP in ratio of total State population in ratio of total State energy consumption in ratio of total

Filippini & Hunt, (2012)	Mundlak version of the Random Effects Model	Energy consumption (trillion Btu)	Real disposable personal income
			Real price of energy (per million Btu)
			Population(1000)
			Average household size (No.of people per housing unit)
			Heating degree days (base:65°F)
			Cooling degree days (base:65°F)
			Share of detached houses
Sun et al., (2019)	TREM (Greene, 2005b)	Value of production in the sector in 2000 year prices	Capital
			Labor as a average number of employees in the sector
			Energy consumption as electricity and fuel use
			CO2 emissions in tCO2 equiavalent
			Annual price of carbon emissions transaction- EV***
			Ratio: Electricity purchased / Energy consumption- EV***
			Annual average electricity price to annual coal price- EV***
			Technical capacity (sales/labor)- EV***
Menegaki, (2013)	DEA + Malmquist method	GDP per capita in PPP terms	GHG emissions in CO2 equivalents
			Share of renewable energy consumption
			Final energy consumption in 1000 toe
			Labor (employment rate as proxy)
			Capital (real gross fixed capital formation as proxy)
Zofío & Prieto, (2001)	DEA	CO2 emissions as undesirable output Value of manufacturing production as desirable output	Labor as total employment
			Capital (Gross Fixed Capital Formation)

* Suggested by Huamman and Hidalgo

** Solid fossil fuels, gas, and petroleum. % of total energy consumption

*** EV= Environmental variable

Appendix 2: Testing for heteroskedasticity of error terms

Testing heteroskdasticty of *u*	Analysis of Variance				
Source	SS	df	MS	F	Prob > F
Between groups	49,847	24	2,077	274,490	0,000
Within groups	2,648	350	0,008		
Total	52,496	374	0,140		

Bartlett's test for equal variances: chi2(24) = 212,0423 Prob>chi2 = 0,000

Testing heteroskdasticty of *v*	Analysis of Variance				
Source	SS	df	MS	F	Prob > F
Between groups	0,228	24,000	0,010	12,310	0,000
Within groups	0,270	350,000	0,001		
Total	0,499	374,000	0,001		

Bartlett's test for equal variances: chi2(24) = 564,0094 Prob>chi2 = 0,000

According to the test performed, both error terms are shown to be heteroskedastic.

Appendix 3: Testing for stationarity of data

Stationarity test

Harris-Tzavalis unit-root test for LN_GDPCO2

H0: Panels contain unit roots	Number of panels	=	25
Ha: Panels are stationary	Number of periods	=	15

AR parameter: Common	Asymptotics	N	-> Infinity
Panel means: Included		T	Fixed
Time trend: Included			

	Statistic	z	p-value
rho	0.3845	-3.2816	0.0005

Kao test for cointegration

H0: No cointegration	Number of panels	=	25
Ha: All panels are cointegrated	Number of periods	=	15

Cointegrating vector:	Same	
Panel means:	Included	Kernel: Bartlett
Time trend:	Not included	Lags: 1,76 (Newey–West)
AR parameter:	Same	Augmented lags: 1

	Statistic	p-value
Modified Dickey–Fuller t	-2,9258	0,0017
Dickey–Fuller t	-2,595	0,0047
Augmented Dickey–Fuller t	-2,0924	0,0182
Unadjusted modified Dickey–Fuller t	-2,9261	0,0017
Unadjusted Dickey–Fuller t	-2,5952	0,0047

Westerlund test for cointegration

H0: No cointegration	Number of panels	=	25
Ha: Some panels are cointegrated	Number of periods	=	15

Cointegrating vector	Panel specific
Panel means:	Included
Time trend:	Not included
AR parameter:	Panel specific

	Statistic	p-value
Variance ratio	-2,2255	0,013

Appendix 4: Allen Partial Elasticity of Substitution

This dissertation adopted the Allen partial elasticity of substitution. This methodology allows to estimate the elasticity of substitution between both inputs used to predict the stochastic frontier analysis (human capital *per* worker and total energy consumption *per* worker). Elasticity of substitution is here presented as:

$$\sigma_{he} = \frac{f_h x_h + f_e x_e}{x_h x_e} \frac{F_{he}}{F} = \frac{f_h f_e (f_h x_h + f_e x_e)}{x_h x_e (2 f_h f_e f_{he} - f_{hh} f_e^2 - f_{ee} f_h^2)} \quad (1)$$

$$\begin{bmatrix} 0 & f_h & f_e \\ f_h & fhh & f_{he} \\ f_e & f_{he} & f_{ee} \end{bmatrix} \quad (2)$$

Note: F corresponds to the bordered hessian matrix determinant while F_{he} corresponds to the cofactor of f_{he} represented below in (7).

To estimate both (1) and (2), a set of partial derivatives, presented below, are computed:

$$f_h = \frac{\partial lny}{\partial lnh} \frac{y}{h} = \varepsilon_h \frac{y}{h} \quad (3)$$

$$f_e = \frac{\partial lny}{\partial lne} \frac{y}{e} = \varepsilon_e \frac{y}{e} \quad (4)$$

$$f_{hh} = \frac{y}{h^2} [\beta_{hh} + \varepsilon_h (\varepsilon_h - 1)] \quad (5)$$

$$f_{ee} = \frac{y}{e^2} [\beta_{ee} + \varepsilon_e (\varepsilon_e - 1)] \quad (6)$$

$$f_{he} = \frac{y}{he} [\beta_{he} + \varepsilon_h \varepsilon_e] \quad (7)$$

Equation (3) and (4) represent the partial derivative of the output in order to both inputs human capital *per* worker and total energy consumption per worker. Also, (4) and (5) represents the second direct partial derivatives in order of both inputs of the stochastic production function.

$$\begin{bmatrix} 0 & 5{,}1519 & 1{,}8976 \\ 5{,}1519 & 5{,}4855 & 3{,}1879 \\ 2{,}6660 & 3{,}1879 & 0{,}4678 \end{bmatrix} \quad (8)$$

Model estimations provided a positive value for σ_{he} around 1,3, showing that both human capital *per* worker and total energy consumption *per* worker are substitutes. Then, an increase in the price of one input increases the quantity used of the second input ($\sigma_{he} > 0$).

Appendix 5: Technical efficiency by country, 2005-2019

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
Austria	0,69	0,69	0,71	0,69	0,70	0,61	0,65	0,65	0,61	0,66	0,62	0,59	0,57	0,60	0,58	0,64
Belgium	0,49	0,48	0,50	0,46	0,49	0,42	0,49	0,47	0,44	0,49	0,45	0,44	0,44	0,44	0,44	0,46
Bulgaria	0,48	0,43	0,41	0,43	0,53	0,49	0,40	0,42	0,47	0,42	0,36	0,37	0,33	0,35	0,37	0,42
Croatia	0,79	0,76	0,75	0,75	0,72	0,71	0,71	0,75	0,76	0,82	0,74	0,71	0,66	0,69	0,69	0,73
Cyprus	0,95	0,86	0,84	0,76	0,77	0,79	0,81	0,86	1,00	0,95	0,85	0,78	0,75	0,79	0,81	0,84
Czech Republic	0,29	0,29	0,29	0,30	0,30	0,28	0,28	0,28	0,28	0,29	0,28	0,27	0,26	0,27	0,28	0,28
Denmark	0,92	0,78	0,80	0,81	0,80	0,73	0,82	0,90	0,85	0,95	0,97	0,91	0,97	0,97	1,00	0,88
Estonia	0,47	0,49	0,39	0,39	0,43	0,31	0,32	0,34	0,30	0,32	0,36	0,33	0,30	0,31	0,45	0,37
Finland	0,43	0,34	0,34	0,38	0,37	0,30	0,34	0,35	0,33	0,35	0,37	0,33	0,35	0,33	0,36	0,35
France	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,98	0,92	1,00	1,00	0,99	0,99	1,00	1,00	0,99
Germany	0,76	0,70	0,74	0,67	0,69	0,58	0,63	0,59	0,54	0,60	0,58	0,57	0,58	0,60	0,63	0,63
Greece	0,64	0,62	0,57	0,58	0,58	0,61	0,54	0,56	0,67	0,66	0,61	0,61	0,59	0,62	0,65	0,61
Hungary	0,60	0,60	0,63	0,61	0,60	0,55	0,56	0,60	0,61	0,63	0,54	0,51	0,47	0,48	0,49	0,57
Ireland	0,76	0,74	0,75	0,70	0,79	0,75	0,86	0,85	0,83	0,87	0,95	0,87	0,95	0,97	1,00	0,84
Italy	0,97	0,94	0,92	0,88	0,97	0,89	0,93	0,92	0,98	1,00	0,96	0,95	0,95	0,93	0,95	0,94
Latvia	1,00	0,98	0,91	0,92	0,87	0,70	0,79	0,80	0,81	0,79	0,80	0,77	0,72	0,65	0,68	0,81
Lithuania	1,00	1,00	0,97	0,96	0,95	0,83	0,85	0,82	0,86	0,85	0,84	0,76	0,73	0,67	0,68	0,85
Netherlands	0,55	0,55	0,54	0,51	0,50	0,42	0,47	0,45	0,44	0,49	0,45	0,43	0,44	0,45	0,47	0,48
Poland	0,45	0,41	0,41	0,40	0,41	0,34	0,36	0,35	0,35	0,37	0,36	0,31	0,28	0,26	0,29	0,36
Portugal	0,94	0,97	0,97	0,98	0,94	0,98	0,99	1,00	1,00	1,00	0,89	0,88	0,78	0,80	0,85	0,93
Romania	0,88	0,84	0,87	0,87	0,95	0,88	0,77	0,77	0,87	0,86	0,83	0,82	0,77	0,76	0,78	0,84
Slovakia	0,48	0,51	0,57	0,54	0,58	0,53	0,57	0,62	0,58	0,66	0,65	0,61	0,55	0,56	0,58	0,57
Slovenia	0,64	0,63	0,63	0,54	0,60	0,54	0,53	0,53	0,54	0,62	0,59	0,53	0,52	0,54	0,57	0,57
Spain	0,88	0,93	0,88	0,97	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,93	0,92	0,99	0,97
Sweden	0,96	0,95	0,94	0,94	0,93	0,80	0,89	0,89	0,92	0,98	0,96	0,96	0,99	1,00	1,00	0,94
Yearly mean	0,72	0,70	0,69	0,68	0,70	0,64	0,66	0,67	0,68	0,71	0,68	0,65	0,63	0,64	0,66	0,67

Appendix 6: Output elasticities with respect to total energy consumption *per* worker, 2005-2019

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
Austria	1,33	1,34	1,37	1,35	1,42	1,33	1,38	1,38	1,36	1,41	1,40	1,41	1,43	1,45	1,44	1,39
Belgium	1,30	1,32	1,37	1,36	1,46	1,42	1,46	1,51	1,56	1,56	1,59	1,68	1,70	1,67	1,75	1,51
Bulgaria	1,95	1,94	1,94	1,95	1,98	1,98	1,96	1,96	1,97	1,96	1,95	1,94	1,93	1,92	1,92	1,95
Croatia	1,79	1,77	1,81	1,85	1,87	1,87	1,88	1,89	1,89	1,90	1,88	1,88	1,87	1,86	1,86	1,86
Cyprus	1,55	1,53	1,63	1,62	1,71	1,69	1,77	1,78	1,80	1,80	1,78	1,77	1,76	1,76	1,77	1,72
Czech Republic	1,82	1,82	1,83	1,83	1,84	1,83	1,84	1,84	1,84	1,84	1,83	1,83	1,82	1,82	1,82	1,83
Denmark	1,78	1,78	1,78	1,78	1,79	1,78	1,79	1,79	1,79	1,79	1,79	1,79	1,79	1,79	1,75	1,78
Estonia	1,78	1,78	1,76	1,76	1,78	1,78	1,78	1,77	1,77	1,78	1,77	1,77	1,77	1,76	1,76	1,77
Finland	0,76	0,68	0,69	0,76	0,99	0,88	0,88	0,91	0,89	0,88	0,90	0,89	0,90	0,84	0,89	0,85
France	1,80	1,81	1,82	1,82	1,84	1,83	1,84	1,83	1,82	1,85	1,85	1,84	1,84	1,84	1,85	1,83
Germany	1,86	1,86	1,87	1,87	1,88	1,87	1,87	1,87	1,87	1,87	1,87	1,87	1,87	1,87	1,87	1,87
Greece	1,88	1,87	1,87	1,87	1,88	1,90	1,90	1,92	1,94	1,93	1,92	1,91	1,92	1,92	1,91	1,90
Hungary	1,88	1,88	1,89	1,89	1,90	1,89	1,89	1,90	1,90	1,90	1,89	1,88	1,87	1,87	1,86	1,89
Ireland	1,61	1,63	1,68	1,76	1,79	1,79	1,80	1,80	1,80	1,80	1,80	1,79	1,79	1,79	1,79	1,76
Italy	1,86	1,86	1,86	1,87	1,90	1,88	1,91	1,91	1,92	1,93	1,92	1,92	1,92	1,92	1,92	1,90
Latvia	1,78	1,74	1,69	1,74	1,74	1,82	1,76	1,79	1,77	1,81	1,80	1,81	1,79	1,78	1,78	1,77
Lithuania	1,90	1,88	1,87	1,87	1,89	1,88	1,87	1,86	1,87	1,86	1,86	1,84	1,83	1,82	1,81	1,86
Netherlands	1,44	1,47	1,50	1,60	1,67	1,76	1,73	1,78	1,82	1,82	1,82	1,82	1,81	1,79	1,77	1,71
Poland	1,96	1,96	1,95	1,95	1,96	1,94	1,94	1,94	1,94	1,95	1,95	1,93	1,91	1,89	1,89	1,94
Portugal	1,88	1,88	1,88	1,89	1,89	1,89	1,90	1,92	1,92	1,92	1,91	1,90	1,89	1,87	1,87	1,89
Romania	2,02	2,02	2,03	2,02	2,05	2,03	2,02	2,02	2,03	2,03	2,02	2,02	2,00	2,00	1,99	2,02
Slovakia	1,83	1,84	1,84	1,84	1,86	1,84	1,85	1,86	1,86	1,87	1,87	1,86	1,84	1,84	1,84	1,85
Slovenia	1,77	1,77	1,77	1,76	1,78	1,78	1,78	1,78	1,79	1,79	1,79	1,78	1,77	1,77	1,77	1,78
Spain	1,87	1,89	1,88	1,90	1,93	1,93	1,93	1,94	1,95	1,95	1,94	1,94	1,92	1,91	1,93	1,92
Sweden	1,18	1,20	1,20	1,23	1,31	1,17	1,27	1,25	1,29	1,34	1,31	1,30	1,31	1,33	1,35	1,27
Yearly Mean	1,70	1,70	1,71	1,73	1,76	1,75	1,76	1,77	1,77	1,78	1,78	1,77	1,77	1,76	1,77	1,75

Appendix 7: Output elasticities with respect to total human capital *per* worker, 2005-2019

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
Austria	4,57	4,58	4,58	4,58	4,57	4,58	4,57	4,57	4,57	4,56	4,56	4,56	4,56	4,55	4,56	4,57
Belgium	4,44	4,43	4,42	4,42	4,41	4,42	4,40	4,40	4,40	4,39	4,40	4,40	4,40	4,40	4,40	4,41
Bulgaria	4,40	4,42	4,42	4,42	4,40	4,40	4,41	4,42	4,43	4,44	4,46	4,48	4,50	4,51	4,52	4,44
Croatia	4,83	4,84	4,80	4,81	4,81	4,82	4,82	4,82	4,83	4,83	4,86	4,87	4,90	4,91	4,93	4,84
Cyprus	5,77	5,77	5,74	5,75	5,73	5,71	5,69	5,67	5,65	5,67	5,70	5,71	5,72	5,71	5,71	5,71
Czech Republic	4,43	4,43	4,42	4,41	4,40	4,40	4,41	4,41	4,41	4,41	4,43	4,44	4,45	4,45	4,46	4,42
Denmark	4,82	4,83	4,83	4,82	4,82	4,83	4,83	4,82	4,82	4,82	4,82	4,82	4,82	4,82	4,82	4,82
Estonia	5,55	5,55	5,57	5,58	5,56	5,57	5,57	5,58	5,58	5,59	5,60	5,61	5,62	5,63	5,63	5,59
Finland	4,91	4,92	4,92	4,92	4,90	4,92	4,92	4,93	4,93	4,93	4,94	4,95	4,95	4,96	4,97	4,93
France	3,40	3,39	3,39	3,39	3,38	3,39	3,38	3,39	3,40	3,37	3,38	3,39	3,39	3,40	3,40	3,39
Germany	3,31	3,32	3,31	3,32	3,31	3,34	3,33	3,33	3,34	3,32	3,32	3,32	3,32	3,32	3,32	3,32
Greece	4,24	4,25	4,25	4,25	4,25	4,24	4,25	4,24	4,23	4,24	4,27	4,28	4,28	4,29	4,30	4,26
Hungary	4,33	4,33	4,33	4,34	4,34	4,35	4,35	4,35	4,35	4,36	4,38	4,39	4,41	4,42	4,42	4,36
Ireland	4,89	4,88	4,85	4,84	4,82	4,83	4,82	4,82	4,83	4,83	4,84	4,84	4,84	4,84	4,84	4,84
Italy	3,35	3,35	3,35	3,35	3,34	3,35	3,34	3,34	3,34	3,33	3,34	3,35	3,35	3,36	3,37	3,35
Latvia	5,16	5,18	5,20	5,19	5,19	5,21	5,22	5,24	5,24	5,26	5,27	5,28	5,31	5,33	5,34	5,24
Lithuania	4,92	4,94	4,96	4,97	4,95	4,97	5,00	5,02	5,02	5,03	5,04	5,06	5,09	5,11	5,12	5,01
Netherlands	4,19	4,19	4,19	4,19	4,18	4,20	4,19	4,19	4,19	4,18	4,19	4,20	4,20	4,20	4,20	4,19
Poland	3,55	3,55	3,56	3,56	3,56	3,59	3,58	3,59	3,59	3,60	3,61	3,63	3,66	3,68	3,70	3,60
Portugal	4,12	4,12	4,13	4,13	4,13	4,14	4,14	4,13	4,14	4,15	4,17	4,18	4,19	4,20	4,21	4,15
Romania	3,79	3,79	3,78	3,78	3,76	3,83	3,83	3,84	3,84	3,85	3,86	3,87	3,90	3,91	3,93	3,84
Slovakia	4,76	4,75	4,74	4,75	4,73	4,74	4,74	4,73	4,74	4,73	4,74	4,75	4,77	4,78	4,79	4,75
Slovenia	5,30	5,30	5,30	5,31	5,29	5,30	5,30	5,30	5,30	5,30	5,32	5,33	5,34	5,35	5,36	5,31
Spain	3,44	3,43	3,42	3,40	3,39	3,40	3,40	3,40	3,40	3,41	3,42	3,43	3,44	3,45	3,45	3,42
Sweden	4,58	4,58	4,58	4,57	4,56	4,57	4,56	4,56	4,56	4,55	4,55	4,55	4,54	4,53	4,53	4,56
Yearly Mean	4,44	4,44	4,44	4,44	4,43	4,44	4,44	4,44	4,45	4,45	4,46	4,47	4,48	4,49	4,49	4,45

Appendix 8: Output elasticities and returns to scale 2005-2019

Country	Human Capital elasticity	Energy consumption elasticity	Returns to scale
Austria	4,568	1,386	5,955
Belgium	4,410	1,515	5,925
Bulgaria	4,442	1,951	6,392
Croatia	4,844	1,858	6,702
Cyprus	5,713	1,715	7,429
Czech Republi	4,423	1,830	6,254
Denmark	4,823	1,784	6,607
Estonia	5,586	1,772	7,357
Finland	4,932	0,850	5,782
France	3,389	1,831	5,220
Germany	3,322	1,871	5,193
Greece	4,258	1,902	6,160
Hungary	4,363	1,886	6,249
Ireland	4,840	1,762	6,602
Italy	3,347	1,901	5,248
Latvia	5,242	1,775	7,017
Lithuania	5,013	1,861	6,874
Netherlands	4,192	1,707	5,898
Poland	3,600	1,937	5,537
Portugal	4,152	1,893	6,045
Romania	3,837	2,019	5,856
Slovakia	4,748	1,849	6,598
Slovenia	5,314	1,777	7,091
Spain	3,418	1,921	5,339
Sweden	4,557	1,269	5,826
Mean	4,453	1,753	6,206

Appendix 9: Decomposition analysis: Sources of decoupling growth between GDP and GHG emissions.

Country	GDP/CO2 growth *	Human Capital per worker accumulation *	Energy consumption per worker accumulation *	Technical change	Technical efficiency change *	Scale effect change *	Random shock
Austria	2,350	0,014	-0,291	0,408	-1,068	-0,003	3,291
Belgium	2,499	0,036	-0,458	0,408	-0,704	-0,004	3,221
Bulgaria	2,938	-0,169	0,497	0,408	-1,730	0,003	3,929
Croatia	2,504	-0,168	-0,133	0,408	-0,914	-0,009	3,320
Cyprus	2,162	0,058	-0,557	0,408	-1,006	-0,005	3,263
Czech Repu	3,578	-0,046	0,004	0,408	-0,258	-0,002	3,472
Denmark	4,174	-0,028	-0,596	0,408	0,535	-0,011	3,867
Estonia	3,725	-0,115	0,249	0,408	-0,197	-0,001	3,381
Finland	2,718	-0,085	0,093	0,408	-1,103	-0,003	3,409
France	2,594	-0,037	-0,715	0,408	-0,002	-0,012	2,952
Germany	2,516	-0,023	-0,083	0,408	-1,205	-0,001	3,420
Greece	2,269	-0,156	-0,963	0,408	0,117	-0,021	2,885
Hungary	2,815	-0,135	0,273	0,408	-1,414	0,000	3,682
Ireland	5,071	0,049	-0,777	0,408	1,889	-0,010	3,511
Italy	2,204	-0,080	-0,904	0,408	-0,123	-0,017	2,921
Latvia	2,104	-0,218	1,073	0,408	-2,529	0,008	3,362
Lithuania	2,960	-0,214	1,805	0,408	-2,539	0,022	3,480
Netherlands	2,041	-0,042	-0,498	0,408	-1,061	-0,008	3,243
Poland	3,562	-0,152	1,553	0,408	-3,005	0,022	4,736
Portugal	2,756	-0,160	-0,237	0,408	-0,628	-0,010	3,383
Romania	4,434	-0,189	0,500	0,408	-0,835	0,003	4,547
Slovakia	4,717	-0,073	-0,260	0,408	1,276	-0,007	3,372
Slovenia	2,741	-0,087	-0,124	0,408	-0,718	-0,006	3,268
Spain	3,146	-0,056	-0,812	0,408	0,782	-0,015	2,838
Sweden	3,603	0,038	-0,760	0,408	0,242	-0,007	3,681
Mean	3,047	-0,082	-0,085	0,408	-0,648	-0,004	3,457

* Compound annual % rate