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Clean and Dirty Energy:
A Time-Varying Estimation of Elasticities

Master thesis, 2023
Master of Science in Business Administration
University of Stavanger Business School
Specialization: Economics

Preface

We (Nicolás and Shanti) are pleased to present this master thesis titled "Clean and Dirty Energy: A Time-Varying Estimation of Elasticities". This thesis is submitted in fulfillment of the requirements for the Master of science in Business Administration in Economics Analysis degree at University of Stavanger (UiS).

This thesis aims to contribute to the existing body of knowledge in Energy economics and Economic growth. It explores the dynamics output elasticities of clean and energy inputs and the elasticity of substitution between both sources of energy. Through this research, we hope to provide a comprehensive analysis and propose meaningful recommendations for future studies in this field.

We would like to express our sincere gratitude to our supervisor Fuchen Zhang for his unwavering support, expertise and invaluable guidance. His insightful comments and constructive feedback have greatly shaped the direction and quality of this thesis. We are grateful for his patience, encouragement, and trust in our abilities.

We extend our heartfelt gratitude to the dedicated staff and esteemed faculty members at University of Stavanger, Business School, whose guidance and support have been instrumental in shaping our knowledge and intellectual growth. We would also like to acknowledge the materials and references that were helpful to the development of this thesis. The works of specialists in the field - researchers, academics, and authors- have served as a guiding light, enhancing our comprehension of the subject matter.

We would also like to thank our family and friends for their support throughout the course, without whom it would not have been possible.

Stavanger, 14.06.2023

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List of Abbreviation

CES: Constant elasticity of substitution
CO_2: Carbon Dioxide
EC: Clean Energy
ED: Dirty Energy
ETI: Energy Transition Index
GO: Gross Output
K: Capital
MES: Morishima Elasticity of substitution
IMS- Intermediate Material and Service inputs
NACE: Statistical Classification of Economic Activities in the European Community
PPP- Purchasing Power Parities
R&D: Research and Development
TJ: Terajule
TV: Time-Varying
USD: United State Dollar
WIOD: World Input output database

Abstract

Purpose – The success of economic green growth requires the degree of elasticity of substitution between the clean and dirty energy inputs to be more than one. This research studies the dynamics of the elasticity of substitution between the two energy inputs in the context of an economic growth model described by a CES nested into Cobb-Douglas specification function energy inputs. We also estimate the output elasticities of clean and dirty energy inputs. We use an updated version of the dataset compared to the previous literature on this field. Our methodology consists of a panel data on a dataset of 38 countries from 2000 to 2014 and a time-varying panel model to analyze the dynamics of the elasticities.

Design/Methodology/Approach – We estimate a linear version of the CES nested into Cobb-Douglas production function. The linear equation comes from the Kmenta approximation. We provide two estimations. First, in line with the previous literature, we estimate the model assuming equal weights in the production function for dirty and clean energy inputs. Here we compute the elasticity of substitution between both sources. For the second, we release that assumption and compute the elasticity of substitution between the two and the output elasticities of both sources. We also estimate a time-varying panel model. We compute the dynamics of the output elasticities of clean and dirty energy inputs and the elasticity of substitution between the energy inputs.

Findings – Under equal weights, we estimate an elasticity of substitution between clean and dirty energy inputs larger than one. However, under different weights, the elasticity estimated is negative. In this case, our estimation shows a large difference in the coefficients of clean and dirty energy inputs. Therefore, we do not support the assumption of equal weights. Our time-varying estimation shows the elasticity of substitutions is negative in half of the analyzed period. The clean energy output elasticity is higher than the dirty energy output elasticities during the whole period. However, the difference between the output elasticities become shorter after 2008.

Originality/Value - Our research makes an original contribution by releasing strong assumptions and by estimating a time-varying model to understand the dynamics of the output elasticities of clean and dirty energy inputs.

Keywords: Clean and Dirty Energy inputs, Panel Data, Elasticity of substitution, Output elasticity, time-varying.

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1. Introduction

According to the theoretical Environmental Kuznets Curve (EKC), the relationship between economic growth and environmental degradation is defined by an inverted U-shaped curve. The main implication of this theory is an automatic decoupling between carbon emissions and economic growth. However, the empirical evidence usually is against this theory (Alvarez-Herranz et al., 2017; Soytas et al., 2007). Instead, empirical evidence finds a N-shaped pattern, which implies a potential return to rising emission levels once economies have achieved negative pollution rates (Alvarez-Herranz et al., 2017). Therefore, economies cannot rely on traditional economic growth to improve the quality of the environment (Soytas et al., 2007). Instead, sustainability or green concepts needs to be included in the definition of economic growth. Consistently, governments around the world have implemented policies to increase the use of clean energy. However, the success of the implemented policies depends on structural conditions of the production system in the economy. One of the key parameters is the elasticity of substitution between clean and dirty energy inputs. Before introducing the importance of the elasticity of substitutions, it is appropriate to see the context of energy consumption. Section 1.1 shows some facts regarding the consumption of clean and dirty energy inputs.

1.1 Background

We build our background with the data we use in our analysis. The data has information for 38 countries and 10 sectors from 2000 to 2014. However, to avoid the outliers and missing values present in the data, we eliminate some observations ending up with data for 37 countries from 2003 to 2014[1]. Section 3 describes the entire data set. *Figure 2* shows that both clean and dirty energy inputs have an increasing pattern, the data shows that both sources exhibit similar trends. The coefficient of correlation between clean and dirty energy is 0.70. Measured per employees engaged, dirty energy consumption shows a decreasing pattern while clean energy is exhibiting a constant behavior*;* depicted in *Figure 1.* Energy Consumption per Employee. When measured per gross output (GO), both sources of energy exhibit a decreasing pattern as depicted in *Figure 3*. In fact, the coefficient of correlation between the energy series in levels and the level of GO is negative. Finally, the annual growth rate of the GO and energy sources per employee shows a

[1] The elimination is done for the background and the descriptive information. However, we use the entire data from 2000 to 2014 and for all 38 countries for our econometric analysis.

positive relationship*;* this is depicted in *Figure 4*. The correlation between the annual growth of GO and dirty energy consumption is 0.10 and that for clean energy and GO is 0.18. The annual growth between both energy inputs is similar and the coefficient of correlation is 0.47.

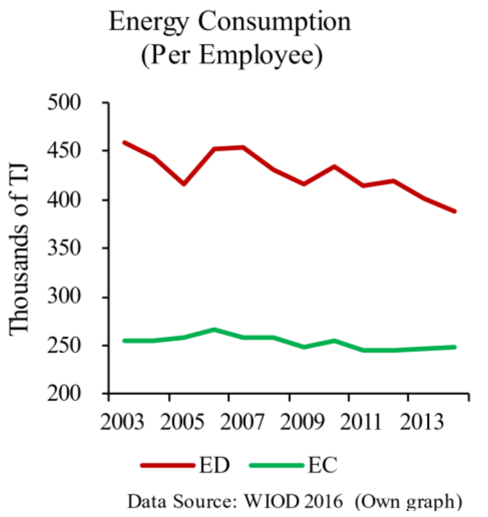

Figure 1. Energy Consumption per Employee

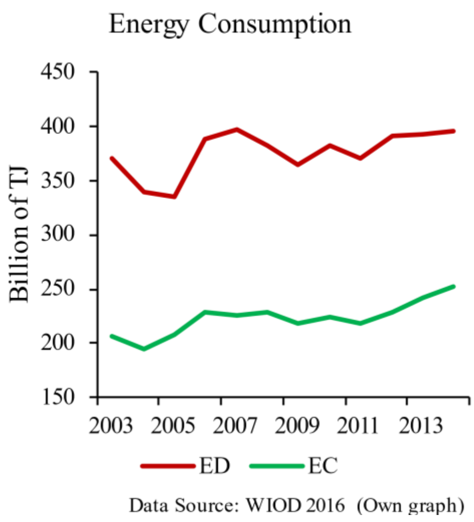

Figure 2. Energy Consumption

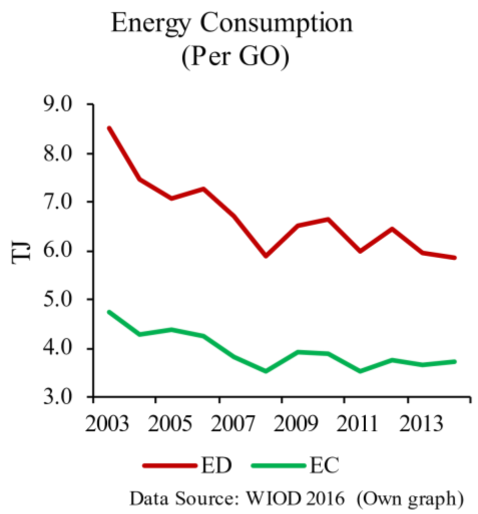

Figure 3. Energy Consumption per GO

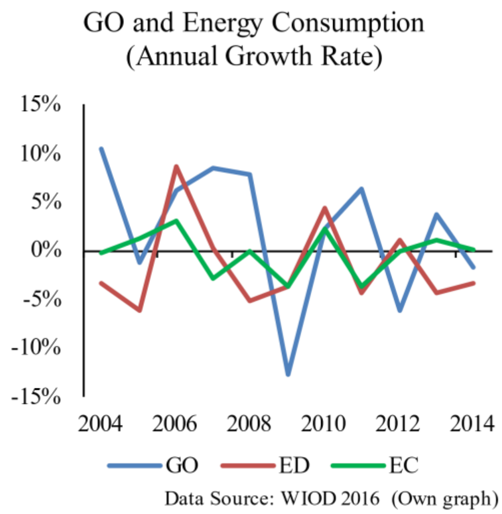

Figure 4. GO and Energy Consumption

Figure 5. Clean and Dirty Energy Input per GO shows the behavior across time from 2003-2014 of the clean and dirty energy inputs per GO of the data aggregated by year. It is observed that the clean energy input has a lower value compared with dirty energy input. The plot shows the

values tend towards the bottom-left with increasing year. This shows that GO is increasing at a higher rate than energy consumption for most of the years.

One of the largest transitions from the highest point 2003 to 2004 was marked by a 13.5% increase in GO. During this period, dirty energy consumption in the production sector slightly decreased while clean energy consumption slightly increased. Consequently, both dirty per GO and clean per GO also decreased from 2003 to 2004. Similar observation can be made for the year 2006-2007.

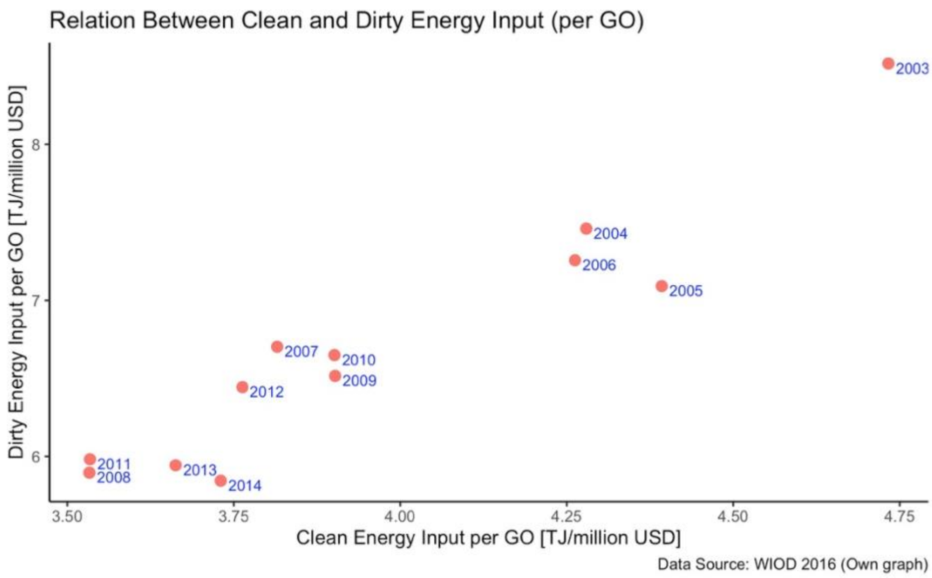

Figure 5. Clean and Dirty Energy Input per GO

Conversely, the data shows that, for the years 2008-2009 and 2011-2012, the values are increasing. These coincided with the global economic crises in 2008 and 2011-12 respectively. It can also be observed from the data from *Table 10*: Yearly Aggregated Data that the GO experienced a huge decline of 12.78% while dirty energy consumption in the production sector decreased by 1.85%, while clean energy consumption also decreased by 3.26% from 2008-2009. The corresponding change in 2011-2012 were 5.98% decrease in GO and 0.67% increase in dirty and 0.65% decrease in clean energy consumption respectively.

In summary, we see some gains in efficiency since the consumption of energy by units of GO is decreasing[2]. Nevertheless, the described context does not allow to say that clean energy inputs

[2] According to the IEA the global economy has used energy 2% more efficient in 2022 compared to 2021. The rate of efficiency has increased slowly in the last years, InternationalEnergyAgency. (2022). *Global energy efficiency progress is accelerating, signalling a potential turning point after years of slow improvement*. IEA. Retrieved 22 May 2023 from

are successfully replacing dirty energy inputs. Therefore, the so-called energy transition might not be taking place as expected despite governments efforts. However, this phenomenon is reshaping the economic system, and understanding the consequences is crucial in order to address it properly.

Energy transition is taking place in governments and firms' agenda. According to the Energy Transition Index (ETI) elaborated by the World Economic Forum, Scandinavian countries are the leaders.

Energy transition has become a key economic growth driving force. It involves several aspects such as: investment to substitute dirty energies, changes in industry level productivity growth and risk premia, (Nodari & Rees, 2022). Thereby, a traditional static linear model might not be the ideal approach to estimate the effects associated to the variables involved in a green model of economic growth since the value of important parameters such as the elasticity of substitution can be affected during the transition.

Table 1: ETI 2021

Ranking	Country	ETI
1	Sweden	79
2	Norway	77
3	Denmark	76
4	Switzerland	76
5	Austria	75
6	Finland	73
7	United Kingdom	72
8	New Zealand	71
9	France	71
10	Iceland	71
113	Mongolia	44
114	Haiti	42
115	Zimbawe	49

Source: World Economic Forum (2021)

https://www.iea.org/news/global-energy-efficiency-progress-is-accelerating-signalling-a-potential-turning-point-after-years-of-slow-improvement

1.2 Research Purpose

Acemoglu et al. (2012), AABH hereafter, have shown the relation between growth and pollution in a framework of directed technical change. The elasticity of substitution between clean and dirty energy inputs plays a crucial role to achieve green long economic growth. This parameter needs to be assessed to decide the optimal long-term environmental policy. An elasticity higher than one is a necessary condition for long-green growth and to make transition to clean energies easier without excessively hurting economic growth. Below one, a tighter policy is needed.

Regarding the empirical findings on the elasticity of substitution, further research like Papageorgiou et al. (2017) (PSS hereafter), estimate elasticities of substitution between clean and dirty energy inputs higher than one for the electricity sector and for the non-energy industries. By applying non-parametric methods to the same data, Malikov et al. (2018) found that the elasticity of substitution for non-energy sector is higher than one only for one-third of the industries/countries.

Far from a constant parameter, the elasticity of substitution between energy inputs is influenced by changes, for instance, in infrastructure. Understanding the dynamics of this parameter is essential to support the efforts in the so-called energy transition.

We extend the research of PSS by estimating the time-varying elasticity between clean and dirty energy inputs. In addition, we provide the elasticities between the gross output and dirty energy inputs and between the gross output and clean energy inputs. We benefited from the second release of WIOD data which allowed us to expand the sample from 26 countries in the PSS paper to 38 countries for the years of 2000-2014[3]. We keep the same distinction between clean and dirty inputs, i.e., dirty are all sources generating CO2 emissions, while clean are all that don't generate CO2 emissions. In addition to the update, our data has two differences: First, we have our data in terms of total employees engaged, instead of total hours by engaged employees as done by the PSS; Second, we aggregated the data in 10 main NACE[4] sectors.

The purpose of our research is thus to contribute to the previous research by estimating the elasticity of substitution between clean and dirty energy with updated data. We perform this by estimating the model with and without assuming equal weights for the energy inputs. Under equal weights we estimate an elasticity of 1.5 while for free weights we get a negative elasticity.

[3] As noted earlier, for the background we use a subsample from 2003 to 2014.
[4] NACE is the statistical classification of economic activities in the European community.

Under free weights we get a coefficient for clean energy notably larger than the coefficient of the dirty energy input, meaning that under equal weights coefficients are biased. We also estimate the dynamics of the output elasticity of clean and dirty energy inputs. We get a large difference between the output elasticity of clean energy input and dirty energy input. However, the difference become shorter between 2008 and 2014.

The rest of the paper is organized as follows. Section 2 Literature Review, Section 3: Data, Section 4: Theoretical framework, Section 5: Econometric Methodology, Section 6: Results, Section 7: Discussion, Section 8: Conclusion.

2. Literature Review

2.1 Economic growth and energy consumption

2.1.1 Theoretical Perspective

Economic growth was conventionally considered a result of technological progress, saving rate and research and development by economists. According to The Solow model (Solow, 1956), sustained economic growth is contingent upon technological advancements. Further research showed that R&D are indispensable factors for economic growth (Romer, 1990). Energy consumption was identified as a relevant variable for economic growth, Kraft and Kraft (1978), however, one of the first estimation of this relationship using a production function that relates capital, labor and electric power to GDP was developed by Beaudreau (1995). This research found that the residual attributed to technological progress in the Solow model almost disappeared when energy consumption was included. One of the first endogenous growth models with energy consumption is (Moon & Sonn, 1996). These authors used this model to explain why some countries exhibit a sustained growth rate without converging to a certain equilibrium rate.

2.1.2 Empirical perspective

The empirical research about economic growth and energy consumption has studied the relationship between these two. Most of this literature has used co-integration techniques in panel data. The evidence strongly supports a close relationship. For instance, (Ozturk et al., 2010) developed a cointegrated panel data analysis for 51 low, medium and high-income countries and found that energy consumption and economic growth are cointegrated. Similarly, Apergis and Payne (2010) found a long-term equilibrium between energy, economic growth, capital formation, and the labor force for nine south Americans countries. In addition, this relationship may not be stable on time. Using a non-parametric panel, Ren et al. (2022) found an inverted U-shaped relationship between economic growth and energy consumption.

There are also studies on the direction of the causality. (Omri, 2014; Ozturk, 2010) are survey papers that summarize the empirical findings in this regard. Ozturk (2010), shows the lack of consensus regarding the existence and the direction relation between economic growth and energy consumption. According to Omri (2014), 29% of the literature supports energy consumption as a key driver for economic growth while 27 % support a bidirectional relation between these two variables.

2.2 Green or Sustainable Economic Growth

2.2.1 Theoretical Perspective

In the literature of economic growth linked to solving environmental concerns, we have observed that green economic growth and sustainable economic growth are similar concepts. Some research focuses on renewable energy which does not include nuclear energy[5], while others focus on clean energy which includes nuclear energy. In general, under "laiseez-faire", the economy does not internalize the global warming externality, and thus policy intervention that internalize global warming externality is necessary. We have found four green adaptations from traditional model of economic growth:

- **The Green Solow Model:** Brock and Taylor (2010) develop this model to include technological progress in the abatement cost of pollution. In this, the forces of diminishing returns and technological progress identified by the original Solow model as fundamental to the growth process may also be fundamental to the EKC finding. In addition, the model predicts convergence in emissions per capita across countries.
- **The Green Endogenous Growth Model:** Acemoglu et al. (2012) introduces endogenous and directed technical changes in a growth model with environmental constraints and limited resources. They show how environmental policies can

[5] Nuclear energy although is a clean source of energy, is an exhaustible resource.

influence the direction of technical change, which can affect economic growth and environmental quality. Besides, if the elasticity of substitution between the clean and dirty energy inputs is higher than one, i.e., these are sufficiently substitutable, then sustainable economic growth can be achieved using temporary policy intervention. However, if the elasticity of substitution between clean and dirty energy is less than 1, it means that the two types of energy are complements. Consequently, permanent government regulation is needed to avoid an environmental disaster.

- **The Green Ramsey Model:** Van Der Ploeg and Withagen (2014) develop a model to analyze the occurrence of the so-called green paradox[6]. The social optimum can be only achieved by policies that internalize global warming externality. The utilized policy is carbon taxes since it does not lead to a green paradox. When taxes are not feasible, the alternative is subsidies on renewable energies. Subsidies lead to a faster extraction of oil in the short-term which exacerbates the damage to the environment. However, once clean energies become the main source, the remaining unextracted oil quantity is bigger than under carbon taxes. The long-term effect on the quality of the environment is ambiguous.
- **The Green Uzawa and Lucas Model:** In this model Jin et al. (2021) show a mechanism that enables fossil fuel-rich countries to save stranded assets and safeguard the wealth and employment associated with fossil fuel. This is because of the beneficial relationship between dirty and clean capital; clean capital accumulation induced by tightened environmental regulation mitigates the polluting effect of dirty capital which creates more room for dirty capital accumulation. This accumulation increases the gross output which increases the resources to boost clean capital accumulation. Therefore, dirty and clean capital can coexist and grow together.

2.2.2 Empirical Perspective

From an empirical perspective, the findings about the relationship between renewable sources of energy and economic growth are mixed. Inglesi-Lotz (2016) uses panel data with a sample of OECD countries and finds a positive relationship between these two variables. However, an extension of that research shows that this is only true for lower and low-middle quantiles in the same sample (Dogan et al., 2020). On the same line, Chakraborty and Mazzanti (2021) find a

[6] The green paradox is a situation in which environmental policies that increase the use of clean energies by substituting dirty in the future encourage oil to be extracted faster which might accelerate global warming (Van Der Ploeg & Withagen, 2014)

significant positive long-term relationship between renewable electricity consumption and economic growth.

2.3 Interfuel Substitution Elasticity

According to Kumar et al. (2015), interfuel elasticity plays an important role in climate change mitigation. The more challenging it is to switch between clean and dirty energy sources, the more expensive climate change efforts become. Interfuel elasticity is one of the most important parameters to evaluate the effectiveness of substitution between energy sources (Stern, 2012).

In a meta-analysis of the interfuel elasticity literature, Stern (2012) found that at the industrial sector level, the shadow elasticities between oil-coal, oil-gas, oil-electricity and gas-electricity are significantly greater than one. Lanzi and Sue Wing (2011) estimated the elasticity of substitution between interfuel (clean and dirty) energy inputs in the energy sector by using dynamic model for OECD countries from 1978-2006 to be 1.6, indicating a positive relationship between the price of fossil fuels and the development of green innovation. Similarly, Meng (2016) also found the elasticity of greater than one (3.6 to be precise), in the interfuel substitution between coal and other fuel in the U.S energy sectors.

Elsewhere, Serletis et al. (2009) have found that the interfuel substitution elasticities between the major energy commodities (coal, oil, gas and electricity) to be less than one. There are findings of elasticities bigger than one between electricity, natural gas and light fuel oil but only limited substitutability between electricity and natural gas (Jadidzadeh & Serletis, 2016).

The study estimating the elasticity of substitution between different fossil fuels and renewable resources was first done by Kumar et al. (2015). The paper applies Morishima Elasticity of substitution (MES)[7] between different fossil fuel and renewable resources using industry level data for OECD countries from 1995-2009. The paper shows the complementary relationship between the renewable and non-renewable energy in metal, chemical, construction, food, mineral, pulp, textile, and wood industries, especially in food and pulp industries.

[7] A manufacturing process's ability to substitute two sources of production—typically labor and capital—while maintaining the same level of output is known as the Morishima elasticity of substitution, Blackorby, C., & Russell, R. R. (1989). Will the real elasticity of substitution please stand up?(A comparison of the Allen/Uzawa and Morishima elasticities). *The American economic review*, *79*(4), 882-888.

2.4 Substitution Between Clean and Dirty Energy

Regarding energy consumption, various forms of energy inputs are utilized to produce goods and services. Energy is commonly divided into two forms namely "clean energy" and "dirty energy". Clean energy refers to energy sources that do not emit carbon dioxide (CO_2) while dirty energy refers to those that emit CO_2. One of the key parameters[8] that indicate if energy inputs are substitutes or complements is the elasticity of substitution. The higher the elasticity the easier the substitution is.

The transition from dirty to clean energy might be costly (Dogan et al., 2020). The reallocation of resources from dirty to clean energy requires incentives. The main policy instruments to redirect resources from dirty to clean energy are carbon taxes and subsidies to clean energy. However, the effectiveness of these policies is related to the production structure of an economy (PSS).

The main condition required in the production structure to increase the share of clean sources and reach green economic growth is the factual possibility of substituting dirty energy by clean. For instance, the electricity sector can adopt clean energy sources more easily than other sectors. On the other side, the industrial process of cement and steel production requires fossil fuels[9], and in this case substitution between dirty and clean energies is more difficult, (PSS).

In this regard, Ma et al. (2008) found that, in China's context, coal is significantly substitutable with electricity and complementary with diesel and gasoline. Furthermore, electricity is found to be substitutable with diesel.

Diverse implications can be derived from the elasticity of substitution. A very low elasticity of substitution means that the economy cannot reduce the dependence of dirty energy. Besides, due to the complementary relationship between clean and dirty a higher consumption of clean energy lead to an increase on dirty energy. This scenario may lead the economy to an environmental disaster, in that case a permanent intervention is required. On the other side, when energy inputs are sufficiently substitutable, so the elasticity of substitution is higher than one, green or sustainable economic growth can be achieved with temporary taxes/subsidies, AABH.

[8] The other parameter is the discount rate, AABH.

[9] Steel and cement production requires high and continuous temperatures which demand and stable and high amount of energy difficult to get from clean energies, Ghoneim, R., Mete, G., & Hobley, A. (2022). *Steel and cement can drive the decade of action on climate change.*

Several extensions of AABH research have been developed and the findings are mixed. On one side PSS, find that the elasticity of substitution in the final good sector is 2.8 in the case of a nonlinear model and 1.4 in the case of a linear model. On the other side, Malikov et al. (2018), using the same data but a non-parametric approach, found that the elasticity is greater than one only for one third of the sample and a mean range of 0.06-0.31. The data in both cases is from 1995 to 2011. In our case we use updated data that we describe in section 3.

2.5 Why time-varying?

Data generation mechanism is quite often affected by intertemporal relationships. It is the case of seasonal effects which is solved by including dummy variables (Tucci, 1995). It can be the case of switching regimes which can be estimated with techniques like Threshold Autoregressive and Markov Switching models (Maitland-Smith & Brooks, 1999). However, the dynamic effects such as the effects linked to the energy transition cannot be captured by those techniques (Fan & Zhang, 2008).

According to Fan and Zhang (2008) in cross-country growth models, like the one presented in our thesis, standard linear model assumptions are not supported by the data. The set of independent variables and the country's growth rate will depend on its state of development, and the dynamical pattern of this relationship is crucial. It is more convenient to treat the parameters of growth models as functions of the state of development, which leads to a standard varying coefficient model.

In the literature energy economics, the application of time-varying techniques has been applied in some research. Ren et al. (2022), found that the relation between energy consumption and economic growth is indeed varying over time. Nevertheless, the dynamics of some key parameters, such as the elasticity of substitution between energy inputs remains non estimated.

According to Mattauch et al. (2015), the elasticity of substitution between clean and dirty energy is not a natural constant. It is influenced by, for example, changes in infrastructure. They expect an increasing elasticity of substitution in the coming decades due to investments that affect infrastructure. However, they do not provide an estimation.

3. Data

3.1 Information about the Data Source

The data utilized in this study was obtained from the World Input-Output Database (WIOD). The WIOD provides transactional values among 56 industries, households, governments, within 43[10] countries and most of them are European countries (Timmer et al., 2015). The database has two data releases: the first, released in 2013, pertains to the period from 1995 to 2011[11], while the second, released in 2016, comprises data from 2000 to 2014[12].

3.2 Information about the Dataset

For our analysis we used the second release from the WIOD database. We used the data from 2000-2014 for econometric analysis. However, certain countries, such as China, The Netherlands, Cyprus, Greece, and Taiwan are excluded from the analysis due to insufficient or poor information. The Netherlands has incomplete information regarding energy data, as China has been excluded due to missing values for hours worked. In the case of Greece, there were inconsistencies in dirty energy information, and there was same issue with Cyprus and Taiwan as well. Furthermore, there were some outliers in the dataset, so we also deleted those outliers.

After the cleansing of the data with the specifications above, the resulting dataset contains 5,633 observations for 38 countries, including: **AUS, AUT, BEL, BGR, BRA, CAN, CHE, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, HRV, HUN, IDN, IND, IRL, ITA, JPN, KOR, LTU, LUX, LVA, MEX, MLT, NOR, POL, PRT, ROU, RUS, SVK, SVN, SWE, TUR, USA** . For the purpose of our analysis, we have aggregated the data in 10 industrial sectors using the NACE 23 industry classification system as defined by the WIOD. Furthermore, our analysis encompasses a total of six variables: Gross Output (GO), Capital (K), Clean Energy (EC), Dirty Energy (ED), the total number of employees engaged (L), and Intermediate Materials and Services (IMS).

All the details of variables, sectors, and countries we covered for our analysis are summarized in '*Table 7: Variable Description*', '*Table 8: Sectors*' and '*Table 9: Countries*' in the appendix section respectively.

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10 In addition, there is one composed country for the rest of the world that we did not include in our analysis.
11 PSS used this release.
12 All the detail information about the WIOD database can be found in (Timmer et al., 2015)

The dataset was constructed through several steps which are described below:

Step1:
Firstly, the energy used by fuel was aggregated into "Clean" and "Dirty" aggregates by adding bio gasoline, biodiesel, biogas, other renewables, electricity, heat production, hydro, geothermal, solar, wind, other sources, nuclear, and waste into the clean aggregate (EC), while all other types of energy-generating technologies such as coal, coke crude, diesel, fuel oil, gasoline, jet fuel, natural gas etc. were summed up in the dirty aggregate (ED).

To obtain all the values per employee engaged, we divided the aggregated values of the variables (GO, K, MS, EC, ED) by total number of employees engaged (L).

Step 2:
Secondly aggregates for service inputs and material inputs were calculated. Intermediates Service Inputs (IIS) aggregates all service products used. All remaining products are classified as intermediate material inputs (IIM). We made the variable Intermediate Material and Service (IMS) by combining IIS and IIM. We extracted data from the input table in WIOD database for intermediate input energy. In the case of intermediates service and material inputs, we extracted data from supply use tables in WIOD database.

Step 3:
Finally, nominal values in local currency were transformed into real values of a common currency, which, in this case, was USD worth in the year 2005. This transformation involved using Purchasing Power Parities (PPPs) with price indices from WIOD. The conversion factors $PPP_{k,i,t}$ for Gross Output (GO) and the capital stock (K) were derived by utilizing the PPP values, $PPP_{k,i,2005}$, and the price indices, $P_{k,i,t}$. The conversion factors are calculated as follows.

$$PPP_{k,i,t} = \frac{P_{k,i,2005}}{P_{k,i,t}} \frac{1}{PPP_{k,i,2005}} \quad ,$$

Where $k \in \{GO, K, IMS\}$, i represents country-industry combination and t is time in year. We get the real values for GO, K, IMS worth in 2005 by multiplying the nominal values for each year with the respective conversion factors. That is, $PPP_{GO,i,t}$ are used for conversion of gross output time-series while $PPP_{K,i,t}$ for the real fixed capital stock data and $PPP_{IMS,i,t}$ for intermediate materials and services time series respectively.

3. 3 Descriptive statistics

Table 2: Descriptive Statistics

Variables	Average	Median	St.D	Minimum	Maximum
GO	175.3	111.0	197.3	1.8	3230.3
K	314.7	118.4	488.4	1.1	5088.6
IMS	101.4	43.7	189.8	0.3	5065.6
ED	1163.8	122.3	2984.1	2.1	32841.3
EC	689.3	42.0	2681.0	0.0	27588.1

Table 2: Descriptive Statistics shows the descriptive statistics of the variables of the data. The values are in US dollars per total number of employees engaged, equivalent to USD worth in 2005 in the sectors shown in Table 8: Sectors. The values for dirty and clean energy are expressed in Terajoules in terms of the total number of employees engaged. Data for the period 2003 to 2014 showed the given statistics. The variables show a rather big difference between minimum and maximum observations. The big dispersion of data is also illustrated by the rather large standard deviations. This might be the case because the dataset consists of both big and small countries.

GO ranged from 1.8 to 3,230.3 USD per employees engaged and Capital ranged from 1.1 to 5088.6 USD per employees engaged. The range is quite high for the variable dirty energy used per employee engaged which ranged from 2.1 to 3,2841.2. The minimum value of clean energy consumed per employee engaged is as low as 0.00 with a maximum at 27,588.1.

Figure 6 and *Figure 7* show the average GO and Dirty Energy and Clean energy per total number of employees engaged in each country from 2003-2014 of all selected sectors respectively. The plot of the variables in the two figures show unsurprisingly that the consumption of dirty energy is generally higher than that for clean energy. It can be observed that the consumption of dirty energy is highest for countries with a bigger GO per employee engaged. This probably hints at more production activity for high GO countries which require more energy. However, the consumption of clean energy is generally low in countries with low GO. This means that for a given country, if the GO is low, it's highly likely that its consumption of clean energy is low as well. However, it is visible that the countries consuming higher amounts of clean energy are mostly countries with higher GO.

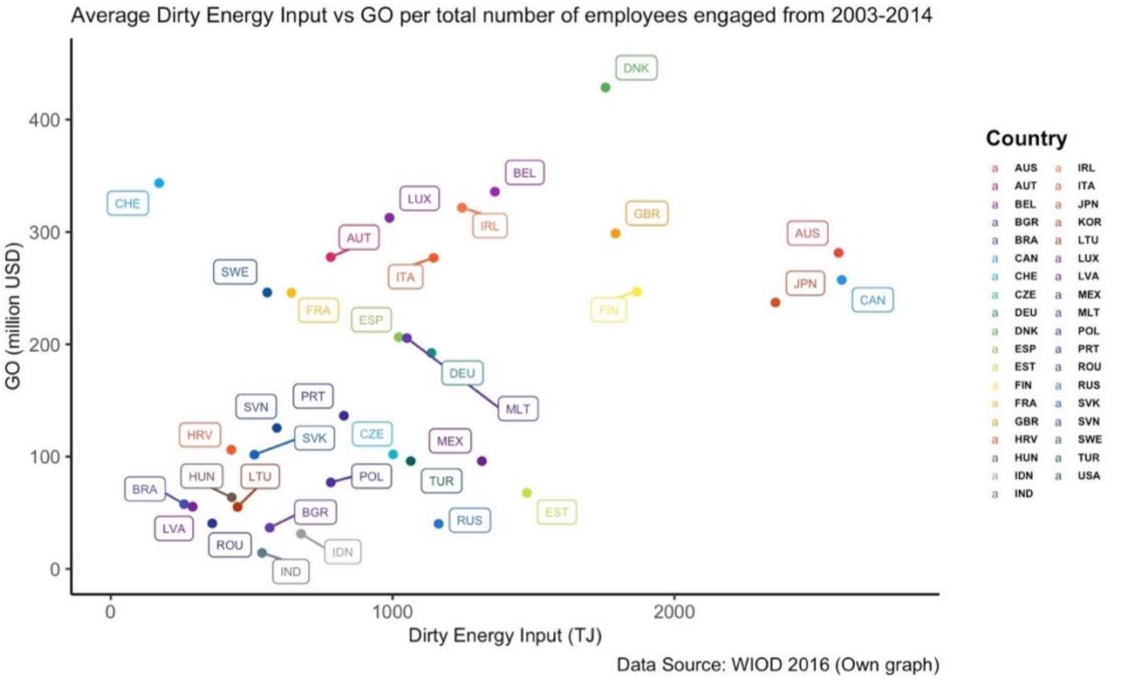

Figure 6. Dirty energy input vs GO per total employees engaged.

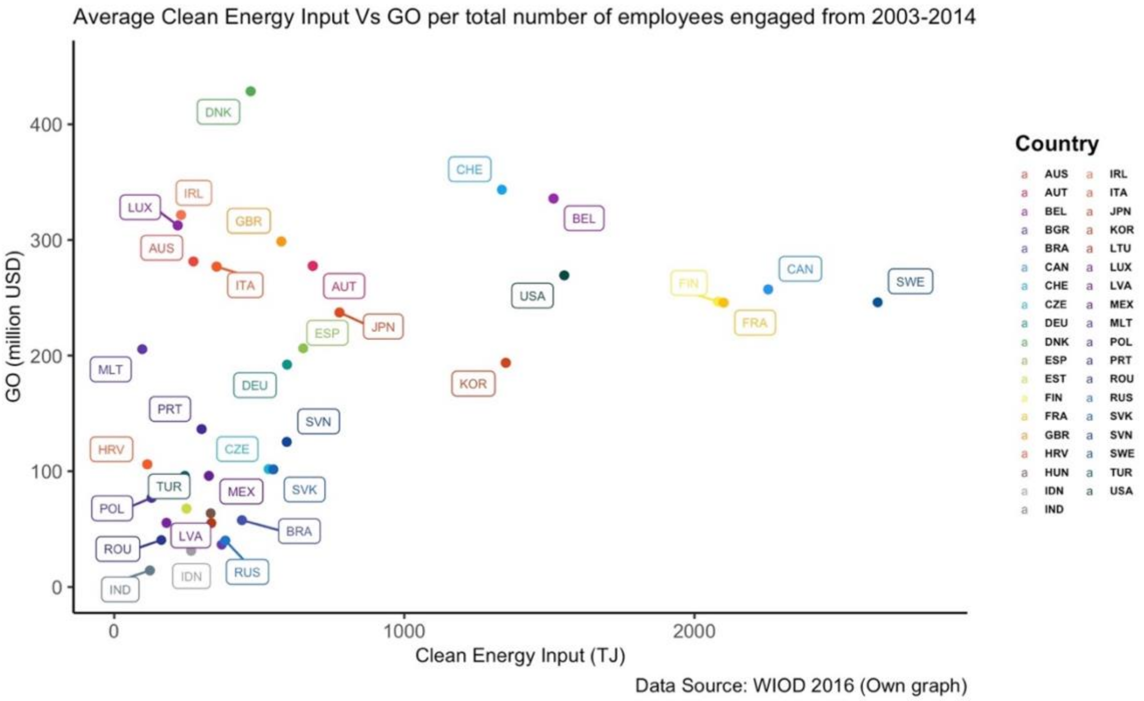

Figure 7. Clean energy input vs GO per total employees engaged.

4. Theoretical framework

Following PSS, we use CES function with neutral technical change to identify the elasticities of substitution. $Equation$ 1 shows the basic two inputs CES for clean and energy consumption.

$$E = A\left[\vartheta(ED)^{\psi} + (1-\vartheta)(EC)^{\psi}\right]^{1/\psi} \tag{1}$$

Where ED is dirty energy consumption, EC is clean energy consumption, ϑ is the share of the dirty energy input, ψ is the substitution parameter and A represents the technological change in dirty and clean inputs respectively. The elasticity of substitution between dirty energy (ED) and clean energy (EC) is $\sigma = {}^{1}/_{1-\psi}$.

The ratio between of the marginal product of ED and EC is:

$$\frac{\frac{\partial E}{\partial EC}}{\frac{\partial E}{\partial ED}} = \frac{1-\vartheta}{\vartheta}\left(\frac{EC}{ED}\right)^{\psi-1} \tag{2}$$

If $\psi > 0$, the relative marginal product of clean inputs declines less than proportionally when the ratio of clean to dirty inputs EC/ED increases. If $\psi < 0$, it declines more than proportionally. A value between 0 and 1 means that clean and dirty energy inputs are substitutes. A value below 0 means that the energy inputs are complements.

In $equation$ 3, the $equation$ 2 is expanded to five inputs in two levels nested CES function[13]. ϕ represents the substitution parameter between energy inputs and non-energy input, χ is the substitution parameter among non-energy inputs and ψ is the substitution parameter between energy inputs. A_{NE} is the technological change for the non-energy inputs. The share of the energy inputs is (ω) while the share for capital, labor and the intermediate materials and services inputs is $(1-\omega)$.

[13] Nested CES production functions is more flexible than the original form of the CES production function. This is because it allows different degrees of substitutability between inputs and unlimited number of inputs, Lagomarsino, E. (2020). Estimating elasticities of substitution with nested CES production functions: Where do we stand? *Energy Economics*, *88*. https://doi.org/10.1016/j.eneco.2020.104752

$$Y = \left\{ (1-\omega){A_{NE}}^{\phi} \left[\frac{\alpha}{1-\gamma}(K)^{\chi} + \frac{\theta}{1-\gamma}(IMS)^{\chi} + \left(\frac{1-\alpha-\theta-\gamma}{1-\gamma}\right)(L)^{\chi} \right]^{\phi/\chi} + \omega A^{\phi}\left([\vartheta(ED)^{\psi} + (1-\vartheta)(EC)^{\psi}]\right)^{\phi/\psi} \right\}^{1/\phi} \quad (3)$$

Since A_{NE} is not neutral, $(1-\omega)A_{NE}^{\phi} + \omega A^{\phi}$ in $equation$ 3 is not equal to 1. Therefore, we adjust the product of the share of the energy inputs and technological change (ωA^{ϕ}) in $equation$ 4 by dividing both sides of $equation$ 3 by $\left((1-\omega){A_{NE}}^{\phi} + \omega A^{\phi}\right)^{\frac{1}{\phi}}$.

$$\mathrm{Y} = \mathrm{A}' \left\{ (1-\gamma)\left[\frac{\alpha}{1-\gamma}(\mathrm{K})^{\chi} + \frac{\theta}{1-\gamma}(\mathrm{IMS})^{\chi} + \left(\frac{1-\alpha-\theta-\gamma}{1-\gamma}\right)(\mathrm{L})^{\chi} \right]^{\phi/\chi} + \gamma\left([\vartheta(\mathrm{ED})^{\psi} + (1-\vartheta)(\mathrm{EC})^{\psi}]\right)^{\phi/\psi} \right\}^{1/\phi} \quad (4)$$

Where, the technological change takes the form of $\mathrm{A}' = [(1-\omega){A_{NE}}^{\phi} + \omega \mathrm{A}^{\phi}]^{1/\phi}$ and the share of the energy inputs the form of $\gamma = \frac{\omega \mathrm{A}^{\phi}}{(1-\omega){A_{NE}}^{\phi} + \omega \mathrm{A}^{\phi}}$. In $equation$ 4 the sum of the shares of non-energy inputs$(1-\gamma)$ and the shares of energy inputs (γ) is equal to 1, and the sum of the share of the 5 inputs is equal to 1.

Since we are interested in the elasticity of substitution between clean and dirty energy, we assume a value of 0 for any other substitution parameter in $equation$ 4. That means unitary elasticity of substitution among non-energy inputs and unitary elasticity of substitution between energy inputs and non-energy inputs. Then, in $equation$ 5, since $\phi = 0$, the whole function Y

takes the form of a Cobb-Douglas, also because $\chi = 0$ the factor with the non-energy inputs takes form of a Cobb-Douglas. The energy part keeps the CES form.

$$Y = A'K^{\alpha}IMS^{\theta}L^{1-\alpha-\theta-\gamma} * \left(\left(\vartheta ED^{\psi} + (1-\vartheta)EC^{\psi}\right)^{1/\psi}\right)^{\gamma} \tag{5}$$

5. Econometric Methodology

For our empirical specification we estimate a linear version of $equation$ 4 for our data which includes information about countries in *Table 9*: Countries and sectors in *Table 8*: Sectors. Taking logs in $equation$ 4 we fall in $equation$ 6.

$$\begin{aligned} lnY_{ijt} = a_{ij} + dt + (1-\alpha-\theta-\gamma)lnL_{ijt} + \alpha lnK_{ijt} + \theta lnIMS_{ijt} \\ + \frac{\gamma}{\psi} ln\left(\vartheta ED_{ijt}^{\psi} + (1-\vartheta)EC_{ijt}^{\psi}\right) + \varepsilon_{ijt} \end{aligned} \tag{6}$$

Where a_i is the constant effect of the country i and sector j, d_t is a time trend, ϑ is the weight of dirty energy input and its complement (1- ϑ) is the weight of the clean energy input, Y_{ijt} is the gross output for the country i and sector j, K is the fixed capital stock, L is the number of employees engaged, IMS is intermediate manufacture and services inputs, ED is the dirty energy input and EC is the clean energy input.

However, $equation$ 6 is not linear in the energy sector. Following PSS, we applied the Kmenta[14] approximation to $equation$ 6. Besides, we get a per employee version.

[14] See Kmenta, J. (1967). On Estimation of the CES Production Function. *International Economic Review*, *8*(2), 180. https://doi.org/10.2307/2525600

$$\frac{lnY_{ijt}}{L_{ijt}} = a_{ij} + dt + \beta_1 \frac{lnK_{ijt}}{L_{ijt}} + \beta_2 ln \frac{EC_{ijt}}{L_{ijt}} + \beta_3 ln \frac{ED_{ijt}}{L_{ijt}} + \beta_4 \left(ln \frac{ED_{ijt}}{EC_{ijt}} \right)^2 + \beta_5 \frac{IMS_{ijt}}{L_{ijt}} + \varepsilon_{ijt} \tag{7}$$

We estimate a panel regression for $equation\ 7$ and compute the elasticity between dirty and clean energy (σ). We compute two output elasticities. The first one, ξ is the elasticity between the gross output and dirty energy, while ς is the elasticity output between the gross output and clean energy.

$$\beta_1 = \alpha$$

$$\beta_5 = \theta$$

i. Elasticity between Dirty and Clean Energy inputs:
   $\sigma = 1/(1 - 2\beta_4(\beta_2 + \beta_3)/\beta_3\beta_2)$
ii. Output elasticity (Clean Energy):
   $\xi = \beta_2 - 2\beta_4 \left(ln \left(\frac{DirtyEnergy}{CleamEnergy} \right) \right)$
iii. Output elasticity (Dirty Energy):
   $\varsigma = \beta_3 + 2\beta_4 \left(ln \left(\frac{DirtyEnergy}{CleamEnergy} \right) \right)$
iv. Weight (Dirty Energy):
   $\vartheta = \frac{\beta_3}{\beta_2 + \beta_3}$
v. Share of the energy inputs:
   $\gamma = \beta_2 + \beta_3$

We develop a time-varying model for $equation\ 7$. For estimation purposes, we use the R package TvReg and follow the methodology of Casas and Fernández-Casal (2022). The model can be represented by the following regression equation.

$$y_{it} = a_{ij} + dt + x_{it}^{\intercal}\beta(z_t) + u_{ijt} \tag{8}$$

Where x_{it} is the vector of independent variables and z_t is a smooth variable that only changes in time. The size of these windows is given by the bandwidth bi, and the weights are given by $K_{bi}(z_t - z) = b_i^{-1} K\left(\frac{z_t - z}{bi}\right)$

The estimators are represented by the following expression:

$$\begin{pmatrix} \hat{\beta}_t \\ \hat{\beta}_{1t} \end{pmatrix} = \begin{pmatrix} S_{T,0}(z_t) & S_{T,1}^{\intercal}(z_t) \\ S_{T,1}(z_t) & S_{T,2}^{\intercal}(z_t) \end{pmatrix}^{-1} \begin{pmatrix} T_{T,0}(z_t) \\ T_{T,1}(z_t) \end{pmatrix} \tag{9}$$

With

$$\begin{gathered} S_{T,s}(z_t) = X^{\intercal} W_{b,t} X (Z - z_t)^s \\ T_{T,s}(z_t) = X^{\intercal} W_{b,t} Y (Z - z_t)^s \end{gathered} \tag{10}$$

Where $W_{bt} = D^{\intercal} K_{b,t}^{*} D$.

Finally, we set a bandwidth of 0.9. We set z_t as time and compute the time varying version of the output elasticities and calculate interval of confidence for ED and EC .

6. Result

6.1 Panel Regression

We estimate the linear equation given in $equation$ 6. *Table 3: Panel Data Estimation* shows the results. $Model\_1$ assumes $\beta_2 = \beta_3$ as PSS, while $Model\_2$ relax that assumption. $Model\_2$ shows a large difference between the coefficient of clean β_2 and dirty β_3 energy inputs, i.e., the difference between the weights. Coefficients for capital (β_1) and for intermediate materials and services inputs (θ) shows reasonable values. We estimate an elasticity of substitution between clean and dirty energy of 1.5 for $Model\_1$ while for $Model\_2$ where we relax the assumption of $\beta_2 = \beta_3$ we get a negative elasticity. In addition, from $Model\_2$ we compute an output elasticity of 0.04 for clean energy inputs and 0.03 for dirty energy inputs.

Table 3: Panel Data Estimation

Panel data

	Dependent variable:	
	log(GO)	
	Model_1	Model_2
d	0.001^{*}	0.001
	(0.0004)	(0.0004)
α	0.380^{***}	0.379^{***}
	(0.008)	(0.008)
γ	0.037^{***}	
	(0.003)	
β_2		0.054^{***}
		(0.005)
β_3		0.018^{***}
		(0.006)
β_4	0.003^{***}	0.005^{***}
	(0.001)	(0.001)
θ	0.409^{***}	0.409^{***}
	(0.007)	(0.007)
Observations	5,633	5,633
R^2	0.856	0.856
Adjusted R^2	0.845	0.846
F Statistic	$6,224.227^{***}$ (df = 5; 5248)	$5,207.361^{***}$ (df = 6; 5247)
Note:		*p<0.1; **p<0.05; ***p<0.01

6.2. Time-Varying Panel Regression

6.2.1 TV Coefficients

We estimate a time-varying regression as showed in $equation\ 7$ for $equation\ 6$. *Table 4*: Resume TV estimation shows descriptive statistics of the estimation. For this estimation we used the package TVReg in R. Unfortunately, the package requires a balanced panel, so we could not get rid of outliers. Thereby coefficients might be biased. We observe a large difference between the average β_2 and β_3. This difference is similar to the difference between β_2 and β_3 in $Model\ 2$.

Table 4: Resume TV estimation

	d	α	β_2	β_3	β_4	θ
Min.	0.000389	0.357500	0.032960	0.005277	0.002919	0.419700
1st Qu.	0.000488	0.359600	0.047810	0.006535	0.004371	0.421600
Median	0.000534	0.360500	0.058950	0.010389	0.005489	0.427400
Mean	0.000515	0.360500	0.056390	0.013849	0.005442	0.429400
3rd Qu.	0.000559	0.361000	0.067090	0.020233	0.006505	0.436100
Max.	0.000569	0.366800	0.070640	0.030106	0.008012	0.448100

Bandwidth: 0,9

Pseudo R-squared: 0,7633

Table 5: TV estimations

	Dependent variable					
	GO					
Year	d	α	β_2	β_3	β_4	θ
2000	0.0005682	0.3577703	0.03296411	0.00739866	0.00291882	0.4419824
	(0.00001347)	(0.00478444)	(0.0034219)	(0.0026705)	(0.00052367)	(0.00478306)
2001	0.00056892	0.3575425	0.03708122	0.00621689	0.00332026	0.4385729
	(0.00001068)	(0.00420465)	(0.00290662)	(0.00242687)	(0.00042024)	(0.00420629)
2002	0.00056644	0.3582502	0.04156584	0.0054286	0.00375998	0.4346846
	(0.00000862)	(0.00378094)	(0.00266237)	(0.00219817)	(0.00035374)	(0.00374087)
2003	0.00056198	0.3592236	0.04587115	0.00527742	0.00418111	0.4308383
	(0.00000741)	(0.00347621)	(0.00268867)	(0.00198739)	(0.00032839)	(0.00337401)
2004	0.00055627	0.3600932	0.04974859	0.00577986	0.00456042	0.4273862
	(0.00000707)	(0.00326575)	(0.0029052)	(0.00179907)	(0.00033739)	(0.00308917)
2005	0.00054966	0.3607108	0.05317076	0.00685355	0.00489784	0.4244908
	(0.00000744)	(0.00313151)	(0.00322103)	(0.00163268)	(0.00036731)	(0.00286665)
2006	0.00054219	0.3610405	0.05620772	0.00840991	0.00520315	0.4222151
	(0.00000833)	(0.00306424)	(0.00358042)	(0.001485)	(0.00040736)	(0.00268998)
2007	0.00053369	0.361094	0.05895304	0.01038883	0.00548879	0.4206027
	(0.0000096)	(0.0030645)	(0.00395913)	(0.00135339)	(0.00045178)	(0.00254963)
2008	0.00052382	0.3609074	0.06148923	0.01275948	0.00576702	0.4197343
	(0.0000112)	(0.00314369)	(0.00435023)	(0.00123811)	(0.00049803)	(0.00244615)
2009	0.00051204	0.3605485	0.06386858	0.01550364	0.00604908	0.4197761
	(0.00001319)	(0.00332607)	(0.00475425)	(0.00114437)	(0.00054497)	(0.00239628)
2010	0.00049752	0.3601533	0.06609255	0.01858292	0.00634504	0.421034
	(0.00001567)	(0.00365174)	(0.00517329)	(0.00108383)	(0.00059171)	(0.00244416)
2011	0.0004791	0.3599991	0.06808066	0.02188399	0.00666411	0.4240064
	(0.0000188)	(0.00417924)	(0.00560654)	(0.00107315)	(0.00063687)	(0.0026724)
2012	0.00045537	0.3605947	0.06964205	0.02515141	0.00701839	0.4293521
	(0.00002276)	(0.00498295)	(0.00604701)	(0.00112586)	(0.00067872)	(0.00318619)
2013	0.00042522	0.362655	0.07052368	0.02799373	0.00743869	0.4375307
	(0.0000276)	(0.00613738)	(0.0064821)	(0.00124195)	(0.00071829)	(0.00404266)
2014	0.00038886	0.366764	0.07063584	0.03010563	0.00801189	0.4481097
	(0.00003325)	(0.00771356)	(0.00689542)	(0.00141225)	(0.00076761)	(0.00520301)
Pseudo R^2	0.7633					

Table 5: TV estimations shows the time-varying coefficients. In general, β_2 and β_3 follows an increasing trajectory. The difference between both coefficients increases in favor of β_2 until 2008, from 2009 to 2014 the difference exhibits a decreasing trajectory.

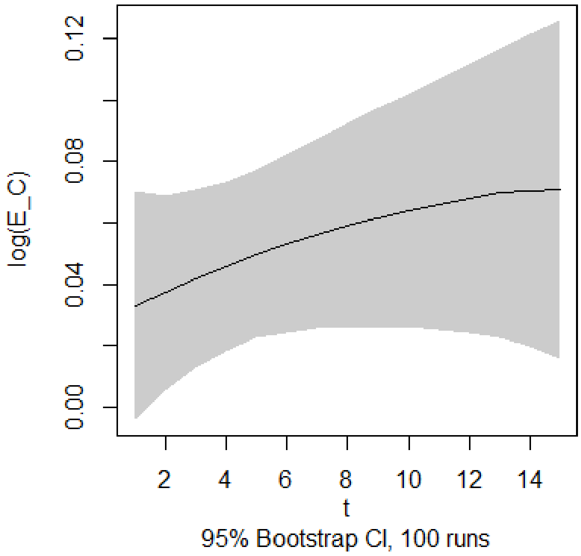

Figure 8. Confidence Interval (EC)

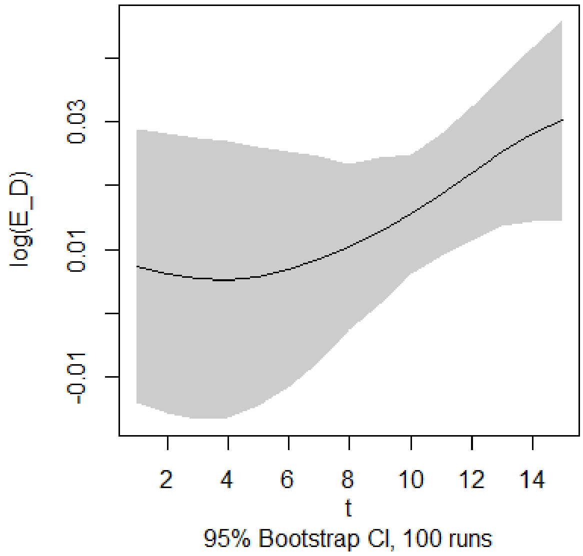

Figure 9. Confidence Interval (ED)

6.3 TV Elasticities

Table 6: TV Elasticities shows the time-varying output elasticities of clean and dirty energy inputs and the time-varying elasticity of substitution between both sources. In general, output elasticities follow an increasing trajectory. The difference between both elasticities increases in favor of clean energy inputs until 2007, from 2008 to 2014 the difference exhibits a decreasing trajectory (*Figure 8.* Confidence Interval (EC)).

Table 6: TV Elasticities

Year	ξ	ζ	σ
2000	0.026	0.015	29.501
2001	0.029	0.014	-4.045
2002	0.032	0.015	-1.766
2003	0.036	0.015	-1.304
2004	0.039	0.017	-1.313
2005	0.041	0.019	-1.630
2006	0.044	0.021	-2.367
2007	0.046	0.024	-4.117
2008	0.047	0.027	-10.925
2009	0.049	0.030	33.076
2010	0.051	0.034	7.993
2011	0.052	0.038	5.123
2012	0.053	0.042	4.161
2013	0.052	0.046	3.882
2014	0.051	0.050	4.151

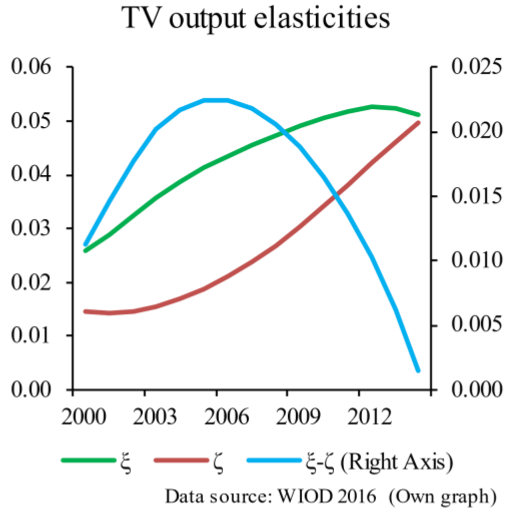

Figure 10. TV Output for elasticities

7. Discussion

We estimated a model similar to PSS and got similar results. Additionally, we estimate a model allowing different weights in clean and dirty energy inputs. We observe a large difference between the coefficients of clean and dirty energy. Therefore, we think that assuming equal weights as PSS seems to be unrealistic and we do not support that assumption. Under equal weights we get an elasticity of around 1.5 and without that assumption we get a negative elasticity. Therefore, with more relaxed assumptions, we cannot conclude that the conditions to support long run green economic growth are granted.

The coefficient of clean energy is notably larger than the coefficient of dirty energy inputs. One reason for this might be policies that encourage the use of clean energy; the implementation of a strict environmental regulation can promote labor division in clean energy production technologies and the final goods sector can get benefits from boosted average labor productivity, (Tang et al., 2019). Another reason could be the inverted U-shape curve frequently observed in the relationship between energy consumption and economic growth. This relationship has not been studied splitting the energy inputs between clean and dirty. Thereby, further research could explore those arguments.

Although our intention was not to show what happen with clean and dirty energy input during crises and we do not provide rigorous answer on that regard, our results show that the difference between the output elasticity of clean and dirty energy inputs follow a decreasing trajectory between 2008 and 2014. That is the period when European countries, which are the majority in our sample, faced difficulties in terms of economic growth. Therefore, our results suggest that crisis discourages the use of clean energy inputs, and we think that further research could go deep on the effects of crisis in the energy transition.

Finally, it is imperative to acknowledge certain limitations within our methodology. $Equation$ 6 might exhibit endogeneity; energy inputs can be easily adjusted in response to productivity shocks, consequently, energy inputs are correlated with the technical change in the error term. In this case, the ordinary least squares reports biased coefficients of flexible inputs. To control for the correlation between energy and technical change and estimate the unbiased coefficients, Levinsohn and Petrin (2003); Olley and Pakes (1996), designed a methodology that expresses the unobserved productivity level of firms as a function of the observed variables by inversing the demand function of one flexible input.

8. Conclusion

The elasticity of substitution between clean and dirty energy inputs is a key parameter to analyze the suitability of conditions for green economic growth. According to previous research, when the elasticity of substitutions is larger than one, the energy inputs are substitutes and long term green economic growth can be achieved with temporary policy intervention.

Far from a constant parameter, the elasticity of substitution between energy sources might be affected by changes in infrastructure and other factors. Therefore, understanding the dynamics of this parameter is a key insight in order to determine the optimal policy intervention.

We first analyze the role of energy inputs in a linear CES function just like PSS. We use an updated version of the WIOD database. Our data covers 38 countries, mostly European, from all over the world divided into 10 aggregated industrial sectors.

Following PSS, we estimated panel data assuming equal weights. Under these circumstances we observe an elasticity of substitution of 1.5. Next, we estimate a model without equal weights. In this model we observe a large difference between the coefficients of clean and dirty energy inputs. Therefore, we do not support the assumption of equal weights. Under the free weights condition, we get a negative elasticity. Therefore, we cannot conclude that the conditions for long term green economic growth are fulfilled.

Under free weights we estimate a time-varying panel model. We compute the elasticity of substitution between clean and dirty energy inputs; however, we get unplausible values. We also estimate the output elasticities of clean and dirty energy inputs. Both output elasticities follow an increasing trajectory. The difference between the outputs elasticities of clean and dirty energy inputs is large but becomes shorter from 2008 to 2014, when many countries in sample were facing crisis.

Further research could find better specifications or methods in order to get most trustable estimations; in this case we suggest to apply the methodology of Levinsohn and Petrin (2003); Olley and Pakes (1996) to fix the bias in the estimation of the production function. In addition, further literature could explore how economic crises affect clean energy adoption and the inverted U shape of the relationship of clean and dirty energy and economic growth.

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Appendix

Table 7: Variable Description

Variable Description and Unit of Measurement
Gross output at real 2005 US dollar (PPP)
Intermediate materials and service input at real 2005 US dollar (PPP)
Real fixed capital stock at real 2005 US dollar (PPP)
Total Number of employees engaged
Energy use of clean sources (in TJ)
Energy use of dirty sources (in TJ)

Notes: TJ = Terajoule.

Table 8: Sectors

Sectors	***Codes***
Agriculture, Forestry & Fishing	A
Mining & quarrying	B
Manufacturing	C
Utilities	D, E
Construction	F
Whole sale & Retail trade	G
Hotel and Restaurants	H
Transport & Communications	I
Financial & Business Services	J, K, L, M
Community, Social & Personal Services	N, O P, Q, R, T

Table 9: Countries

Country	Codes	Country	Codes
Australia	AUS	Lithuania	LTU
Austria	AUT	Luxembourg	LUX
Belgium	BEL	Malta	MLT
Brazil	BRA	Mexico	MEX
Bulgaria	BGR	Norway	NOR
Canada	CAN	Poland	POL
Croatia	HRV	Portugal	PRT
Czech Republic	CZE	Romania	ROU
Denmark	DNK	Russia	RUS
Estonia	EST	Slovakia	SVK
Finland	FIN	Slovenia	SVN
France	FRA	South Korea	KOR
Germany	DEU	Spain	ESP
Hungary	HUN	Sweden	SWR
India	IND	Switzerland	CHE
Indonesia	IDN	Taiwan	TWN
Ireland	IRL	Turkey	TUR
Italy	ITA	United Kingdom	GBR
Japan	JPN	United States of America	USA
Latvia	LVA		

Table 10: Yearly Aggregated Data

Year	GDP_per_labor	Dirty_energy	Clean_Energy	Capital	I_MS	GDP_per_clean	GDP_per_dirty
2000	130.83	1225.34	722.57	240.89	61.60	0.18	0.11
2001	123.52	1301.00	738.90	230.60	58.06	0.17	0.09
2002	129.56	1330.99	755.33	242.66	61.18	0.17	0.10
2003	152.37	1375.23	734.45	279.91	81.57	0.21	0.11
2004	169.82	1382.47	752.47	305.33	90.16	0.23	0.12
2005	182.11	1386.79	785.14	310.80	114.35	0.23	0.13
2006	175.22	1413.80	766.20	304.74	96.69	0.23	0.12
2007	190.37	1433.10	749.68	329.67	106.30	0.25	0.13
2008	204.39	1359.07	747.93	351.84	120.75	0.27	0.15
2009	178.96	1333.91	723.53	337.70	98.11	0.25	0.13
2010	183.36	1393.62	736.08	334.21	105.57	0.25	0.13
2011	194.22	1336.41	713.01	350.65	119.36	0.27	0.15
2012	182.59	1327.38	717.65	335.56	110.22	0.25	0.14
2013	188.72	1297.81	719.72	348.53	122.81	0.26	0.15
2014	185.10	1261.02	721.62	347.85	114.73	0.26	0.15