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Eco-innovation impact on CO_2 emissions and Energy productivity in EU countries

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Master in Economics

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Resumo

A crise climática é um dos maiores problemas que a humanidade está a enfrentar e a solução parece estar longe de ser alcançada, já que, outros problemas, dependentes do desempenho económico dos países, também prendem a atenção dos governos. Por esta razão, devem ser estudadas soluções em consonância com os objetivos relativos à atividade económica e de proteção ambiental. A Eco-inovação poderá ser uma dessas soluções e, por isso, tem vindo a atrair a atenção de investigadores. Este estudo pretende, então, dar um contributo acerca deste tema. Para compreender o impacto da Eco-inovação, são utilizadas duas variáveis, nomeadamente, um rácio com PIB/Energia e outro com PIB/Emissões. Estas variáveis permitem entender o impacto da Eco-inovação na produtividade energética e de emissões. Utilizando dados em painel e um modelo ARDL, esta relação é explorada, tanto no curto como no longo prazo, permitindo controlar a Dependência Transversal, problema que decorre devido à elevada dependência entre os países da União Europeia, que constituem a amostra do nosso estudo. Os resultados não sugerem relação de longo prazo entre Eco-inovação e PIB/Energia e PIB/Emissões. O mesmo se verifica no curto prazo em relação à variável PIB/Emissões, embora tenha sido encontrado um efeito negativo de muito pequena escala em relação ao PIB/Energia. Os resultados obtidos sugerem que é possível manter o mesmo nível de PIB utilizando a Eco-inovação, pelo menos para o consumo energético em países da UE.

Palavras-Chave: Eco-Inovação, Consumo Energético, Emissões de CO_2, Produtividade, Dependência Transversal.

Classificação JEL: C33, Q55

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Abstract

Climate crisis is one of the biggest problems that humanity is facing, and the solution seems to be far away from being reached, since there are other problems that depend on the economic performance of the countries that need also to be addressed by governments. For this reason, solutions must be studied in line with both objectives relating to economic activity and environmental protection. Eco-innovation can be one of those solutions and, therefore, it has been attracting the attention of researchers. This study intends to make a contribution to this theme. To understand the impact of Eco-innovation, two variables are used, namely, a ratio with GDP/Energy and another with GDP/Emissions. These variables will allow understanding the impact of Eco-innovation on Energy and CO_2 Emissions productivity. Using a panel data and an ARDL model, this relationship is explored, both in the short and in the long term, allowing controlling for the Cross-sectional Dependence, a problem that arises due to the high dependency between the countries of the EU, which constitute the sample of our study. The results do not suggest a long-term relationship between Eco-innovation and GDP/Energy and GDP/Emissions. The same is verified for GDP/Emissions in the short term, though a very small-scale negative effect was found for GDP/Energy. The results suggest that it is possible to maintain the same level of GDP using Eco-innovation, at least for Energy consumption in EU countries.

Keywords: Eco-innovation, Energy consumption, CO_2 emissions, Productivity, Cross-sectional Dependence.

JEL classification: C33, Q55

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List of abbreviations

ADF – Augmented Dickey Fuller

ARDL – Autoregressive Distributed Lag

CADF – Cross-sectional Augmented Dickey Fuller

CD – Cross-sectional Dependence

CIS – Community Innovation Survey

DFE – Dynamic Fixed Effect

EC – European Commission

Eco-I – Eco-innovation

ECT – Error Correction Term

ETS - Emissions Trading System

EU – European Union

G7 – Group of 7

GHG – Greenhouse gases

IEA – International Energy Agency

IPS – Im-Pesaran-Shin

LSDV – Least Square Dummy Variable

MG – Mean Group

OECD - Organization for Economic Co-operation and Development

PMG – Pooled Mean Group

ROI – Return on Investment

TPES - Total Primary Energy Supply

UN – United Nations

UNFCCC - United Nations Framework Convention on Climate Change

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1. Introduction

Global climate is undoubtedly one of the biggest challenges that humanity is facing. Impacts are observed in health, political stability, and conflicts due to temperature, precipitation, and extreme weather conditions. But those impacts are also observed, in many studies, regarding important economic variables such as productivity and economic growth, especially in the poorest countries (Dell et al., 2013).

Policymakers seem to be aware of the situation because, according to the United Nations (2019), the number of environment-related laws and environmental entities has increased exponentially since 1972. Nevertheless, The United Nations (UN) concludes that, in some cases, the effort to transpose the law to a practical sense is not enough or the laws, or their implementation, are ineffective. This means that there is still much to do in order to deal with climate change and that better information is needed, for the sake of the effectiveness of environmental-related policies.

But not only policy makers are aware of this problematic situation. Studies involving global environmental assessment have been increasing across the years, as well as the number of authors and countries involved. Terms like “climate change” and “sustainability” have been holding more attention in recent years (W. Li & Zhao, 2015). On the other hand, from an economic point of view, Ruiz-Real et al. (2018) find a recent increase of publications concerning “Circular Economy” and “Environment Economics” and observe that “Eco-innovation, eco-design, and waste management” topics are also engaging academic attention.

Furthermore, media coverage of climate change has been more active in countries with functional governance systems suggesting that this problem is mainly considered as a “rich countries issue” (Barkemeyer et al., 2017), which seems contradictory to some literature like the study from Dell et al. (2013) that reveals the poorest countries to be more impacted by climate change.

A possible explanation for this dichotomy is the fact that, in some developing countries, due to severe poverty, the main concern is related to the economic growth, which gives environmental action a secondary priority (Beckerman, 1992). Indeed, even in the European countries and in the US, public opinion shows a lot of inconsistencies regarding the trade-off between economic growth and environmental protection, with most people giving more importance to economic growth, even though many believe that both objectives are achievable (Drews et al., 2018).

The previous dichotomy between economic growth and environment protection may explain political uncertainty and different perception of environmental aspects across countries, including the European ones. According to the European Social Survey (2018), within the European Union (EU) countries, people acknowledge climate change but show less motivation to promote a large-scale change in environmental practices, putting less support on policies with high costs. The survey also finds patterns of low engagement to climate change and low support of low-carbon emissions in some European regions like Central and Eastern countries. The same low commitment is verified in environmental risk perception, probably due to sociocultural determinants (Balžekiene & Telešiene, 2017). This difference is important to be analyzed in environmental-related studies on EU countries, because, as there is a common agenda, there are also different levels on coping with climate change and environmental protection.

In fact, it is possible to observe a general trend in greenhouse gases (GHG) emissions and energy consumption in the EU, but also disparities at the national level (European Environment Agency, 2020). EU has been decreasing its emissions in a steady way since 1990, being successful in accomplishing the 20% target for 2020 reduction compared to the 1990 emissions levels. Nevertheless, the efforts on emissions reduction diverge among countries. The European Environment Agency (2020) Report points out 11 Member States, like Austria, Belgium, Bulgaria, Cyprus, Estonia, Finland, Germany, Ireland, Luxembourg, Malta, and Poland, that show an emissions level in Effort Sharing[1] sectors higher than the targets they have settled and conclude that 21 countries have to accelerate the average annual reduction of GHG emissions in order to accomplish the 2030 targets. The sectors with greater responsibility in GHG emissions in the EU are the Energy sector, Agriculture, and Industrial processes with 77,9%, 10,1%, and 8,7%, respectively, in 2015 (European Commission, 2017), following a global trend in terms of percentage distribution through sectors (Ritchie & Roser, 2020).

Regarding energy efficiency, the results are not as positive as in emissions, since the targets are not being accomplished, even though there is a relatively recent downgrade trend. The transport sector represents the largest share (33% in 2015) in final energy consumption (European Commission, 2017).

[1] The Effort Sharing legislation establishes annual greenhouse gas emission targets for 2013–2020 and 2021–2030, concerning emissions from most sectors not included in the EU Emissions Trading System (mostly high intensity energetic industries), such as transport, buildings, agriculture and waste.

Increasingly, the solution to fight against climate degradation appears to be in policies to promote environmental protection without disregarding economic growth. Other types of policies, focused on behavioral change, could face people´s opposition and would take time that it is not available to deal with climate change (Jänicke, 2012). Therefore, the promotion of innovation and knowledge-based solutions seem to be the best way to combine both demands (Jänicke, 2012).

This thesis approaches technology-based solutions with an environmental purpose and their impacts on CO_2 emissions, that will be referred as Emissions for simplicity reasons, and energy consumption, both in the short and long-run. By understanding whether Eco-innovation is promoting efficiency, especially in CO_2 emissions and energy consumption, it will be possible to conclude whether it is feasible to maintain the same level of GDP in the UE countries and at the same time to decrease the environmental degradation.

The study focuses on 20 EU countries that will be split by region to allow taking conclusions regarding the cohesion of the EU regions. Most of the Eco-innovation studies in Europe are based in surveys, such as Doran and Ryan (2016), which cover a small period of time, and use the panel data methodology at the country level, therefore addressing a low number of countries. The novelty of this study is the approach to a wider range of countries from the EU, in a 21-year period, where both short and long-term impacts of Eco-innovation on Energy and CO_2 Emissions productivity will be analyzed. EU countries will be divided into geographic Regions to allow for conclusions regarding the existence or not of cohesion in the Eco-innovation impact.

The research contributes to the debate concerning environmental action without disregarding the economic growth. In other words, by testing the effects of Eco-innovation on Energy/Emissions and GDP, it will be possible to check whether the same level of GDP can be sustained or increased with less energy consumption and less level of emissions.

These aspects require some econometric tools to test for Cross-sectional Dependence, Unit Roots and Cointegration, which will be explained and presented both in the methodology and in the results section.

The thesis is divided into six sections. In Section 2 a review on the existing literature is performed, concerning the background of environmental studies and methodologies used, focusing the attentions on firms and country level studies. Section 3 explains the type of data and the methodology used. Section 4 presents the analysis of the results. To check the robustness of the results, a different methodology approach is employed in Section 5. Finally, in Section 6, the main conclusions are presented, as well as some indications for further studies.

2. Literature Review

2.1 Eco-innovation

"Eco-innovation" can be a solution to promote efficiency without compromising economic development (Jänicke, 2012). Therefore, it is essential to define it in order to better approach it through the literature review.

Rennings (2000) states the importance of distinguishing Eco-innovation from other types of innovation because Eco-innovation has its own important characteristics. One of the main differences is the motivation towards Eco-innovation, as it aims to reduce environmental impact. Eco-innovation may come from different actors, like firms and governments, and has different natures- technological, organizational, social, or institutional. In other words, Eco-innovation presents a "greener" motivation behind its development, which it is not found in other general innovations.

Even though there are different natures of Eco-innovation, they mostly stick with each other in order to have a successful outcome, especially technology, which is often seen as a sign of progress and innovation, but without regulation and other incentives, the environmental purpose might not be met (Hellström, 2007; Norgaard, 1994; Rennings, 2000).

Kemp and Pearson (2007), in turn, focus more on the results of the Eco-innovation than on its motivation, because in the end the results are what matter. Also, the authors refer that Eco-innovation should be a novelty to the organization that develops or adopts it, and it must be the better alternative in terms of environmental impact. This definition is in line with the Organization for Economic Co-operation and Development (OECD).

In order to measure Eco-innovation, different approaches that try to incorporate the characteristics of Eco-innovation are being used. García-Granero et al. (2018) provide a comprehensive review of Eco-innovation indicators at the firm level. They present 30 different indicators, divided through 4 main groups: *product; process; organization, and marketing Eco-innovation*. The one that seems to be closed to the efficiency of materials and resources relates to process innovation. From this type of Eco-innovation, it stands out indicators like reduction, recycling, and reuse of certain resources and materials, R&D investments, development and acquisition of environmental-related technologies and patents.

2.2 Eco-innovation in firms

The growing pressure to tackle carbon emissions and to gain control over climate change puts governments and policymakers in a delicate situation as policies must be effective, but at the same time should not endanger firms (Doran & Ryan, 2012). Having this in mind it is important to infer about Eco-innovation impacts in firms. In case those results are positive, policymakers could develop regulations to promote Eco-innovation in firms.

The more traditional idea is that investment in Eco-innovation would be a burden to companies due to the amount of highly costs associated to it (Porter & van der Linde, 1995). This idea is defended by Walley and Whitehead (1994) who are against the notion that win-win situations can frequently occur in companies that invest on environmental matters, as this hypothesis is quite rare. Nevertheless, Porter and van der Linde (1995) state that the investment in Eco-innovation would bring a competitive advantage, increase in profits, and decrease in pollution. The idea that Eco-innovation ends up in higher costs and profit minimization is the result of a static view where important variables, such as technology, are immutable. Porter and Van der Linde (1995) argue that this view is wrong, as environmental regulation would make Eco-innovation as a response to it. Moreover, Eco-innovation may affect the process or even the product and, thus, exceed the compliance costs.

Ambec and Lanoie (2008) performed an overview on the existing empirical findings of improvement in both environmental and economic/financial performance, providing evidence of Porter's hypotheses. The authors gave importance to long-term studies, for being more reliable and found evidence that environmental performance is associated to better financial results or, at least, not worst ones. They also pointed out different possible channels to explain this relation. *Better access to certain markets; Differentiating products; Selling pollution control technologies; Risk management and relations with external stakeholders; Cost of materials, energy, and services; Cost of capital; Cost of labor*. Nevertheless, these channels needed deeper studies since evidence was residual.

Recent studies have been focusing on surveys due to lack of data availability and because those cover a wide range of companies. An example of such a study is performed by Doran and Ryan (2016) who used the Irish Community Innovation Survey (CIS) as the main instrument to analyze the impact of 9 different types of Eco-innovation in Irish companies' performance, proxied by productivity. Results were ambiguous on the determinants of Eco-innovations over productivity as only two of the process innovations (reduced CO_2 footprint and increased recycling of waste, water, or materials) had this positive relationship. One of the product innovations (improved recycling of product after use) affected negatively the productivity and the other innovations had no impact.

Ryszko (2016), in turn, tried to approach the role of companies' proactiveness using a sample of almost 300 Polish Companies to study if an environmental strategy, incorporated in firm's short and long-run plans, and technological Eco-innovation had a positive impact on firms' performance. It was found that having an environmental strategy does not show significance to explain firms' performance, though, it explains technological Eco-innovation, which in turn has shown to have a positive significance in firms' performance, recovering the idea of synergies needed in more dimensions than the technological one.

Tang et al. (2018) inquired a smaller sample composed by 188 Chinese manufacturing companies, whose Eco-innovation was divided into process and product. Findings suggested that Eco-innovation in process helps to positively predict firms' performance, measured by a total variable score based on sales volume, market share, return on investment (ROI), and customer satisfaction. On the other hand, Eco-innovation in product, for certain levels, does not have the same impact, diverging from what was observed in the Doran and Ryan (2016) study.

Demirel and Danisman (2019) used a wide sample from a survey of 10,618 European SMEs for the year of 2016, which allowed taking conclusions based on different types of Eco-innovation divided between process and product innovations. The conclusions were different from the previous study since Eco-innovation in the design of products positively contributed to firm's growth, while most of the Eco-innovation processes had no significance. The fact that these studies used different approaches to measure firms' performance, allows understanding different channels where Eco-innovation may affect firms' performance.

Madaleno et al. (2019) focused on the environmental gains of introducing different types of Eco-innovation and their impacts on both turnover and employment growth on a sample of 63,303 European firms. Contrary to the previous studies, the authors found negative relation between the environmental benefits gained by the introduction of an Eco-innovation action and the two dependent variables, putting responsibilities on the initial costs demanded to introduce such innovations.

The problem of studies based on surveys is that they often cover a small number of years, being incapable of capturing the long-run effects of Eco-innovation. The viability of these surveys may be also questioned. Del Río et al. (2016) address these problems by identifying some flaws in Eco-innovation studies in firms like the lack of panel data studies, which is more viable than the usual probit and logit models. This happens due to insufficient databases, originating deficiency in long period studies, and regional effects. Treatment to Eco-innovation variables is also aimed since most of the times are *proxied* by general innovation, in legitimate databases, or obtained by researcher's surveys, compromising the size of the sample.

There are, in fact, few studies close to the economic reality, due to the scarcity of information in relation to firm's Eco-innovation activities. An initial study on a specific sector, like the European paper industry, was performed by Wagner et al. (2002) who found evidence of negative impact on the financial performance of Eco-innovation, measured by an index based on the productivity of emissions. However, a more recent study conducted by Lee & Min (2015) performed a restricted model using both fixed and random factors on Japanese manufacturing companies, using green R&D as the main explanatory variable, and found positive impacts on firms' financial performance and on carbon emissions.

Table 2.1 presents a summary of the methodologies and variables found in the literature to study Eco-innovation and its impacts on firm's performance.

Table 2.1- Different Methodologies and Variables regarding Eco-innovation in firms' studies

Authors	Methodology	Independent Variables	Eco-innovation measure
Wagner et al. (2002)	European paper industry analysis using simultaneous equations	SO_2, NO*x* and COD emissions / ROCE, ROE and ROS	Index based on the productivity of emissions
Lee and Min (2015)	Restricted Model on Japanese manufacturing companies	CO_2 emissions / Tobin's Q	Investment in Green R&D
Doran and Ryan (2016)	Multivariate probit model based on Irish Community Innovation Survey	Productivity (Turnover per worker)	9 different types of Eco-innovation
Ryszko (2016)	Partial least squares model based on a	Market share, profit growth,	Sixteen environmental practices / Six items

	sample of Polish companies	average ROS and average ROI	related to Eco-innovation
Tang et al. (2018)	Hierarchical regression analysis based on a sample of Chinese companies	Total variable score based on sales volume, market share, ROI and customer satisfaction	Green product innovation / Green process innovation
Demirel and Danisman (2019)	Robust cross-sectional regression based on a sample of European SME	Revenue Growth	Green product innovation / Green process innovation
Madaleno et al. (2019)	OLS and simultaneous equation models on European firms	Turnover / Employment Growth	Environmental gains of introducing different types of Eco-innovations

SO_2 – Sulfur Dioxide **NO_x** – Nitrogen Oxides **COD** – Chemical Oxygen Demand **ROCE** – Return on Capital Equity **ROE** – Return on Equity **ROS** – Return on Sales **ROI** – Return on Investment **SME** – Small and Medium Enterprises **OLS** – Ordinary Least Squares

Source: Own elaboration

2.3 Cross-country analysis

Since data availability at the firm level is a problem in studying Eco-innovation, some authors have moved their attention to the country-level analysis to draw conclusions. Databases like OECD databases, Our World in Data, International Energy Agency (IEA), Eurostat, and other national communications from governments allow collecting data from environmental action as a whole.

Santra (2017) studied the impact of environmental-related technologies on both energy and CO_2 emissions, using panel data and a Least Square Dummy Variable (LSDV) regression model for the BRICS countries. The author used the data available in the OECD Green Growth Indicators, which allowed treating energy efficiency and CO_2 emissions efficiency as GDP per level of energy usage / CO_2 emissions. In this way, it was possible to infer that Eco-innovation, *proxied* by the *per capita* number of patents registered in each country, helped maintaining the same level of GDP with less environmental impact.

In a study involving EU countries, Beltrán-Esteve et al. (2019) analyzed the environmental productivity, by using a model that considered two different outputs resulting from the combination of inputs like labor and capital: the good one, represented by GDP, and the bad one, represented by the environmental degradation, measured as air contamination. Environmental productivity results from maintaining the good output level with less environmental impact, and it is explained by better efficiency, local innovations, and global innovation. Conclusions suggest that both local and global innovations have a positive impact on the so-called environmental productivity, but with a dichotomy between wealthier countries, leaders in the European environment technology, and the remaining EU countries. Nevertheless, efficiency has dropped in both types of countries, which suggest difficulties to catch up with the best environmental technology.

Chen and Lee (2020) introduced spatial level to analyze the spillover effects of technological innovation and CO_2. They found that there is a spatial correlation in CO_2 emissions and R&D intensity, an enabler of technological development. Although no global relation between technological development and reduction of CO_2 emissions was found, there was evidence that the development of technology in higher-income countries helps reducing the level of CO_2 emissions in neighboring countries.

A very recent analysis performed by Ding et al. (2021) focuses on the most industrialized countries that compose the Group of 7 (G7). It intends to understand the relationship between a set of variables and the level of CO_2 emissions using a dynamic panel data. The international trade, total energy consumption, GDP, and Eco-innovation measured by the percentage of environmental technology in total technologies were the set of variables considered. From this study, an interesting conclusion has been reached – the Eco-innovation was statistically significant to reduce CO_2 emissions both in the short and long run. In fact, the use of dynamic panel data is being increasing in environmental studies such as J. Li et al. (2020), which use techniques of dynamic panel data to test the long run relationship between different variables and Renewable Energies.

Table 2.2 summarizes some methodologies and variables used in similar studies at the country level.

Table 2.2 - Different Methodologies and Variables about Eco-innovation in cross-countries studies

Authors	**Methodology**	**Independent Variables**	**Eco-innovation measure**
Santra (2017)	LSDV regression model using data from BRICS countries	GDP per unit of CO_2 emissions / GDP per unit of TPES	*Per capita* environmental technologies

Beltrán-Esteve et al. (2019)	Luenberger-metafrontier approach to EU-28 countries	GDP / Air contamination	Measured by the gap between GDP and environment degradation
Chen and Lee (2020)	Generalized Nesting Spatial model on 96 countries	*Per capita* CO_2 emissions	% of R&D expenditure as total of GDP
Ding et al. (2021)	Autoregressive distributed lags model on G7 countries	Metric of CO_2 emissions	% of environmental technology in total technologies

Source: Own Elaboration

2.4 Main barriers to Eco-innovation

Knowing the Eco-innovation limitations, besides the previously mentioned financial costs, and what is holding it back in terms of diffusion and agents' acceptance, it is crucial to promote Eco-innovation. Following this idea, the Commission of the European Communities (2004) early claimed that unclear or extensive legislation and lack of proper research regarding Eco-innovation are also a burden to Eco-innovation.

Implementation time also suggests having an important role in Eco-innovation, as firms prefer to implement Eco-innovations in anticipation of regulations (Arguedas & Hamoudi, 2004).

More recent studies continue to approve this idea on adaptation time. For example, patents, which are an incentive to eco-innovate as they can protect the profits of innovative firms from other companies, are seen as an obstacle to more radical and abrupt Eco-innovation (Kiefer et al., 2018).

Attached to this idea of adaption time, Cheng & Shiu (2012) explained that to introduce Eco-innovation in an organization some important activities must be conducted like training and learning processes and, most importantly a long-term strategy should be adopted. Nevertheless, these implementations can have negative implications on the short-term results of organizations (Albers & Brewer, 2003).

According to many studies, size is also an important variable to be taken into account, because small and medium-sized companies have more difficulties to eco-innovate due to the financial capability and complexity of Eco-innovation (Dong et al., 2014; Pinget et al., 2015).

2.5 Eco-innovation to promote efficiency

Eco-innovation can be an approach to promote efficiency, and this is one of the great motivations for agents to pursue Eco-innovation (Bossle et al., 2016). But should efficiency be a major concern? There is a debate concerning this theme, which has serious implications to environmental policy.

Brookes (1990) argued that pursuing efficiency is a wrong path towards environmental action because efficiency would lead to higher consumption levels, completely disregarding the environmental purpose, which the author claimed to be a famous paradox in environmental studies, the so-called- Jevons' Paradox. Jevons' Paradox comes from the William Stanley Jevons's study on the possible exhaustion of coal exploration. The British economist reached the conclusion that, by efficiency gains in coal usage, higher consumption of this resource was reached, due to a rebound effect. This effect translates into the effective prices decrease of materials that, as a consequence, generate higher demand, being counter-productive with the initial environmental objective (Alcott, 2005). Jevons' ideas opened a debate on the pursuing of efficiency, not in coal, but in emissions and energy usage. If Jevons' Paradox is right, a great number of environmental strategies are missing the point (Alcott, 2005) and a shift to other policies is needed. Nevertheless, most of this paradox argumentation relies on theoretical arguments and, even the few empirical evidence is inconclusive and, sometimes, biased by periods of economic growth (Sorrell, 2009). Nonetheless, Sorrell (2009) states that it is important to study the logic behind the famous paradox, because in the initial stage of technology diffusion, there are examples of increased energy consumption alongside with energy-efficient technology.

The discussion seems not to cease as authors advocate that rebound effects on energy-efficiency exist but are residual at the whole economy level (Steinhurst & Sabodash, 2011). Many authors actually advise policies involving efficiency as a crucial instrument (Jänicke, 2012; Zhang & Cheng, 2009), while others confirm the existence of Jevon's Paradox and completely disregard efficiency policy (Polimeni & Polimeni, 2006) or defend that those policies should be accompanied by other instruments like taxes (Freire-González & Puig-Ventosa, 2015), or simple state that the estimated rebound effects are poorly developed and need further robust studies (Nadel, 2012).

It is clear that more evidence is needed to support or reject Jevons' Paradox. However, policies towards efficiency have already been taken, and for that reason it is important to acknowledge what are those policies and their outcome, which is the main purpose of the next chapter.

2.6 EU policies to promote energy and emissions efficiency

United Nations Framework Convention on Climate Change (UNFCCC) in 1992 was the first signalization of international efforts to tackle climate degradation, which includes EU participation. However, the strongest climate policy actions in EU started at the beginning of the millennium coinciding with the ratification of Kyoto Protocol (Albulescu et al., 2019).

Since then, a set of measures has been taken in order to accomplish the reduction of GHG and more sustainable energy usage. From these measures, stands out the ones promoting energy efficiency involving investment, international cooperation, and restriction of certain products that fail to meet minimum standards (Commission to the European Council and the European Parliament, 2007)[2]. For GHG emissions, the 2020 Climate & Energy Package[3] biggest instrument was the Emissions Trading System (ETS), and the support to low carbon technologies through programs like NER300, a funding program for low carbon technologies and Horizon 2020, a research and innovation program that searches for more competitiveness and sustainability in UE.

Albulescu et al. (2019) performed a recent analysis to better understand the impact of renewable energies and EU regulations. The authors conclude that EU is importing more eco-friendly technologies, the fiscal stimulus is important for renewable energy production, and policies to sustain energy efficiency are effective in controlling pollution.

In a recent press release, European Commission (2020) announced new climate ambitions to reach in the year of 2030 that reinforce the reduction of GHG emissions. The objective is to reduce at least 55% of GHG emissions in 2030 in relation to the 1990's emission levels. The press release highlights, among other legislations to be presented in 2021, the objective to reinforce energy efficiency and renewable energy policies, as well as the revision of ETS to better adapt it to the future needs. We can conclude that EU will continue to have an agenda on GHG emissions tackling and energy efficiency will persist as an important tool to reach European environmental objectives.

[2] See also Directive 2012/27/EU.
[3] A set of laws to accomplish EU climate targets in 2020.

3. Data and Methodology

3.1 Variables Definition

This research follows the work of Santra (2017) regarding the variables used in a study of the effect of technological innovation on energy and CO_2 emissions productivity on BRICS countries. Nevertheless, a different approach will be performed as more years and a different set of countries are explored.

This study focuses on two different dependent variables to study energy productivity and emissions released. For the energy productivity, a GDP ratio with the Total Primary Energy Supply (TPES) is used to measure the improvements in the energy efficiency to generate an output level. In other words, the higher the ratio the more efficient the energy use will be. On the emissions productivity, another GDP ratio is used, but with CO_2 emitted from fuel combustion (USD/kg). CO_2 is a good measure for all GHG, because, according to European Commission (2017), CO_2 accounted for 81.2% of the total GHG emissions on EU countries.

Considering the wide ranges where Eco-innovation may appear, it is important to narrow this study to technology. There are two main reasons for such choice. The first one is associated with tractability as the available information for Eco-innovation, measured as patents, is much more related with technology (Kemp and Pearson; 2007). The second reason is associated to the object of this study - the efficiency -, as efficiency is a possible factor for agents to invest on Eco-innovation in a technological perspective (Horbach et al., 2012; Rennings, 2000).

Therefore, Eco-innovation, which is the explanatory variable of this study, is *proxied* by the number of patents concerning environmental-related technologies. According to Kemp and Pearson (2007) patent analyses ensure that Eco-innovation is useful and inventive, whose main advantage in relation to R&D is that information of patents for environmental purposes is usually available, which does not frequently happen for R&D. In order to allow for countries comparison, the variable is present as per million residents.

To ensure the quality of patents concerning environmental technologies, the family size[4] chosen was "2 or greater", because according to OEDC Green Growth indicators, family size of 1 includes low value technologies, and could originate biased results.

[4] "A patent family is a collection of patent applications covering the same or similar technical content" (European Patent Office, 2017)

Santra (2017) consider that the time span he used was too short (3 years) to analyze the impact of Eco-innovation. From general innovation studies using patents, it is possible to conclude that patented technology take time to produce results (Crosby, 2000). This may be explained by later diffusion of technology (de Noni et al., 2018) and different learning rates (Lam et al., 2017). Long-run estimation needs an adequate time-period that should not be exaggerated so the model does not lose degrees of freedom. Even though those patents may produce results in a certain number of periods after its implementation, is interesting to test for short-run impacts in this study, since the productivity of both emissions and energy may be affected, in the short-run, by the application of the patented technology and the adaptation time to Eco-innovation.

The remaining variables act as control variables. Energy Intensity has been considered in some studies to have impact on emissions fluctuations (Acaravci & Ozturk, 2010; Shahbaz et al., 2015; Wang et al., 2005) and in energy consumption. In *per capita* terms, this variable allows reflecting efforts to increase energy efficiency and to reduce carbon emissions. Nevertheless, according to IEA (2020), this variable has some disadvantages because factors like temperature have an impact on the energy intensity of a country, which may affect the energy efficiency results. However, IEA (2020) also considers the variable to be often used as an energy efficiency indicator.

Real GDP *per capita* indicates the level of economic activity of the countries, which could be related to higher levels of energy consumption and CO_2 emissions (Aye & Edoja, 2017; Chiou-Wei et al., 2008), but also to more capacity to deal with Eco-innovation.

Finally, the percentage of renewable energy supply in TPES is another control variable since it is usually related to energy efficiency (Gielen et al., 2019) for its possible contribution to reducing emissions (Zoundi, 2017).

The variables included in the model were analyzed in their logarithmic form, as GDP and population are variables that tend to grow overtime (Acemoglu, 2008).

All the data was extracted from the OECD Green Growth Indicators database, which comprises data towards green growth to support policy decisions and inform the public.

Table 3.1 presents a summary of the analyzed variables and the nomenclatures used to define them.

Table 3.1 – Variables' Description

Variables	Meaning	Description

Dependent Variables		
lCO2_PROD	Productivity of emissions	GDP (US$ 2015) per unit of CO_2 emissions from fuel combustion
lENER_PROD	Productivity of Energy usage	GDP (US$ 2015) per unit of TPES
Explanatory Variable		
lINOV	Measure of Eco-innovation	Patents of environment-related technologies per million of habitants
Control Variables		
lENER_INT	Energy Intensity	TPES/Population
lRGDP	Real Gross Domestic Product	Real GDP *per capita* (US$ 2015)
lREN_ENER	Renewable Energies	Percentage of Renewable Energy in TPES

3.2 Sample

The studied period is from 1995 to 2016 (the last period available in the database), resulting in 21 years. This time-period includes three important moments for the European climate action:

• The moment before the implementation of the Kyoto Protocol, which coincided with the first efforts of the UN to have a common climate agenda, by establishing national programs in order to reduce greenhouse gas emissions and to submit regular reports, which came into force in 1994.

• The moment of the signature of the Kyoto Protocol and its implementation, a period that goes from 1997 to 2005, and represented the biggest global effort to apply measures to fight against climate degradation.

• The definition in 2010 of the objectives to be achieved in 2020, that focus on energy efficiency and GHG emissions control.

3.3 Regions

To perform a regional analysis of the European Union countries, it was used the regional division of the UN Statistical Unit that divides Europe into four different regions. In order to represent each region, five countries with similar Eco-innovation levels from each region were selected to form homogeneous groups with the help of the recent years Eco-innovation Index, an index that demonstrates the Eco-innovation performance of each UE member state, implemented by the European Commission (EC). This index is useful to the Eco-innovation policy in the UE as it helps in the progression of Eco-innovation practices, making sense to use it as a proper analysis instrument (Park et al., 2017). Figure 3.1 illustrates the countries used in this study.

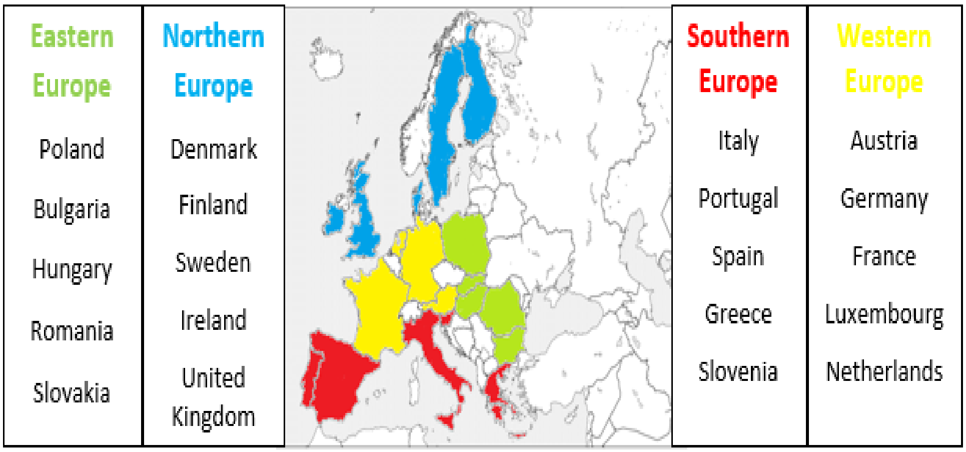

Figure 3.1- Countries and Regions approached

Eastern Europe region is usually associated with less developed countries due to the troubled past marked by political instability. In comparison to other regions, environmental policies and public support have had less impact, which explains the weak electoral results of parties with an ecological agenda (Waller & Millard, 1992). In the Eco-innovation Index of 2019, this region places a lot of countries in the lowest position in the so-called *Countries catching up with Eco-I* (Eco-innovation).

Northern Europe, on the other hand, is a European region associated with more development and green initiatives, mainly in the Scandinavian region. According to the Nordic Council of Ministers, - a council composed by the EU countries of Denmark, Finland, and Sweden -, Nordic countries have a developed cooperation in environmental matters and are aware of their position in climate change tackling (Sundtoft, 2018). Most of the countries that represent this region have the highest index classification of *Eco-I Leader*. Only Ireland is under that classification, with *Average Eco-I performers* denomination.

Southern Europe, also known as the Mediterranean region, benefited from EU influence regarding environmental policy. Nevertheless, the rhythm of national compliance is quite heterogeneous (Fernández et al., 2010), which is observable with the different positions occupied by Mediterranean countries. Italy and Spain are *Average Eco-I performers,* but with a performance above EU average, Portugal follows EU Average, Slovenia is under that average and Greece has the worst classification in this selection belonging to the *Countries catching up with Eco-I* group.

Western Europe follows Northern region in terms of environmental awareness (Balžekiene & Telešiene, 2017). Most of the countries, like Austria, Germany, and Luxembourg, were placed in the highest positions in Eco-innovation in recent years, with Luxembourg being the leader of this index in 2019. France and the Netherlands were in the second-highest classification, but with performances above EU average and close to their peers.

3.4 Panel Data

To analyze the impact of Eco-innovation in emissions and energy productivity, the data was organized in panel form. Panel data contains time-series observations of a certain number of individuals, having a cross-sectional dimension and a time series dimension that allows taking inferences both from the group effect, in this case, the country/region, and from the time effect.

Panel data has a wide application to economic studies and, therefore, cross-country/cross-state panels have gained more attention as this instrument allows for better policy decision (Arellano, 2003).

In comparison to cross-sectional or time-series data, panel data enjoys some advantages because it contains more data variability and thus, originates improved econometric estimations (Hsiao, 2007, 2014). Panel data also allows for individual heterogeneity control, which is an important feature, as studies with time series or cross-section data, with no control over individual heterogeneity, take the risk of being biased (Baltagi, 2008).

Nevertheless, there are some issues that may arrive related to unobserved heterogeneity across individuals, derived from unobserved data, which may affect the statistical findings (Hsiao, 2014). Other problematic situations like heteroskedastic and serial correlation of the errors may appear, and some econometric tools should be applied to overcome them (Arellano, 2003). Baltagi (2008) addresses the problem of cross-section dependence (CD), mainly for macro panels.

3.5 Cross-Sectional Dependence

Cross-sectional dependence (CD), an issue related to high dependence of the agents analyzed in a sample, can occur due to unobserved factors common to all units that affect each individual, making them correlated with each other. This problem deserves attention, because, according to Phillips & Sul (2003), its disregarding may probably lead to improper statistical conclusions, and so, withdraw most of the advantages of panel data related to the closeness with the economic reality.

In fact, in a sample like the one used in this study, with all the countries belonging to the EU and, in consequence, having similar rules and strategies in environmental and economic action, there is a high probability of CD, which creates the need for adapted data modeling.

In order to confirm the existence of CD in the sample, a statistical test suggested by Pesaran (2004, 2020) is conducted. The author presents two other CD tests (the spatial dependence and the Breusch-Pagan) and explains their limitations and how his test overcomes them. The test of spatial dependence (Moran, 1948) is a test that introduces the spatial dimension through a spatial weight matrix. The problem with this matrix is the critical dependence that its choice may have on the results. The other test (Breusch & Pagan, 1980) uses a Lagrange Multiplier, whose main advantage is its easiness to compute, though, it may show size distortions for larger cross-sectional units and small time periods (Baltagi et al., 2012).

Pesaran (2004), in turn, proposes an approach based on OLS regression for each panel data unit, which in the present study is for each country. After that, the following step is to use the collected residuals from the OLS and compute the average of all the correlation coefficients pairs that allow for cross-sectional dependence. The test assumes the following form:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{p}_{i,j}\right) \tag{1}$$

$\hat{p}_{i,j}$ represents the estimation of the pair-wise correlation of the residuals, N the individuals of the panel and T the time-period. Pesaran (2004) test is robust to single or multiple breaks in slope coefficients, error variances and unit roots.

3.6 Unit Roots

To perform the methodology necessary to analyze the relation between Eco-innovation and Emissions/Energy Productivity the variables should not be integrated of an order higher than one.

Im et al. (2003) proposed a test (IPS), based on the Augmented Dickey Fuller (ADF) regression that allows for heterogeneity of the panel and serially correlated errors. In this case, it is necessary to use an appropriate number of lags so that the following *t*-bar test can produce viable results:

$$W_{Tbar} = \frac{\sqrt{N}\{tbar_{NT} - \frac{1}{N}\sum_{i=1}^{N} E[t_{iT}(p_i,0)|\beta_i = 0]\}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} Var[t_{iT}(p_i,0)|\beta_i = 0]}} \Rightarrow N(0,1) \qquad (2)$$

$E[t_{iT}(p_i,0)|\beta_i] = 0$ and $Var[t_{iT}(p_i,0)|\beta_i] = 0$ are, respectively, mean and variance values estimated by the authors for certain lag (p) and T periods that are responsible for the standardization of the *t*-bar statistic, which is the statistic that results from the average of Dickey–Fuller statistics computed for each N in the panel.

However, this test may have some problems when dealing with larger N's (Harris et al., 2010) and does not account for CD. For that reason, a second test is applied to compare the results and infer better conclusions about the stationarity of the variables.

Indeed, Pesaran (2007) overcomes this problem by suggesting a test based on a different version of the ADF, where the "cross-section averages of lagged levels and first-differences of the individual series" are considered, making it a Cross-Sectional ADF (CADF) Therefore, the CIPS test contains the CADF as can be seen in Eq.3:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{3}$$

Even though this test is a simple way to solve the CD problem, it has its limitations, namely the fact that it is based in a one-factor model, which means that, for all the members of the panel, there is only one common factor that can affect each one of them. In a country-level panel, this may be too limiting, since in this case there are different common factors affecting panel members.

3.7 Cointegration

When approaching the long-run relation of variables, it is important to verify if the variables are cointegrated, that is, if there is co-movement between a set of variables in the long-run.

Pedroni's solution (Pedroni, 1999) seems to be a good method to study this type of relation due to its faculties when dealing with heterogeneity of the residuals. The suggestion is to run seven statistics on the residuals of the regression. It is possible to divide those seven statistics into two types: homogeneous statistics, in which the cointegration vector is homogenous for all the panel, and the group statistics, which considers that the cointegration vector varies for each panel member, a characteristic that may be interesting in this study, as there is a high probability of different characteristics among countries.

According to Gutierrez (2003), the test performs well when the dimension of the panel increases, which for this case is completely adequate.

However, the CD obliges, again, to perform another test to robust the conclusions. Westerlund (2007) cointegration test accounts for CD using bootstrap techniques. The decision on the number of lags is also crucial, since an exaggerated number of lags will certain cause an erroneous statistical inference. For this purpose, there are four different statistics (V, Rho, PP and ADF), but with a similar division between group and all-panel statistics allowing for analogous conclusions.

3.8 Causality inference

To reach a suitable analysis on the relation of Eco-innovation on the productivity of energy and emissions, the type of regression chosen must have some characteristics like being upright when dealing with a relatively large panel, as the one approached here, and giving a proper analysis to the study specifications since the panel groups are countries from the EU, which may imply some relations between them.

There are some methods usually applied to dynamic panel data, namely the Dynamic Fixed Effects (DFE), Mean Group (MG) (Pesaran & Smith, 1995), and Pooled Mean Group (PMG) (Pesaran et al., 1999). In order to choose the best estimator, a Hausman test (Hausman, 1978) will be performed and its result will define the estimator, which for simplicity will be developed in the next section.

The estimation of the models will be conducted using Stata Command xtpmg that can handle the three previous estimators.

The starting point is to apply an Autoregressive Distributed Lag (ARDL) dynamic model that will suffer transformations according to the type of estimator used:

$$y_{i,t} = \sum_{j=1}^{p} \lambda_{i,j} y_{i,t-j} + \sum_{j=0}^{q} \sigma_{i,j} x_{i,t-j} + \mu_i + \varepsilon_{i,t} \tag{4}$$

$x_{i,t-j}$ are the explanatory variables, $y_{i,t}$ are the dependent variables, $\lambda_{i,j}$ and $\sigma_{i,j}$ are the coefficients, μ_i the slope of interception and $\varepsilon_{i,t}$ the error term.

4. Results and Discussion

The main objective of this study is to analyze the impact of Eco-innovation on Energy and Emissions Productivity, both in short and long-run, and to assess whether it is possible to maintain or even increase the economic output level, while decreasing the environmental impact through the implementation of Eco-innovation measured as the number of patents *per* million of habitants.

Also, by dividing the EU countries into different geographic regions, we can observe if the impact of Eco-innovation differs among them.

4.1 Descriptive analysis

Therefore, it is important to previously analyze the evolution of Emissions, Energy Productivity and Eco-innovation in the period that goes between 1995 and 2016. For that purpose, the raw data was plotted into a linear graphic (Appendices A, B and C) for each country and the logarithmic form was summarized, in Table 4.1, to better complete the analysis, enabling the comparison at both country and region level.

Table 4.1 - Descriptive analysis of the Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
lENER_PROD	440	9.1697	.33364	8.2257	10.104
lCO2_PROD	440	1.4829	.39580	.32820	2.5801
lINOV	440	1.8399	1.4705	-3.9120	4.4835
lENER_INT	440	1.2682	.33619	.67958	2.2596
lRGDP	440	10.437	.43679	9.1113	11.587
lREN_ENER	440	1.9788	.8976	-.2391	3.7617

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP**- Real Gross Domestic Product **lREN_ENER**- Renewable Energies

In terms of energy productivity, a tendency of growth in all countries is verified. However, countries suggest different energy productivity levels and growth paces, whose differences can be also observed among regions.

The Eastern Region, as expected, presents the lowest energy productivity levels as the mean of the Energy Productivity in logarithmic expresses. Hungary has the highest level of energy productivity in the first period, which can explain the less accentuated growth of the variable in comparison with its peers. Even so, in 2016 this country presented the highest level of energy productivity, rounding the 11,000 US Dollars per unit of TPES. In the opposite side, Bulgaria presents the lowest level in both 1995 and 2016. It is also important to mention that Czech Republic and Slovakia indicate a small stagnation until the year of 2000, though from that year on both countries started to keep up with the increasing growth trend.

On the other side, the Northern Region is one of the regions that present the highest levels of energy productivity at the end of the sample period, with only one country having less than 10,000 US Dollars per unit of TPES in 2016 (Finland). Here the highlight goes to Ireland, whose growth increased from around 10,000 to almost 25,000 US$/TPES. With a decreasing growth around 2008, Ireland quickly recovered in the last years. UK present an increasing growth trend in almost all the sample, contrasting with the rest of the countries which had more ups and downs in their path. However, at the end of the sample period, the Energy Productivity levels of the region are the highest, though it does not have the highest mean of Energy Productivity, which belongs to Southern Region. This aspect is probably related to the temperature in both regions that result on different energy needs (IEA, 2020).

In the Southern Region it is found a different behavior from the other regions. The initial values of energy productivity are higher than in the Northern Region, but the growth tendency started much later. For Greece, this tendency only started in 2000, while for Italy, Portugal and Spain it started even later in 2005. Slovenia behaves more closely to an Eastern Region country, which can be explained by its proximity with countries from this region. Greece also displays a curious drop, the highest in all countries, in 2010. Even with a slow start, this region generally displays levels of Energy Productivity closed to the Northern and Western regions.

The Western region has similar starting values in comparison to the Northern region, but the growth is slower. Likewise, as Eastern and Northern Regions, it starts the growth trend around 1995, but in 2000 a stagnation period took place for France, Germany and Austria. In this same year, Luxembourg and The Netherlands started a drop on energy productivity levels until 2005. After that, the Western Region retook the growth trend demonstrating similar levels among countries, highlighting Luxembourg with the highest levels of the Region in 2016.

Regarding the CO_2 productivity, as this variable is based on CO_2 emitted from fuel combustion, which is a type of TPES, a relation to energy consumption is expected. Furthermore, many studies point out the relation between CO_2 emissions and Energy consumption (Acaravci & Ozturk, 2010; Sharif Hossain, 2011). In fact, it can be observed that the behaviors of CO_2 productivity in each region are quite similar to the Energy productivity.

The Eastern Region presents the lowest levels of CO_2 productivity, when compared to other regions and, again, Hungary presents the better results, with Slovakia right after. The remaining countries do not even reach the 3.5 GDP/CO_2 emissions or barely reach this level.

Ireland is the country with the highest Energy productivity level in 2016, while for CO_2 productivity, is Sweden who takes the first place with around 13 GDP/CO2 emissions. On the other hand, Finland continues with the lowest emissions productivity levels in the region. Differently from Energy Productivity, this Region has the highest means of CO_2 Productivity in logarithmic form.

In Italy, Portugal and Spain, the growth in the CO_2 productivity, like in energy productivity, has started later than in other countries. Slovenia continues to behave closely to an Eastern Region country, both in terms of levels and growth. Greece also presents levels close to the Eastern Region, but with the same drop in CO_2 productivity as in energy productivity, in 2010.

Finally, in the Western Region, there is no novelty in comparison to the analysis of Energy Productivity.

Concerning the Eco-innovation, this variable generally grows across countries. Nevertheless, its behavior is much more inconsistent than the previous variables, possible due to the need of capital formation in order to innovate and, consequentially, to have a patented technology (Ortiz-Villajos, 2009). This idea is corroborated with the highest value on the standard deviations presented in Table 4.1.

In terms of the number of patents per million of habitants, it is clear that the Northern and Western Regions are the greatest responsible for the Eco-innovation in the EU. Denmark reaches the highest number of patents registered in the sample with around 90, in 2010. In Luxembourg it is observed a different behavior of Eco-innovations, as there is no growth trend, but an up and down tendency through the years, instead. However, this might have happened because Luxembourg has reached its Eco-innovation peak faster than its neighbors, suggesting that this country has realized much earlier than other countries that Eco-innovation is a strategy to a better environmental performance.

The remaining regions are way behind the previous two, with the Eastern Region presenting the worst results in Eco-innovation. This time, Slovenia is not close to the Eastern Region countries, having the highest number of patents per million habitants followed by Italy.

Finally, Tables 4.2 and 4.3 allow concluding the correlation between variables. It is possible to observe that the regressors do not have a perfect or linear representation of one another. The most problematic case may be the correlation between the lRGDP and lINOV. Nonetheless, this correlation appears to be mostly pushed by the Eastern Region, since in the remaining regions (Appendix D) the correlation is acceptable. Also, the variable lRGDP will suffer from further transformations, as it is going to be presented next.

Table 4.2 - Variables Correlation | Energy Productivity

	lENER_PROD	lINOV	lENER_INT	lRGDP
lENER_PROD	1			
lINOV	0.3969	1		
lENER_INT	-0.1455	0.6588	1	
lRGDP	0.6512	0.8047	0.6557	1
lREN_ENER	0.1212	0.2495	-0.0683	0.0427

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP**- Real Gross Domestic Product **lREN_ENER**- Renewable Energies

Table 4.3 - Variables Correlation | Emissions Productivity

	lCO2_PROD	lINOV	lENER_INT	lRGDP
lCO2_PROD	1			
lINOV	0.6230	1		
lENER_INT	0.1447	0.6588	1	
lRGDP	0.6580	0.8047	0.6557	1
lREN_ENER	0.4472	0.2495	-0.0683	0.0427

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP**- Real Gross Domestic Product **lREN_ENER**- Renewable Energies

4.2 Cross-Sectional Dependence

As mentioned before, a Pesaran (2004) test was conducted to test the existence of CD. From Table 4.4 it is clear that the null hypothesis of cross-section independence is rejected at 1% level.

This test confirms the existence of dependency between countries, which is highly plausible, since the sample is based on countries from the EU. Having this in mind, CD will be accounted in order to present reliable results.

Table 4.4 - Cross-Sectional Dependence

Variables	CD-test	p-value	Correlation
lENER_PROD	57.54	0.000	0.890
lCO2_PROD	58.90	0.000	0.911
lINOV	48.91	0.000	0.756
lENER_INT	29.59	0.000	0.458
lRGDP	53.58	0.000	0.829
lREN_ENER	57.46	0.000	0.889

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP**- Real Gross Domestic Product **lREN_ENER**- Renewable Energies

4.3 Unit Roots

In order to test for the relation among energy/emissions productivity, Eco-innovation and the other explanatory variables, the variables should not be integrated of an order higher than 1 if we use an ARDL model, otherwise it will be impossible to reach any conclusion about the variables' relation.

For that purpose, Im et al. (2003) test was used. However, since CD is presented on this sample and this test does not deal with CD, Pesaran (2007) test was also used. Indeed, as Pesaran test may be too restricting on country-level data by not considering more than one base factor, it imposes the use of both tests and their comparison for a better analysis.

Both tests are clear about the order of integration of energy productivity, energy intensity, renewable energies and real GDP *per capita*. Besides some differences in the order of variables integration on both tests, none of the remaining variables has an integration order higher than 1, making possible to use ARDL model.

Table 4.5 - Unit Roots | Im et al. (2003) & Pesaran (2007)

Variables	IPS		CIPS	
	W-t-bar statistic	p-value	t-bar statistic	p-value
lENER_PROD	3.6380	0.9999	-1.970	0.155
D.lENER_PROD	-8.8932	0.0000	-3.318	0.000
lCO2_PROD	4.5125	1.0000	-2.036	0.093
D.lCO2_PROD	-9.6357	0.0000		
lINOV	-1.1437	0.1264	-3.006	0.000
D.lINOV	-10.5951	0.0000		
lENER_INT	2.3344	0.9902	-1.832	0.353
D.lENER_INT	-6.7124	0.0000	-3.215	0.000
lRGDP	-2.1602	0.0154	-2.620	0.000
lREN_ENER	5.3774	1.0000	-1.885	0.267
D.lREN_ENER	-8.1041	0.0000	-3.299	0.000

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation
lENER_INT- Energy Intensity **lRGDP**- Real Gross Domestic Product
lREN_ENER- Renewable Energies

4.4 Cointegration

To infer for the relation among the variables analyzed in this study, it is important to test for cointegration. The first test used was the one developed by Pedroni (1999), which does not account for CD but has the advantage of dealing with this study's small panel dimension in comparison to Westerlund (2007) test which performs better in larger samples.

Table 4.6 gives seven statistics that allow taking conclusions on cointegration between Energy Productivity, Eco-innovation, Energy Intensity, Real GDP and Renewable Energies. Five out of seven statistics present an absolute value higher than 2, as well as all the group statistics that consider a different cointegration for each panel member, which means that there is no reason to reject cointegration among the variables, making sense to study their long-run relation.

Regarding the Emissions Productivity the results are not as positive as in relation to the Energy Productivity, thus it is not a suitable result to find a long-run relation. In Table

4.7 it is shown that four out of seven statistics are higher than 2, in absolute terms. Since there is CD, another test was performed in order to compare results.

Table 4.6 - Cointegration Pedroni (1999) | Energy Productivity

Test Statistics	Panel	Group
V	1.271	
Rho	2.607	4.555
PP	1.78	3.452
ADF	3.889	4.724

Table 4.7- Cointegration Pedroni (1999) | Emissions Productivity

Test Statistics	Panel	Group
V	-.01797	
Rho	.5118	2.351
PP	-2.762	-2.224
ADF	.9423	2.215

The Westerlund (2007) cointegration test deals with CD by bootstrapping techniques. According to Pattengale et al. (2010) most of studies that use bootstrap techniques use a number of replications between 100 and 500. Having this in mind, a total of 400 replications were chosen.

The Westerlund (2007) test is not so clear in proving cointegration between Energy Productivity and the remaining variables, with half of the statistics presenting a robust *p*-value that does not reject the null hypothesis of no cointegration. For *Gt* and *Pt* statistics it is possible to reject the null hypothesis at a 5% significance level.

For the Emissions Productivity, it is clear that the hypothesis of cointegration is not verified since the null hypothesis is not rejected for any statistic. However, the long-run relation will still be tested. On one side, because the periods used to test cointegration may be too short, like in the case of the Westelund (2007) test, which only allowed for 1 lag given the sample size, and, on the other side, because even if there is no cointegration in all countries together, it does not mean that there is no cointegration in some of the countries. As a region analysis will also be performed, it does make sense to check for a long-run relation, having in mind that no relation may be found due to the Westerlund (2007) cointegration test.

Table 4.8- Cointegration Westerlund (2007) | Energy Productivity

Statistic	Value	z-value	Robust p-value
Gt	-8.975	-30.422	0.040
Ga	-0.076	6.165	0.165
Pt	-4.814	1.907	0.023
Pa	-0.383	3.506	0.378

Table 4.9- Cointegration Westerlund (2007) | Emissions Productivity

Statistic	Value	z-value	Robust p-value
Gt	5.069	30.649	0.988
Ga	-0.060	6.175	0.995
Pt	-1.362	4.632	0.905
Pa	-0.111	3.672	0.915

4.5 Causality Inference - Energy Productivity

The first step to perform the analysis based on the ARDL model is to define an adequate lag structure of the variables. As it was mentioned in the methodology section, Eco-innovation, as measured by patents, may take some time to produce results. Santra (2017) used 3 lags to study this variable, but in this study the number of lags will be augmented to 5 to capture patents' results in a larger period. The remaining variables will be lagged by 1 period, as they act as control variables.

The second step is to choose the best estimator. This task will be performed using the Hausman test, whose results are displayed in Table 4.10. Taking the first estimator pair's prob-value it makes clear that the homogeneity hypothesis cannot be rejected and for that reason the PMG estimator is better for the model than the MG estimator. The same stands in comparison to the DFE estimator, where, once again, the homogeneity hypothesis is not rejected. For that reason, PMG estimator is the chosen one.

Table 4.10 - Hausman Test for MG, PMG and DFE estimators

	MG | PMG	DFE |PMG
chi2	1.20	5.87
Prob>chi2	0.8784	0.2090

PMG estimator (Pesaran et al., 1999) combines the short-run feature of allowing the interception of short-run coefficients and the error-variances to vary for each country, with the long-run feature of constraining the long-run coefficients to be equal among countries as would the DFE estimator. In this way, PMG acts like a combination of both features of the previous estimators (Blackburne & Frank, 2007).

The PMG is based on the ARDL model presented in the methodology section but with the following difference:

$$\Delta y_{i,t} = \theta_i(y_{i,t-1} - \beta_i x_{i,t}) + \sum_{j=1}^{p-1} \lambda_{i,j} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \sigma_{i,j} \Delta x_{i,t-j} + \mu_i + \varepsilon_{i,t} \tag{5}$$

θ_i represents the speed of adjustment coefficient which denotes how fast the variables would return to the equilibrium in the long run, given a certain shock and it is calculated by averaging all the coefficients estimated for each group . $(y_{i,t-1} - \beta_i x_{i,t})$ is the Error Correction Term (ECT) and β represents the long-run coefficient.

θ_i should be negative and significant in order to prove a long-run relation. If not, there is no evidence of such relation.

Table 4.11 provides the coefficients and significance values for each variable in the model. The results confirm the suspicions of no long-run causality taken from the Pedroni's Cointegration test. By looking at the ETC, it is possible to conclude that only the Eastern Region shows evidence of long-run causality at a 5% level of confidence, which allows concluding that only this region has a long-run analysis.

Regarding control variables, Real GDP *per capita*, as expected, has a high impact on Energy productivity, meaning the level of GDP *per capita* is important to reduce the energy levels without compromising the economy of a given country. The variable is significant at a 1% level for all the groups and sub-groups analyzed. The same results were found in Santra (2017).

On the other hand, at a 1% significance level, the Energy Intensity has the opposite impact in the UE and in all European regions. This result seems to be normal as the more sources of energy a country owns, the more energy is potentially used, contributing for a worse ratio of GDP / Energy Consumption. These findings do not go in line with Santra's results, as no significance was found regarding this variable. However, there are other studies where relations between Energy Intensity and Energy productivity are found (IEA, 2020).

Finally, Renewable Energy sources show no significance in Energy Productivity in any instance, which is corroborated by Santra (2017). Nevertheless, it is expected that the variable has a significant impact on the emissions level, an inference that will be taken further on.

Concerning the Eco-innovation impact on Energy Productivity, it is clear that it is negative in all European Regions and in the EU countries as a whole, except for the Northern Region where the INOV variables have no significance. Although the impact of Eco-innovation is negative, it is quite small. In the sample of the EU countries, if a unit of Eco-innovation increases, it will affect Energy Productivity in only -0.0018, considering a 10% significance level, in the short run. Excluding the Northern Region, in the remaining three regions the behavior is quite similar.

These results are different from the similar study on BRICS countries from Santra (2017). One of the reasons for this difference may be related to the number of countries approached, which is larger than in Santra (2017) and Ding et al. (2021). Another important difference is that in those studies the countries are geographically dispersed and do not represent a political and economic union like the EU.

The Eastern Region, where it was observed that the levels of energy productivity are the smallest, is the only region where a long-run analysis of Eco-innovation can be made. For a lag equal to 4 and a significance level of 1%, the negative impact slightly increases, but still remains in a low level. Four periods are far from being a too long period and for that reason it can capture those financial losses and learning periods that were mentioned in the Section 3, related to the costs of investment, implementation and personnel formation.

In terms of comparison among regions, all of them show similar behavior especially regarding the control variables. For that reason, when considering Energy Productivity, it is possible to conjecture cohesion among all EU countries, having no regional impact.

Table 4.11 - Energy Productivity Causality Inference

	EU	Eastern Region		Northern Region	Southern Region	Western Region
		Short run	Long-run			

ECT	.0338 (0.116)	-.1617 (0.039)	-	-.1463 (0.370)	-.1393 (0.152)	-.0132 (0.168)
lINOV	-.0018 (0.061)	-.0014 (0.076)	-.0077 (0.004)	-.0059 (0.138)	.0013 (0.060)	-.0039 (0.003)
lRGDP	1.0013 (0.000)	1.0091 (0.000)	1.1122 (0.000)	.9912 (0.000)	.9816 (0.000)	1.0099 (0.000)
lENER_INT	-.9662 (0.000)	-1.0140 (0.000)	-1.0025 (0.000)	-1.0079 (0.000)	-1.0066 (0.000)	-.9995 (0.000)
lREN_ENER	.0025 (0.311)	.0107 (0.166)	.0086 (0.239)	-.0045 (0.364)	-.0015 (0.776)	-.0019 (0.164)

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP**- Real Gross Domestic Product **lREN_ENER**- Renewable Energies

4.6 Causality Inference - Emissions Productivity

For the homogeneity to hold, the same lag structure will be applied in the study of the Emissions Productivity. It is worth noting that in both models the dependent variable is the only one that changes, while all the remaining independent and control variables stay the same.

The Hausmann test was performed in order to reach the proper estimator, however the results were inconclusive. Nevertheless, in the previous model the cointegration tests indicated no signs of long-run relation between the variables. Therefore, it is possible to ensure that in the model with Emissions Productivity the likelihood of having a long-run co-movement is quite small, meaning that the long-run difference between the PMG and the MG estimators is nonexistent.

Nevertheless, the PMG estimator is used instead of the MG estimator because according to Pesaran et al. (1999) it estimates the short-run relations for small/medium time spans more efficiently than the MG estimator, even though the results may be biased because of the short-run coefficients. After defining the lag structure and the estimator used, it is possible to proceed to the results' analysis.

Regarding the control variables, lRGDP and lENER_INT display similar results to the previous model. Real GDP *per capita* continues having a high impact on the dependent variable, at a 1% level of confidence in every group, meaning that the level of GDP *per capita* is important to reduce emissions. Similar results were found in Santra (2017). In Ding et al. (2021), the authors found a negative relation between GDP and CO_2 emissions, but this is not incompatible with the results found here. Indeed, the more a country produces, the more emissions it will release, but at the same time the higher the GDP the better the conditions will be to reduce GHG emissions.

In contrast, Energy Intensity impact is negative for all groups, at a 1% level of confidence, meaning that countries depend on the use of fossil fuels, which produce GHG emissions. This result is highly expected and is in line with Santra (2017).

One of the biggest differences in comparison with the previous model with Energy productivity is that the percentage of Renewable Energies is significant to explain the CO_2 Emissions productivity, except in the Western Region. For the Eastern Region, the level of confidence is 5% and 1% for the remaining regions. The Northern Region stands out with the highest coefficient concerning renewable energy, which makes sense since in this region renewable energies are well developed and accomplishing the renewable energies objectives (Cross et al., 2015).

These results represent the impact of renewable sources of energy that, having no need to burn fossil fuels, do not produce GHG and help maintaining the same economic level, measured by GDP. This idea is supported by Santra (2017) and Ding et al. (2021).

Nonetheless, Eco-innovation failed to be significant in this model in all groups. Comparing both models, it is possible to conclude that Eco-innovation in the UE is more focused on energy usage than on CO_2 emissions control. However, energy usage and emissions level are correlated (Ozturk & Acaravci, 2010) and, for that reason, it seems that UE strategy for Eco-innovation is focused on energy issues.

Long-run analysis was not possible to take, as ETC was not statistically significant for any group, as expected. This fact supports the cointegration tests, making the lack of conclusions on the Haussmann test not an issue.

Table 4.12 - Emissions Productivity Causality Inference

	EU	Eastern Region	Northern Region	Southern Region	Western Region
ECT	.0358 (0.885)	1.0556 (0.603)	-.8953 (0.678)	.2258 (0.431)	1.3133 (0.806)
lINOV	-.0052 (0.736)	-.0044 (0.608)	-.0229 (0.563)	-.0039 (0.850)	.1022 (0.148)
lRGDP	1.0169 (0.000)	1.0027 (0.000)	.7648 (0.000)	1.1639 (0.000)	1.4621 (0.000)
lENER_INT	-1.0650 (0.000)	-.8617 (0.000)	-.8774 (0.000)	-1.1122 (0.000)	-1.1132 (0.000)

lREN_ENER	.1282 (0.003)	.1282 (0.018)	.3519 (0.003)	.1198 (0.000)	.0756 (0.281)

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP-** Real Gross Domestic Product **lREN_ENER**- Renewable Energies

Both models give suggestions about the European approach when dealing with two major problems: Energy Consumption and GHG emissions.

For the latter, one of the strategies is related to finding greener sources of energy alternatives, here represented by Renewable Energy that will serve as a substitute to the more traditional and pollutant energy sources, responsible for a substantial percentage of emissions. In fact, Arshad (2020) findings corroborate this strategy, stating that renewable sources of energy are propulsors of economic growth and abatement of emissions.

Relatively to the Energy consumption model, the results allow inferring that the environmental related technology is more concerned with Energy rather than with Emissions, a fact proved by the number of "*Climate change mitigation technologies related to energy generation, transmission or distribution"* that, according to OECD Green Growth indicators, have been surpassing the number of "*Air pollution abatement* technologies", especially in recent years. What might contribute for that is the fact that energy has costs for the productive agents, resulting in an incentive to invest in Eco-innovation to promote efficiency (Paraschiv et al., 2012). Moreover, Energy usage is correlated with GHG Emissions and, thus reducing energy consumption indirectly affects positively the level of GHG emissions.

The fact that all the regions present similar results show that there are no signs of regional effects in relation to Eco-innovation and the way it affects the productivity of Energy and Emissions. Furthermore, with such homogeneous results obtained in the 5 different groups, there is evidence that they reflect the reality of the UE environment. Besides, the control variables had the expected behaviors, reinforcing the conclusions of this study.

The biggest differences in comparison with Santra (2017), whose variables were similar to the ones used in this study, are the negative coefficient of Eco-innovation in relation to Energy productivity and the insignificance of Eco-innovation regarding Emissions productivity. These differences can be explained by the inclusion of different countries in each study. Indeed, in the study of Santra (2017) the BRICS countries are widely spread across the globe, while in the present study the countries are located in one continent and represent a political and economic union. Furthermore, Eco-innovation strategy may vary across countries as some may focus on technology to reduce Emissions whereas others may focus on technology to reduce energy consumption. Da Silva et al. (2021) studied the impact of Eco-innovation on a sample of European firms admitted differences between energy efficiency and CO_2 abatement, founding a high correlation between the incentive to save energy costs and Eco-innovation, which may explain these results.

Ding et al. (2021) study also finds different conclusions in terms of CO_2, though the results are not so divergent. Besides the country sample, which focus only on G7 countries, the study only focuses on the reduction of Emissions, and does not approach the productivity component.

In our study, the objective of reaching long-run Eco-innovation conclusions was not met, except for the Eastern Region. However, more efforts should be addressed in further studies in order to check for the existence of efficiency gains in the long-run, since in the short-run implementation costs may prejudice productivity.

Finally, the conclusions reached are useful to understand the role that policy makers should have in terms of supporting Eco-innovation. Considering the objective of reducing environmental impact without harming economy, governments may have confidence to promote Eco-innovation to reach that objective. Nevertheless, governments should have an active role on promoting incentives, friendly taxes or laws to compensate companies, since efficiency gains are not clear, and companies may be reluctant in adopting Eco-innovation devoting their efforts for other priorities.

However, it is important to refer that fighting against environmental degradation is not a one-way solution, requiring a complex plan of action. In conclusion, besides the focus on Eco-innovation in this study, there are many variables like environmental policy stringency, incentives, size and age of companies, environmental taxes, among others, whose impact should also be studied.

In the next section, some tests will be performed to check for the robustness of the results achieved.

5. Robustness Tests

To test the results' robustness, a different methodology is going to be used in order to confirm if the results remain the same.

Ditzen (2018) elaborated a Stata command, xtdcce2, that allows for the analysis of dynamic panel data, considering CD. The main feature of this command is its adaptability to the different needs of the data, being effective with unbalanced panels, for example. Besides that, it allows for different estimators and uses a combination of estimation procedures that were used in Section 3. All these features make the command more complex, though as it deals with CD and dynamic panels, it is useful to test the robustness of the results and it can be simplified to serve that purpose by considering a similar approach to the MG estimator.

Again, the analysis will separately focus on Energy Productivity and CO_2 Productivity, considering the 4 regions of Europe.

Table 5.1 presents the results regarding Energy Productivity. It is possible to conclude that for all Regions, in the short run, Eco-innovation presents statistical significance, except for the North European Region, a result also found before. The EU countries as a whole, the Southern Region and the Western Region show statistical significance to a 5% level, while the Eastern Region shows statistical significance only at a 10% level.

Similar to the results presented in Section 4, Eco-innovation has a diminished negative impact on Energy Productivity, except in Southern Region where the impact is positive, but also of modest dimensions.

These results confirm the idea that Eco-innovation does not seriously harm Energy Productivity, at least in the short term. Given that, it is possible to confirm the robustness of the previous results, regarding Energy Productivity.

Table 5.1- Energy Productivity Robustness test

	EU	Eastern Region	Northern Region	Southern Region	Western Region
lINOV	-.0019 (0.036)	-.0005 (0.088)	-.0036 (0.184)	.0008 (0.041)	-.0046 (0.028)
lRGDP	.9964 (0.000)	.9898 (0.000)	1.0006 (0.000)	.9893 (0.000)	1.0058 (0.000)
lENER_INT	-.9960 (0.000)	-1.0167 (0.000)	-.9789 (0.000)	-.9942 (0.000)	-.9942 (0.000)

lREN_ENER	.0022 (0.303)	.0055 (0.430)	-.00002 (0.992)	.0042 (0.352)	-.0007 (0.799)

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP**- Real Gross Domestic Product **lREN_ENER**- Renewable Energies

Moving to Emissions Productivity, Table 5.2 delivers comparable results as the ones found before. Eco-innovation has no statistical impact on Emissions Productivity, but, on the other hand, Renewable Energy has positive and significative impact, recovering the idea that, in EU, Renewable Energies is more related to Emissions than Eco-innovation, which, as it was observed, is more related to Energy. The only Region without Renewable Energy's significance was the same as in Section 4, which was Western Region.

Table 5.2 - Emissions Productivity Robustness Test

	EU	Eastern Region	Northern Region	Southern Region	Western Region
lINOV	-.0077 (0.404)	.0039 (0.437)	-.0384 (0.168)	-.0132 (0.216)	.0170 (0.288)
lRGDP	1.0143 (0.000)	1.0107 (0.000)	.9638 (0.000)	1.0899 (0.000)	1.3182 (0.000)
lENER_INT	-1.0228 (0.000)	-.8937 (0.000)	-1.0599 (0.000)	-1.0698 (0.000)	-1.3318 (0.000)
lREN_ENER	.1353 (0.000)	.1309 (0.004)	.2628 (0.009)	.1103 (0.000)	.0373 (0.508)

lENER_PROD- Productivity of Energy usage **lINOV**- Measure of Eco-innovation **lENER_INT**- Energy Intensity **lRGDP**- Real Gross Domestic Product **lREN_ENER**- Renewable Energies

Summarizing, it is possible to infer that those conclusions taken from the previous section are robust to a different methodology, with similar results in all Regions. In terms of Energy productivity, the results maintained a quite small negative impact, and no impact of Eco-innovation was verified in Emissions Productivity.

Also, the regional results were homogeneous, since any significant difference was found between Regions, reinforcing the idea of EU cohesion in Eco-innovation impact.

In conclusion, the robustness of the results is verified, which reinforces the conclusions taken in this study.

In the Conclusions section, the analysis will be extended, some weaknesses of the study will be presented and, also, some future research suggestions will be provided.

6. Conclusion

Environmental degradation is one of the biggest fights that humanity is facing and a problem that has been accumulating through the years. Besides the efforts of policy makers there is much more to do in order to reach a more sustainable economic system.

If in one side governments have to deal with climate crisis, they also have to deal with claims for better life conditions, employment and politics to end poverty, which can be translated into the expansion of the economic activity, meaning more production that may increase environmental degradation as a consequence.

In fact, although it is evident that climate crisis is a problem, it that does not imply cohesion of public opinion regarding the trade-off between economic growth and environmental protection. That is why attentions are being drawn to solutions that reach both objectives and explore win-win situations, in particularly in EU.

As a political and economic union, EU defines its strategy in order to tackle climate crisis, defining objectives and targeting levels of emissions and the achievement of more energy efficiency. There are in fact some positive points concerning emissions and energy efficiency, but there are also some disparities between the member states that should not be ignored and may be related to the differences in the importance given to environmental policies, highlighting even more the need for environmental policies that do not harm the Economy.

One of those solutions may come from Eco-innovation. Eco-innovation is an innovation that arises from different natures, like technological, organizational, social, or institutional, and promotes more sustainable activities, reducing their environmental impact.

The objective of this study was to verify if policies that concern both environmental and economic objectives in UE context are possible, by studying the impact of the Eco-innovation, measured by the number of patents of Environmental-related technology, on CO_2 emissions and energy productivity. In other words, the main objective was to infer if Eco-innovation maintains the same level of GDP, when reducing the energy needs or the emissions that result from the productive process.

In terms of studies concerning Eco-innovation, it is possible to find studies approaching Eco-innovation in firms, but most of them are dependent on surveys that cover a few numbers of periods. Also, there is a small number of databases about Eco-innovation in firms and for that reason this study focused on a country level, since more databases are available like the one used in this research – the Green Growth Indicators from OECD. Regarding the variables, the study follows similar steps as Santra (2017), which study the impact of Eco-innovation on the productivity of emissions and energy but using a different methodology.

Besides finding the relation between Eco-innovation and productivity of emissions and energy, this study also intends to analyze the short and long-run impact of that relation. In that sense an ARDL model was used allowing testing the inference in both periods. Also, a period that goes since 1995 to 2016, the available years on the OECD Database, was analyzed in order to cover a proper time span.

Since the sample of this study comprises 20 countries of the UE distributed in 4 different regions, and hence there was a high possibility that those countries would show cross-dependence (CD) between them, some econometric tools had to be used to check for CD, which was confirmed by performing a CD test.

Concerning the energy productivity, a quite small negative impact was found in the short-term period. Although this impact is negative, it is possible to confirm that, in the EU, Eco-innovation allows maintaining the same level of productivity when reducing the energy needs, trusting on the quality of the patents which serve that exact purpose. This result reinforces the use of Eco-innovation as a way to fight against climate crisis without seriously warming the economy.

Regarding the CO_2 emissions productivity, no relation was found with Eco-innovation. However, Renewable Energy has shown to be statistically significant in contrast to the Energy productivity model, which was not. Comparing both results, some conclusions concerning UE strategy can be taken, as Eco-innovation is more related with energy efficiency than with emissions, and emissions abatement are more related with renewable energies.

Regionally, there is evidence that the impact of Eco-innovation seems to be similar to the impact in each EU member state, with the biggest differences remaining in the level of Energy/Emissions productivity and on the number of environment-related technology. For that reason, environmental policies should be aware of those different levels inside the EU. Considering the different levels on environment-related patented technology in the EU countries, one interesting variable to approach in further studies, would be the number of environment-related imported technology, which would give a more realistic idea of how much Eco-innovation a country has at its disposal.

In the long run no significance was found in energy and emissions productivity with Eco-innovation. Some efforts in future research should be done in order to try to find out this type of relation considering the hypothesis of efficiency gains in the long run. For that purpose, the sample of the study should not be so wide as the one presented in the study, which although it has its advantages by giving a general view, it loses some specificities that an analysis focused on one sector or companies of a country would give. However, the lack of databases with such information is an obstacle for such analysis. For that reason, governmental agencies should collect this type of data, allowing to better conclusions in future studies.

An important aspect of studies using patents is to know how much time they need to actually produce effects, especially when considering environmental-related technologies and their time to actually start having environmental benefits.

It is also crucial to understand that climate crisis is not a one-solution problem and considering only Eco-innovation to fight against it is reductive. A complex combination of different factors should be considered and variables like environmental stringency, number of environmental agencies, environmental policies of companies, and social awareness, are examples of variables that should be studied in further studies in order to better understand what different agents can do to solve climate crisis, without a great prejudice of the economy.

In sum, this study reaches conclusions that support Eco-innovation, but it should be seen as a starting point to more profound research on the theme using more complex models, with variables that capture different types of Eco-innovation, variables that affect positively and negatively Eco-innovation , among others that were mentioned in the literature review. Also, the methodology used can be adapted to those complex models due to its adapting capabilities to the research's needs.

There is much to do in order to win the fight against climate crisis and for that reason more academic research regarding Eco-innovation and other solutions that fight climate degradation without compromising economic performance, should be employed to better advise policy makers in environmental subjects.

Bibliography

Acaravci, A., & Ozturk, I. (2010). On the relationship between energy consumption, CO2 emissions and economic growth in Europe. Energy, 35(12), 5412–5420. https://doi.org/10.1016/j.energy.2010.07.009

Acemoglu, D. (2008). Introduction to Modern Economic Growth. Princeton University Press.

Albers, J. A., & Brewer, S. (2003). Knowledge Management And The Innovation Process: The Eco-Innovation Model. Journal of Knowledge Management Practice, 4, 1–10.

Albulescu, C. T., Artene, A. E., Luminosu, C. T., & Tămășilă, M. (2019). CO2 emissions, renewable energy, and environmental regulations in the EU countries. Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-019-06155-1/Published

Alcott, B. (2005). Jevons' paradox. Ecological Economics, 54(1), 9–21. https://doi.org/10.1016/j.ecolecon.2005.03.020

Ambec, S., & Lanoie, P. (2008). Does It Pay to Be Green? A Systematic Overview Executive Overview. Academy of Management Perspectives, 45–62.

Arellano, M. (2003). Panel Data Econometrics- Advanced Texts in Econometrics (M. Arellano, G. Imbens, G. E. Mizon, A. Pagan, & M. Watson, Eds.; 1st ed.). Oxford University Press.

Arguedas, C., & Hamoudi, H. (2004). Controlling Pollution with Relaxed Regulations. Journal of Regulatory Economics, 26, 1–85.

Arshad, Z. (2020). The Role of Macroeconomic Variables in Energy and Environmental Modelling: Econometric Evidence from Asian countries.

Aye, G. C., & Edoja, P. E. (2017). Effect of economic growth on CO2 emission in developing countries: Evidence from a dynamic panel threshold model. Cogent Economics and Finance, 5(1). https://doi.org/10.1080/23322039.2017.1379239

Baltagi, B. H. (2008). Econometric Analysis of Panel Data (3rd ed.). John Wiley & Sons Ltd.

Baltagi, B. H., Feng, Q., & Kao, C. (2012). A Lagrange Multiplier test for cross-sectional dependence in a fixed effects panel data model. Journal of Econometrics, 170(1), 164–177. https://doi.org/10.1016/j.jeconom.2012.04.004

Balžekiene, A., & Telešiene, A. (2017). Vulnerable and Insecure? Environmental and Technological Risk Perception in Europe. Environmental Behaviour and Attitudes in Europe in a Historical and Cross-Cultural Comparative Perspective, 31–55.

Barkemeyer, R., Figge, F., Hoepner, A., Holt, D., Kraak, J. M., & Yu, P. S. (2017). Media coverage of climate change: An international comparison. Environment and Planning C: Politics and Space, 35(6), 1029–1054. https://doi.org/10.1177/0263774X16680818

Beckerman, W. (1992). Economic Growth and the Environment: Whose Growth? Whose Environment? In World Developmenr (Vol. 20, Issue 4).

Beltrán-Esteve, M., Giménez, V., & Picazo-Tadeo, A. J. (2019). Environmental productivity in the European Union: A global Luenberger-metafrontier approach. Science of the Total Environment, 692, 136–146. https://doi.org/10.1016/j.scitotenv.2019.07.182

Blackburne, E. F., & Frank, M. W. (2007). Estimation of nonstationary heterogeneous panels. The Stata Journal, 7(2), 197–208.
Bossle, M. B., Dutra De Barcellos, M., Vieira, L. M., & Sauvée, L. (2016). The drivers for adoption of eco-innovation. In Journal of Cleaner Production (Vol. 113, pp. 861–872). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2015.11.033
Breusch, T., & Pagan, A. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. The Review of Economic Studies, 47(1), 239–253. https://doi.org/https://doi.org/10.2307/2297111
Brookes, L. (1990). The greenhouse effect- the falacies in the energy efficiency solution. Energy Policy, 18(2), 199–201.
Chen, Y., & Lee, C. C. (2020). Does technological innovation reduce CO2 emissions?Cross-country evidence. Journal of Cleaner Production, 263. https://doi.org/10.1016/j.jclepro.2020.121550
Cheng, C. C., & Shiu, E. C. (2012). Validation of a proposed instrument for measuring eco-innovation: An implementation perspective. Technovation, 32(6), 329–344. https://doi.org/10.1016/j.technovation.2012.02.001
Chiou-Wei, S. Z., Chen, C. F., & Zhu, Z. (2008). Economic growth and energy consumption revisited - Evidence from linear and nonlinear Granger causality. Energy Economics, 30(6), 3063–3076. https://doi.org/10.1016/j.eneco.2008.02.002
Commission of the European Communities. (2004). Stimulating Technologies for Sustainable Development: An Environmental Technologies Action Plan for the European Union.
Commission to the European Council and the European Parliament. (2007). An Energy Policy for Europe. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=LEGISSUM%3Al27067
Crosby, M. (2000). Patents, Innovation and Growth. The Economic Record, 76(234), 255–262.
Cross, S., Hast, A., Kuhi-Thalfeldt, R., Syri, S., Streimikiene, D., & Denina, A. (2015). Progress in renewable electricity in Northern Europe towards EU 2020 targets. In Renewable and Sustainable Energy Reviews (Vol. 52, pp. 1768–1780). Elsevier Ltd. https://doi.org/10.1016/j.rser.2015.07.165
da Silva, P., Robaina, M., Meireles, M., & Madaleno, M. (2021). Eco-Innovation and Emissions Trading: a sectoral analysis for European countries. APPEN2021 Virtual Conference - Energy Transition and Sustainability, 20(6). https://doi.org/10.1080/13662716.2013.833375
de Noni, I., Orsi, L., & Belussi, F. (2018). The role of collaborative networks in supporting the innovation performances of lagging-behind European regions. Research Policy, 47(1), 1–13. https://doi.org/10.1016/j.respol.2017.09.006
del Río, P., Peñasco, C., & Romero-Jordán, D. (2016). What drives eco-innovators? A critical review of the empirical literature based on econometric methods. In Journal of Cleaner Production (Vol. 112, pp. 2158–2170). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2015.09.009
Dell, M., Jones, B. F., & Olken, B. A. (2013). What Do We Learn from the Weather? The New Climate-Economy Literature. http://www.nber.org/data-appendix/w19578
Demirel, P., & Danisman, G. O. (2019). Eco-innovation and firm growth in the circular economy: Evidence from European small- and medium-sized enterprises. Business Strategy and the Environment, 28(8), 1608–1618. https://doi.org/10.1002/bse.2336

Ding, Q., Khattak, S. I., & Ahmad, M. (2021). Towards sustainable production and consumption: Assessing the impact of energy productivity and eco-innovation on consumption-based carbon dioxide emissions (CCO2) in G-7 nations. Sustainable Production and Consumption, 27, 254–268. https://doi.org/10.1016/j.spc.2020.11.004

Ditzen, J. (2018). Estimating dynamic common-correlated effects in Stata. In The Stata Journal (Vol. 18, Issue 3).

Dong, Y., Wang, X., Jin, J., Qiao, Y., & Shi, L. (2014). Effects of eco-innovation typology on its performance: Empirical evidence from Chinese enterprises. Journal of Engineering and Technology Management - JET-M, 34, 78–98. https://doi.org/10.1016/j.jengtecman.2013.11.001

Doran, J., & Ryan, G. (2012). Regulation and firm perception, eco-innovation and firm performance. European Journal of Innovation Management, 15(4), 421–441. https://doi.org/10.1108/14601061211272367

Doran, J., & Ryan, G. (2016). The Importance of the Diverse Drivers and Types of Environmental Innovation for Firm Performance. Business Strategy and the Environment, 25(2), 102–119. https://doi.org/10.1002/bse.1860

Drews, S., Antal, M., & van den Bergh, J. C. J. M. (2018). Challenges in Assessing Public Opinion on Economic Growth Versus Environment: Considering European and US Data. Ecological Economics, 146, 265–272. https://doi.org/10.1016/j.ecolecon.2017.11.006

European Commission. (2017). 7th National Communication & 3rd Biennial Report from the European Union under the UN Framework Convention on Climate Change (UNFCCC).

European Commission. (2020). State of the Union: Commission raises climate ambition and proposes 55% cut in emissions by 2030.

European Environment Agency. (2020). Trends and projections in Europe 2020. Tracking progress towards Europe’s climate and energy targets. https://doi.org/10.2800/830157

European Patent Office. (2017). Patent families.

European Social Survey. (2018). European Attitudes to Climate Change and Energy: Topline Results from Round 8 of the European Social Survey.

Fernández, A. M., Font, N., & Koutalakis, C. (2010). Environmental governance in southern europe: The domestic filters of Europeanisation. Environmental Politics, 19(4), 557–577. https://doi.org/10.1080/09644016.2010.489711

Freire-González, J., & Puig-Ventosa, I. (2015). Energy Efficiency Policies and the Jevons Paradox. International Journal of Energy Economics and Policy, 5(1), 69–79. www.econjournals.com

García-Granero, E. M., Piedra-Muñoz, L., & Galdeano-Gómez, E. (2018). Eco-innovation measurement: A review of firm performance indicators. In Journal of Cleaner Production (Vol. 191, pp. 304–317). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2018.04.215

Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wagner, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. Energy Strategy Reviews, 24, 38–50. https://doi.org/10.1016/j.esr.2019.01.006

Gutierrez, L. (2003). On the power of panel cointegration tests: A Monte Carlo comparison. Economics Letters, 80(1), 105–111. https://doi.org/10.1016/S0165-1765(03)00066-1

Harris, D., Harvey, D. I., Leybourne, S. J., & Sakkas, N. D. (2010). Local asymptotic power of the Im-Pesaran-Shin panel unit root test and the impact of initial observations. Econometric Theory, 26(1), 311–324. https://doi.org/10.1017/S0266466609090768

Hausman, J. A. (1978). Specification Tests in Econometrics. Econometrica, 46(6), 1251–1271.

Hellström, T. (2007). Dimensions of environmentally sustainable Innovation: The structure of eco-innovation concepts. Sustainable Development, 15(3), 148–159. https://doi.org/10.1002/sd.309

Horbach, J., Rammer, C., & Rennings, K. (2012). Determinants of eco-innovations by type of environmental impact - The role of regulatory push/pull, technology push and market pull. Ecological Economics, 78, 112–122. https://doi.org/10.1016/j.ecolecon.2012.04.005

Hsiao, C. (2007). Panel data analysis-advantages and challenges. Test, 16(1), 1–22. https://doi.org/10.1007/s11749-007-0046-x

Hsiao, C. (2014). Analysis of Panel Data (D. W. K. Andrews & J. C. Ely, Eds.; 3rd ed.). Cambridge University Press.

IEA. (2020). Energy Efficiency Indicators. https://www.iea.org/reports/energy-efficiency-indicators

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

Jänicke, M. (2012). "Green growth": From a growing eco-industry to economic sustainability. Energy Policy, 48, 13–21. https://doi.org/10.1016/j.enpol.2012.04.045

Kemp, R., & Pearson, P. (2007). Final report MEI project about measuring eco-innovation. http://www.merit.unu.edu/MEI

Kiefer, C. P., González, P. D. R., & Carrillo-hermosilla, J. (2018). Drivers and barriers of eco-innovation types for sustainable transitions: A quantitative perspective. Business Strategy and the Environment, 28(1), 155-172. https://doi.org/10.1002/bse.2246

Lam, L. T., Branstetter, L., & Azevedo, I. M. L. (2017). China's wind industry: Leading in deployment, lagging in innovation. Energy Policy, 106, 588–599. https://doi.org/10.1016/j.enpol.2017.03.023

Lee, K. H., & Min, B. (2015). Green R&D for eco-innovation and its impact on carbon emissions and firm performance. Journal of Cleaner Production, 108, 534–542. https://doi.org/10.1016/j.jclepro.2015.05.114

Li, J., Zhang, X., Ali, S., & Khan, Z. (2020). Eco-innovation and energy productivity: New determinants of renewable energy consumption. Journal of Environmental Management, 271. https://doi.org/10.1016/j.jenvman.2020.111028

Li, W., & Zhao, Y. (2015). Bibliometric analysis of global environmental assessment research in a 20-year period. Environmental Impact Assessment Review, 50, 158–166. https://doi.org/10.1016/j.eiar.2014.09.012

Madaleno, M., Robaina, M., Ferreira Dias, M., & Meireles, M. (2019). Dimension effects in the relationship between eco-innovation and firm performance: A European comparison. Energy Reports, 6, 631–637. https://doi.org/10.1016/j.egyr.2019.09.038

Moran, P. A. P. (1948). The interpretation of statistical maps. Journal of the Royal Statistical Society: Series B (Methodological), 10(2), 243–251.

Nadel, S. (2012). The Rebound Effect: Large or Small? www.aceee.org

Norgaard, R. (1994). Development Betrayed: The End of Progress and a Coevolutionary Revisioning of the Future. Routhledge.

Ortiz-Villajos, J. M. (2009). Patents and Economic Growth in the Long Term. A Quantitative Approach. Brussels Economic Review, 52(3).

Ozturk, I., & Acaravci, A. (2010). CO2 emissions, energy consumption and economic growth in Turkey. In Renewable and Sustainable Energy Reviews (Vol. 14, Issue 9). Elsevier Ltd. https://doi.org/10.1016/j.rser.2010.07.005

Paraschiv, D., Mihai, ;, Nemoianu, E., Laura; Langă, C., Adriana, ;, & Szabó, T. (2012). Eco-innovation, Responsible Leadership and Organizational Change for Corporate Sustainability. In Amfiteatru Economic Journal (Vol. 14). http://hdl.handle.net/10419/168760http://creativecommons.org/licenses/by/4.0/www.econstor.eu

Park, M. S., Bleischwitz, R., Han, K. J., Jang, E. K., & Joo, J. H. (2017). Eco-innovation indices as tools for measuring eco-innovation. Sustainability (Switzerland), 9(12). https://doi.org/10.3390/su9122206

Pattengale, N. D., Alipour, M., Bininda-Emonds, O. R. P., Moret, B. M. E., & Stamatakis, A. (2010). How many bootstrap replicates are necessary? Journal of Computational Biology, 17(3), 337–354. https://doi.org/10.1089/cmb.2009.0179

Pedroni, P. (1999). Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors. Oxford Bulletin of Economics and Statistics, 61(S1), 653–670.

Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics, 22(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H. (2020). General diagnostic tests for cross-sectional dependence in panels. Empirical Economics, 60, 13–50. https://doi.org/10.1007/s00181-020-01875-7

Pesaran, M. H., Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. Journal of the American Statistical Association, 94(446), 621–634. https://doi.org/10.1080/01621459.1999.10474156

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics, 68, 79–113.

Phillips, P. C. B., & Sul, D. (2003). Dynamic panel estimation and homogeneity testing under cross section dependence *. In Econometrics Journal (Vol. 6).

Pinget, A., Bocquet, R., & Mothe, C. (2015). Barriers to environmental innovation in SMEs: Empirical evidence from french firms. Management (France), 18(2), 132–155. https://doi.org/10.3917/mana.182.0132

Polimeni, J. M., & Polimeni, R. I. (2006). Jevons' Paradox and the myth of technological liberation. Ecological Complexity, 3(4), 344–353. https://doi.org/10.1016/j.ecocom.2007.02.008

Porter, M. E., & van der Linde, C. (1995). Toward a New Conception of the Environment-Competitiveness Relationship. In Journal of Economic Perspectives (Vol. 9, Issue 4).

Rennings, K. (2000). Redefining innovation-eco-innovation research and the contribution from ecological economics. In Ecological Economics (Vol. 32). www.elsevier.com/locate/ecolecon

Ritchie, H., & Roser, M. (2020). Emissions by sector. Our World in Data. https://ourworldindata.org/emissions-by-sector

Ruiz-Real, J. L., Uribe-Toril, J., Valenciano, J. D. P., & Gázquez-Abad, J. C. (2018). Worldwide research on circular economy and environment: A bibliometric analysis. International Journal of Environmental Research and Public Health, 15(12). https://doi.org/10.3390/ijerph15122699

Ryszko, A. (2016). Proactive environmental strategy, technological eco-innovation and firm performance-case of Poland. Sustainability (Switzerland), 8(2). https://doi.org/10.3390/su8020156

Santra, S. (2017). The effect of technological innovation on production-based energy and CO2 emission productivity: Evidence from BRICS countries. African Journal of Science, Technology, Innovation and Development, 9(5), 503–512. https://doi.org/10.1080/20421338.2017.1308069

Shahbaz, M., Solarin, S. A., Sbia, R., & Bibi, S. (2015). Does energy intensity contribute to CO2 emissions? A trivariate analysis in selected African countries. Ecological Indicators, 50, 215–224. https://doi.org/10.1016/j.ecolind.2014.11.007

Sharif Hossain, M. (2011). Panel estimation for CO2 emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries. Energy Policy, 39(11), 6991–6999. https://doi.org/10.1016/j.enpol.2011.07.042

Sorrell, S. (2009). Jevons' Paradox revisited: The evidence for backfire from improved energy efficiency. Energy Policy, 37(4), 1456–1469. https://doi.org/10.1016/j.enpol.2008.12.003

Steinhurst, W., & Sabodash, V. (2011). The Jevons Paradox and Energy Efficiency A Brief Overview of Its Origins and Relevance to Utility Energy Efficiency Programs.

Sundtoft, T. (2018). The Nordic countries in the green transition – more than just neighbours. In The Nordic countries in the green transition – more than just neighbours. Nordic Council of Ministers. https://doi.org/10.6027/anp2018-752

Tang, M., Walsh, G., Lerner, D., Fitza, M. A., & Li, Q. (2018). Green Innovation, Managerial Concern and Firm Performance: An Empirical Study. Business Strategy and the Environment, 27(1), 39–51. https://doi.org/10.1002/bse.1981

United Nations. (2019). Environmental Rule of Law- First Global Report.

Wagner, M., van Phu, N., Azomahou, T., & Wehrmeyer, W. (2002). The relationship between the environmental and economic performance of firms: an empirical analysis of the European paper industry. Corporate Social Responsibility and Environmental Management, 9(3), 133–146. https://doi.org/10.1002/csr.22

Waller, M., & Millard, F. (1992). Environmental Politics in Eastern Europe. Environmental Politics, 1(2), 159–185. https://doi.org/10.1080/09644019208414019

Walley, N., & Whitehead, B. (1994). It's Not Easy Being Green. Harvard Business Review .

Wang, C., Chen, J., & Zou, J. (2005). Decomposition of energy-related CO2 emission in China: 1957-2000. Energy, 30(1), 73–83. https://doi.org/10.1016/j.energy.2004.04.002

Westerlund, J. (2007). Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics, 69(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Zhang, X. P., & Cheng, X. M. (2009). Energy consumption, carbon emissions, and economic growth in China. Ecological Economics, 68(10), 2706–2712. https://doi.org/10.1016/j.ecolecon.2009.05.011

Zoundi, Z. (2017). CO2 emissions, renewable energy and the Environmental Kuznets Curve, a panel cointegration approach. In Renewable and Sustainable Energy Reviews (Vol. 72, pp. 1067–1075). Elsevier Ltd. https://doi.org/10.1016/j.rser.2016.10.018

Appendices

A. Energy Productivity by Region

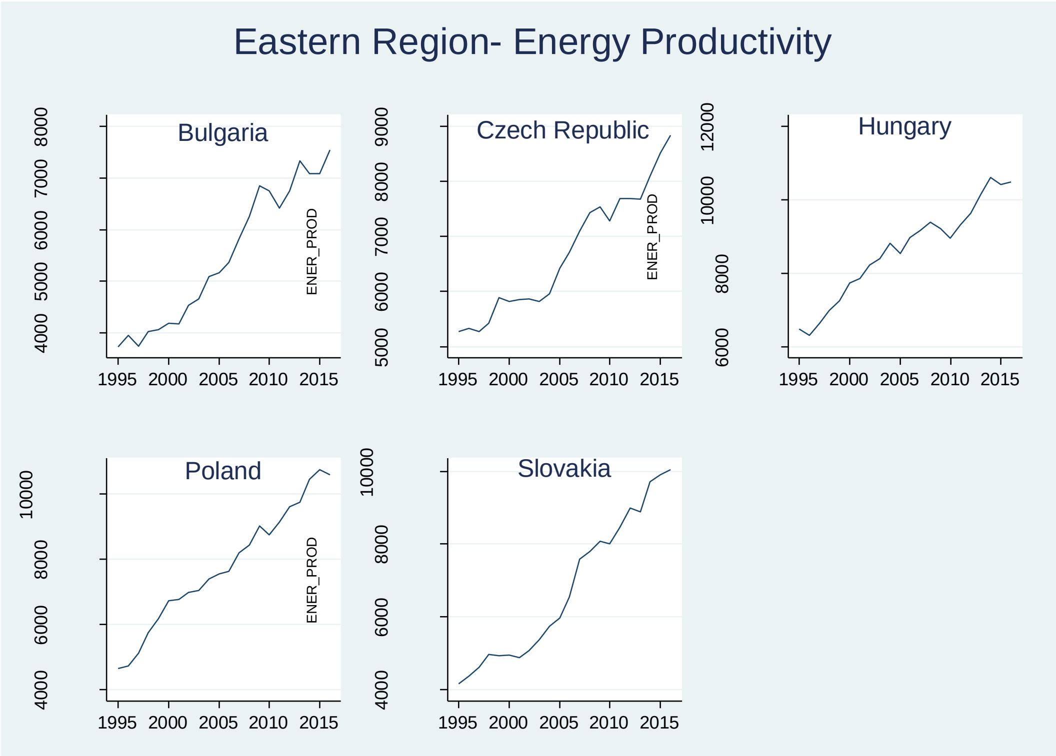

Figure A.1 – Eastern Region – Energy Productivity

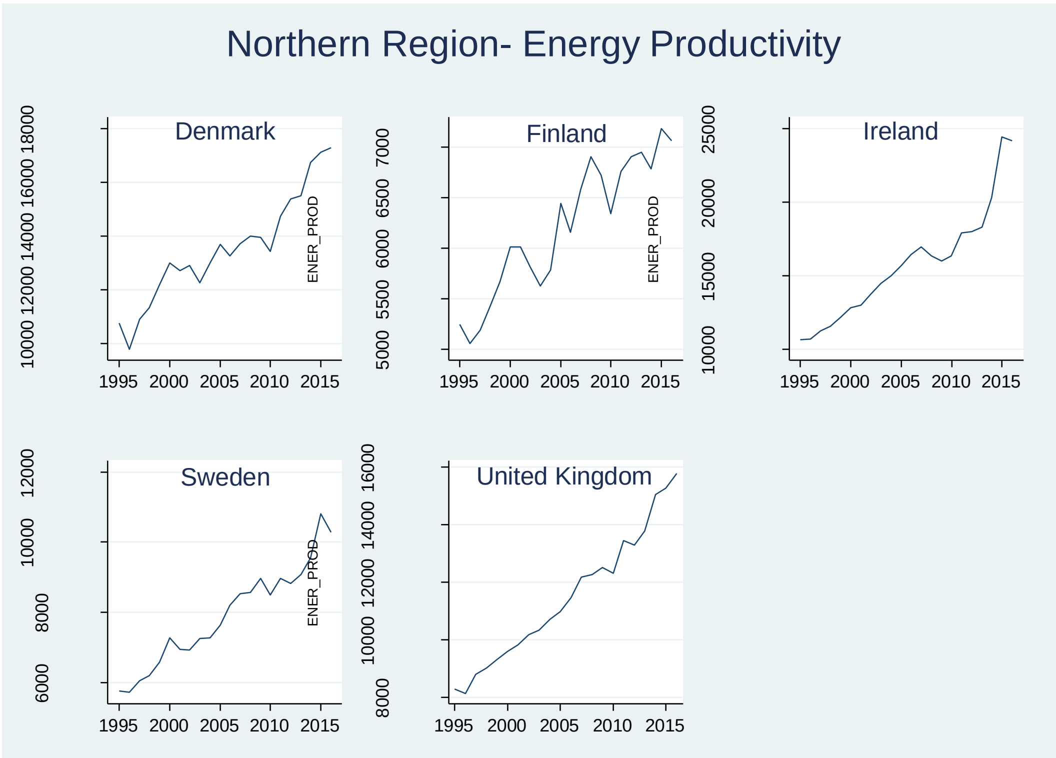

Figure A.2 - Northen Region – Energy Productivity

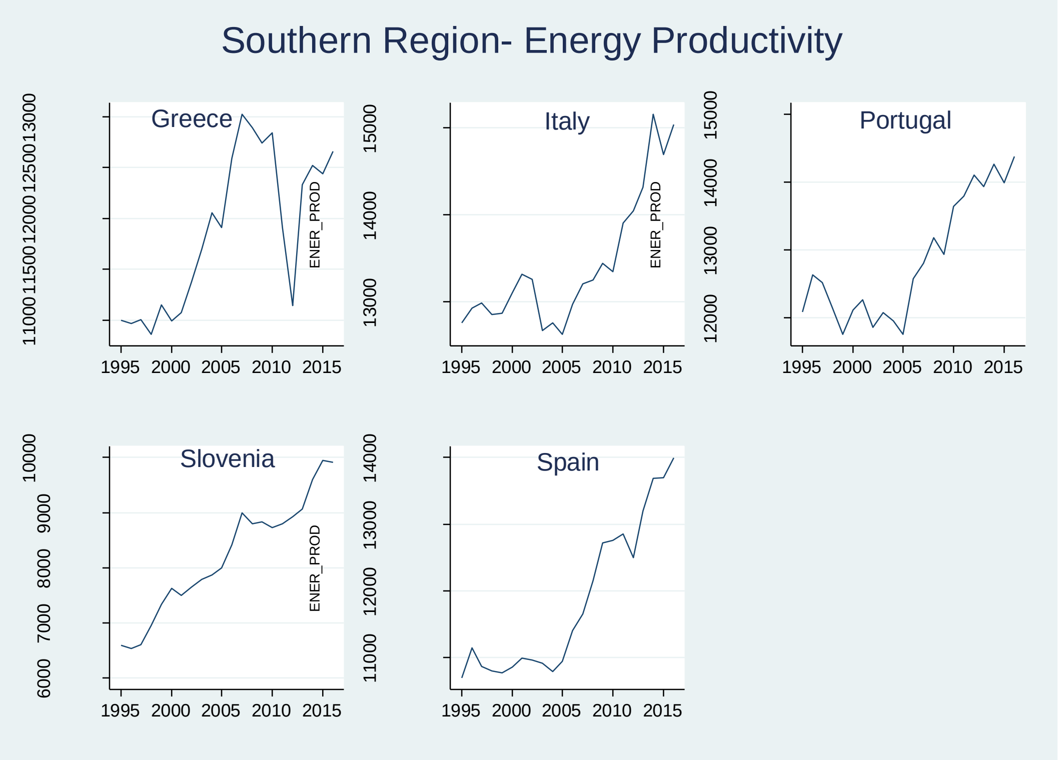

Figure A.3 - Southern Region – Energy Productivity

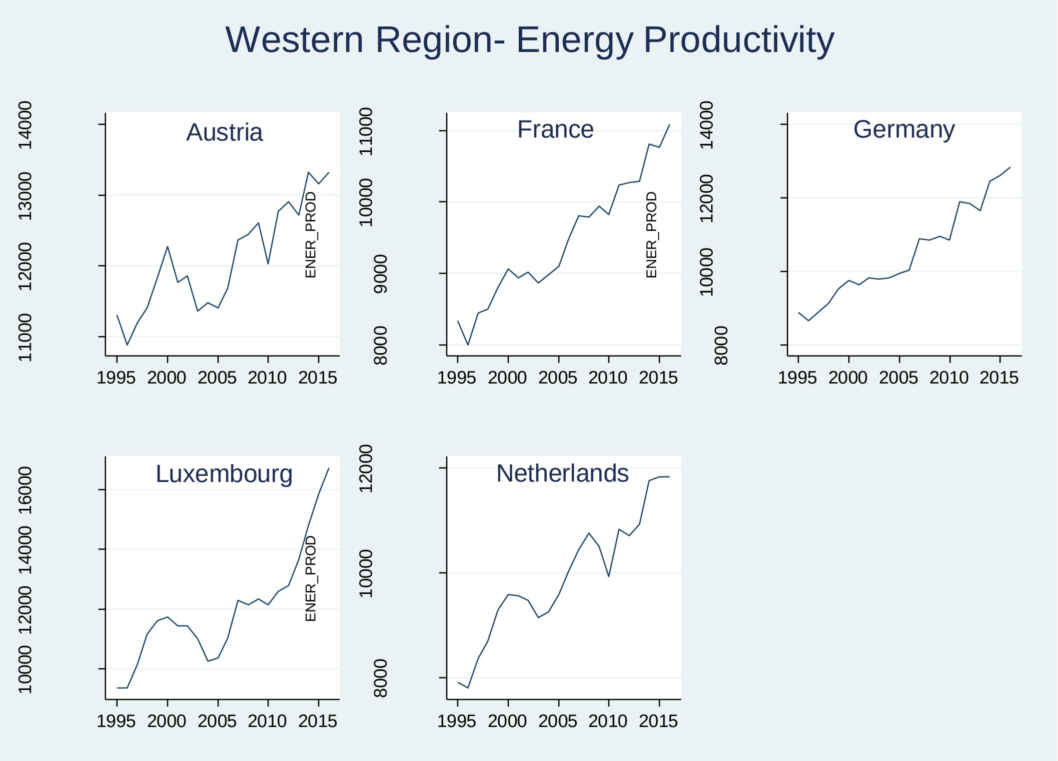

Figure A.4 - Western Region – Energy Productivity

B. Emissions Productivity by Region

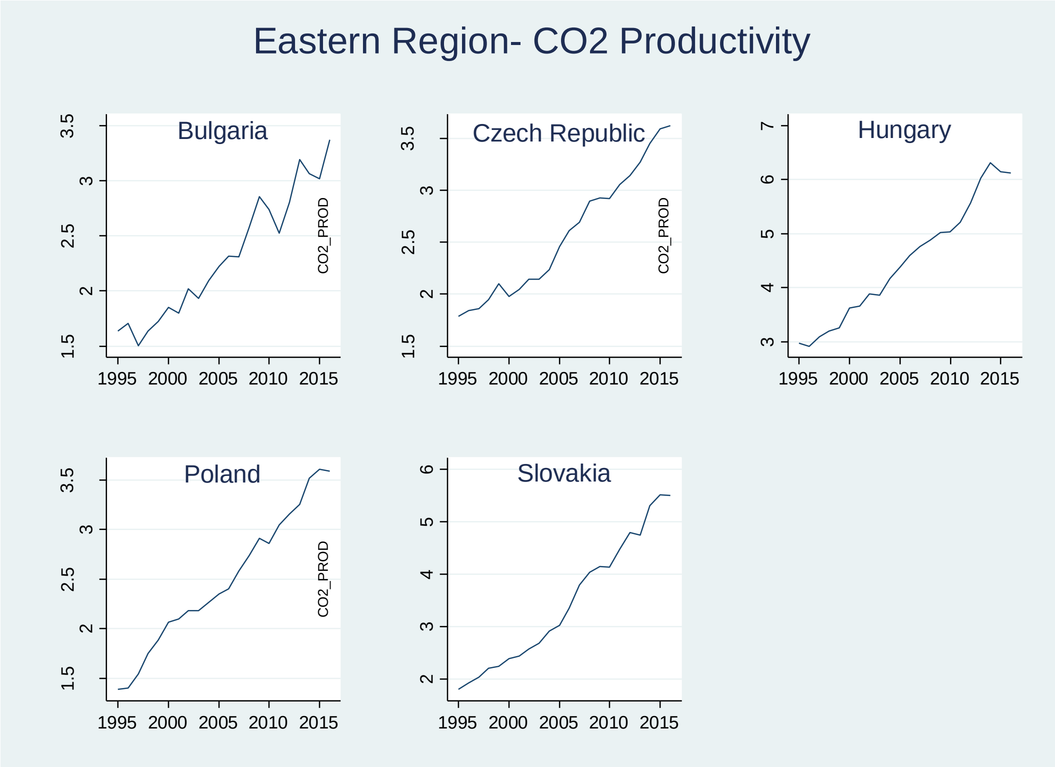

Figure B.1 - Eastern Region - Emissions Productivity

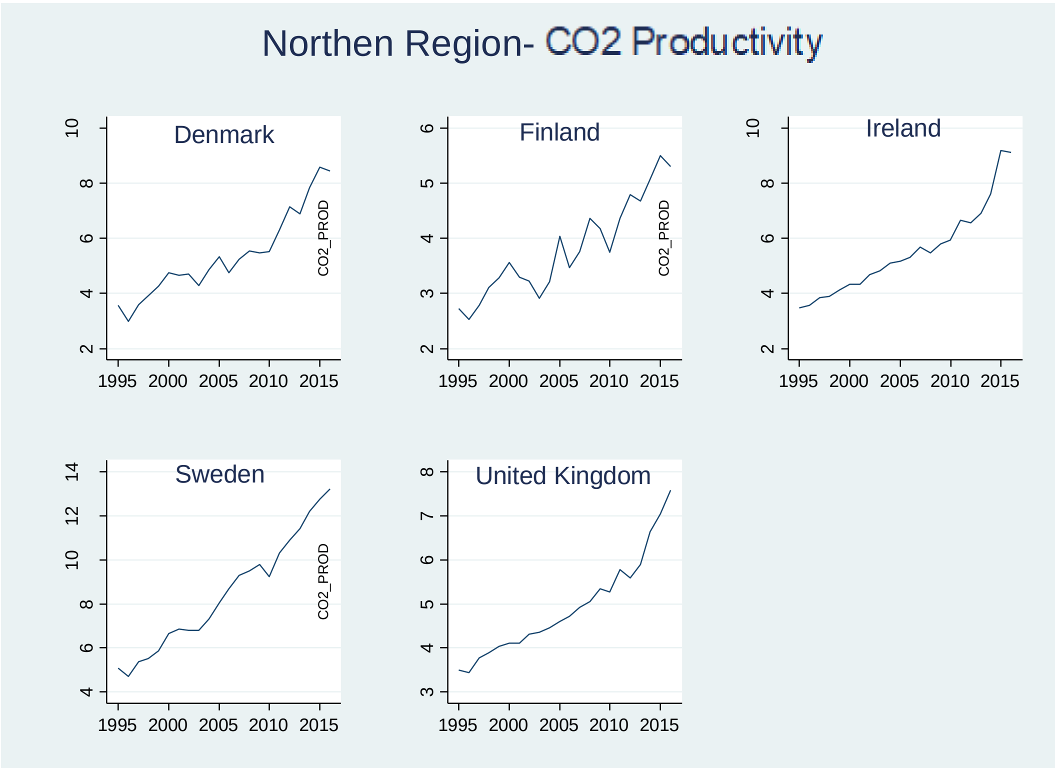

Figure B.2 - Northern Region - Emissions Productivity

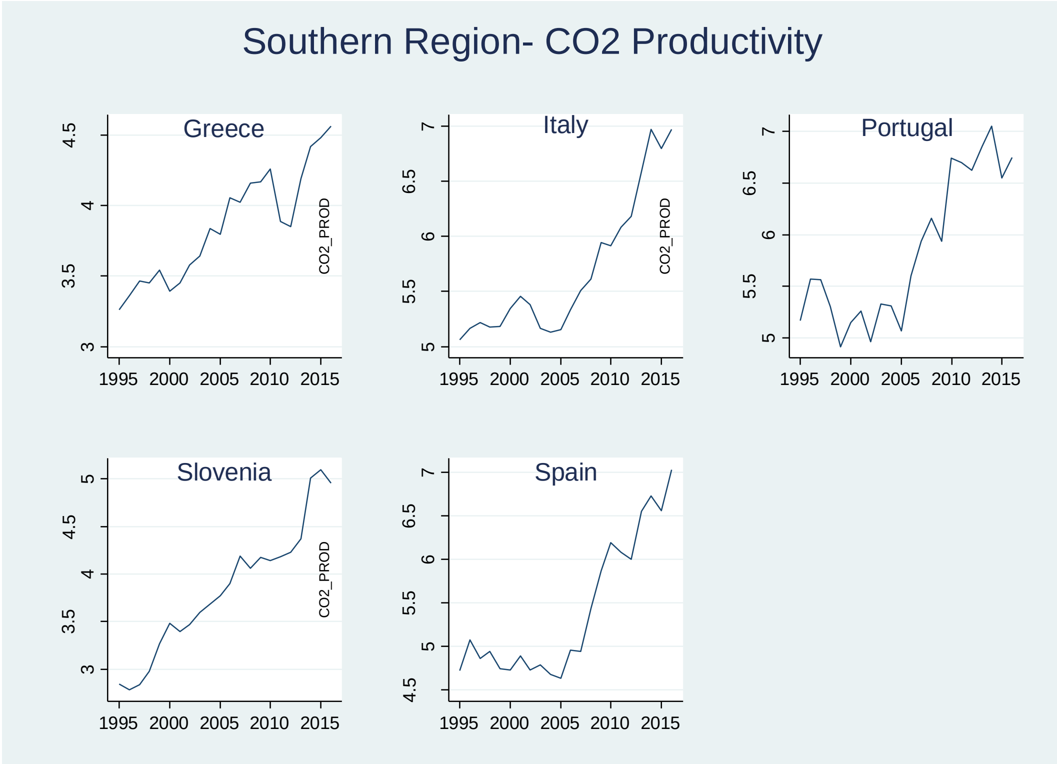

Figure B.3 - Southern Region - Emissions Productivity

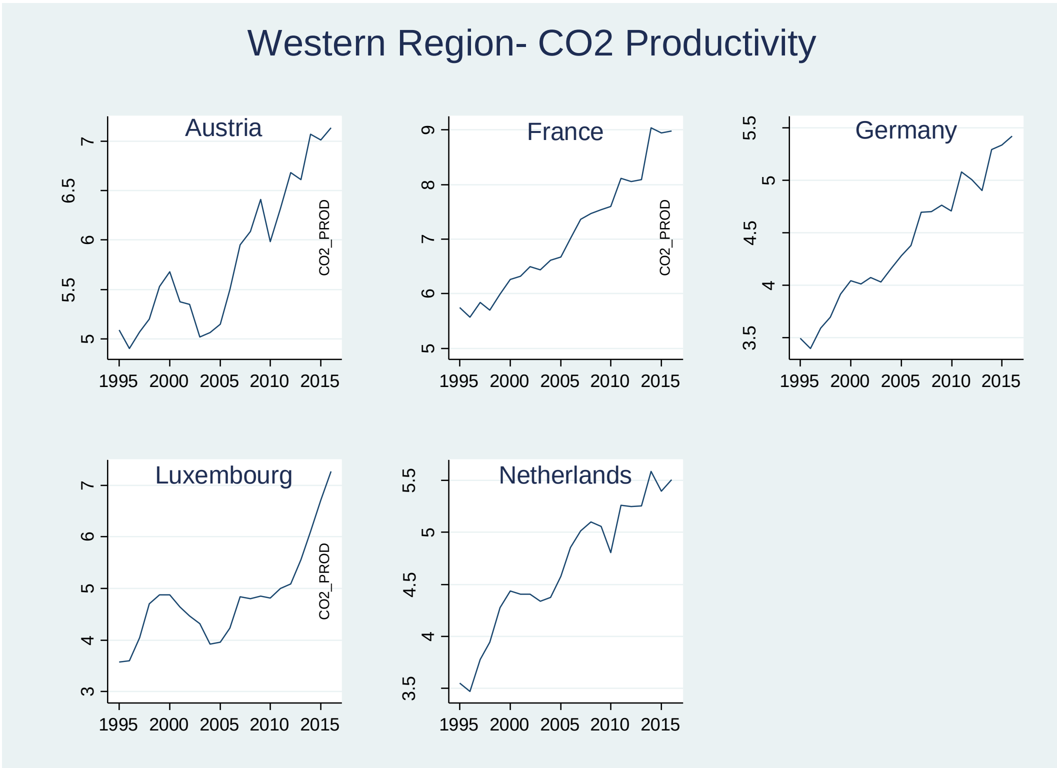

Figure B.4 - Western Region - Emissions Productivity

C. Eco-innovation by Region

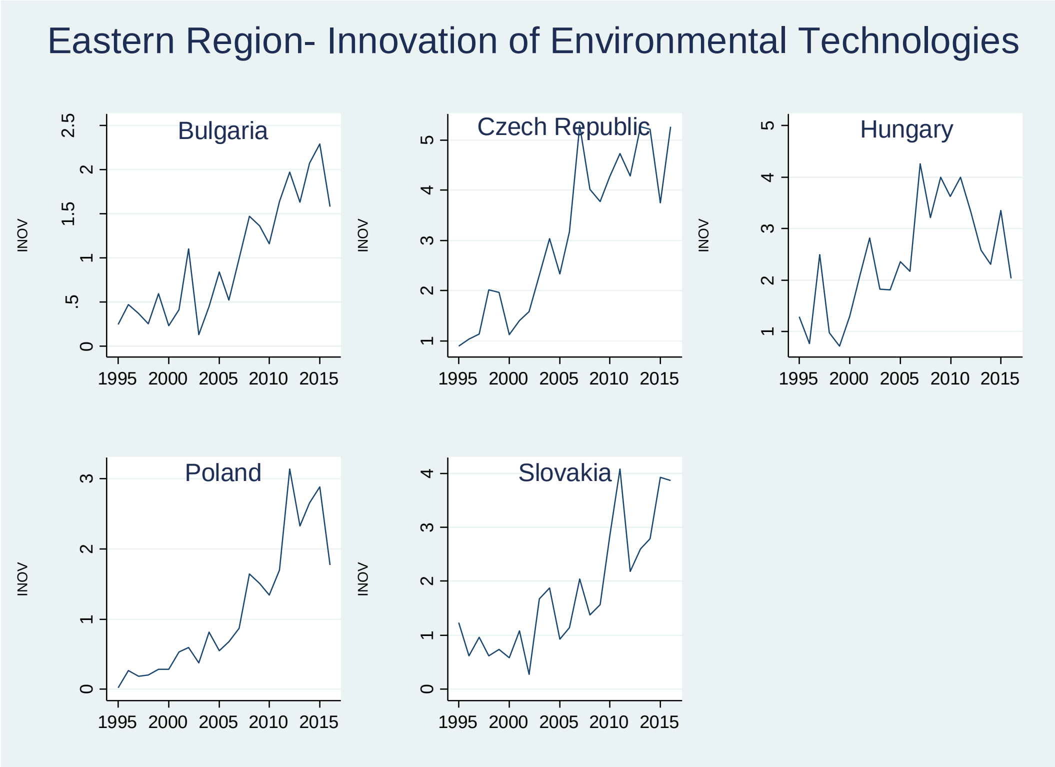

Figure C.1 - Eco-innovation in Eastern Region

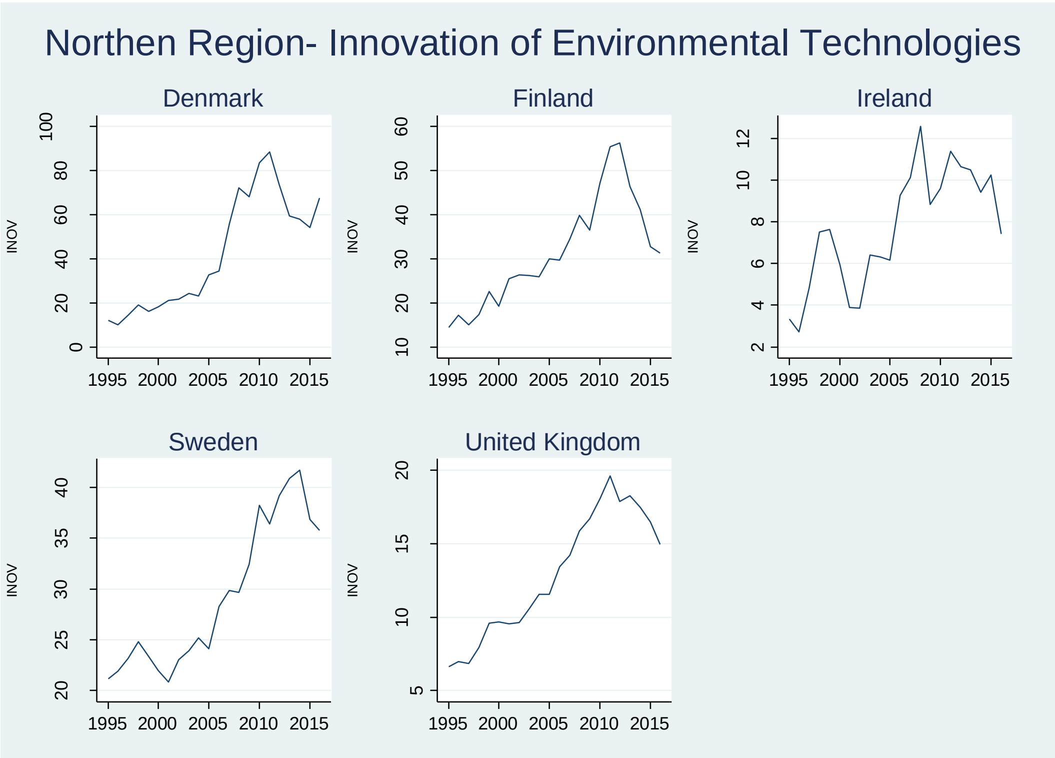

Figure C.2 - Eco-innovation in Northern Region

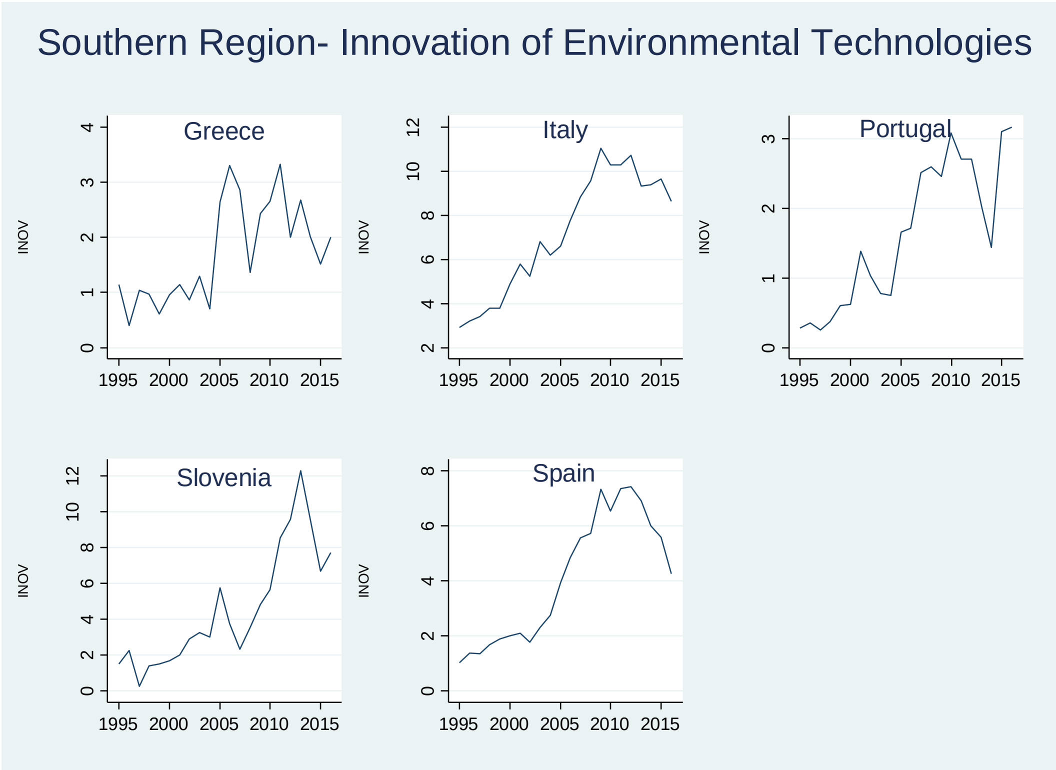

Figure C.3 - Eco-innovation in Southern Region

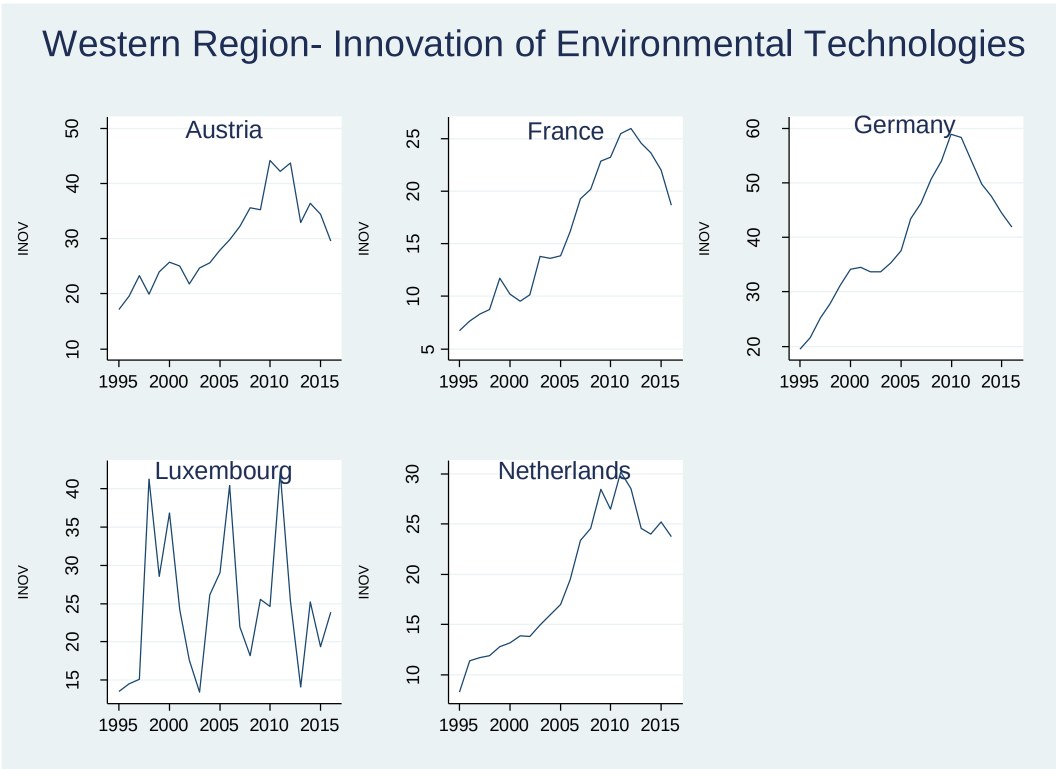

Figure C.4 - Eco-innovation in Eastern Region

D. Descriptive Results

Table D.1 – Variables Summary | Eastern Region

Variables	Observations	Mean	Standard Deviation	Min	Max
lENER_PROD	110	8.8276	.2758	8.2257	9.2825
lCO2_PROD	110	1.0506	.3702	.3282	1.8421
lINOV	110	.2874	.9619	-3.9120	1.6658
lENER_INT	110	1.0769	.2077	.8198	1.5026
lRGDP	110	9.9045	.32589	9.1113	10.4544

Table D.2 - Variables Summary | Northern Region

Variables	Observations	Mean	Standard Deviation	Min	Max
lENER_PROD	110	9.2310	.3839	8.5285	10.1039
lCO2_PROD	110	1.6591	.3620	.9279	2.5801
lINOV	110	2.9415	.7545	1.0079	4.4835
lENER_INT	110	1.4376	.2968	.9917	1.9615
lRGDP	110	10.6692	.1592	10.2989	11.1523

Table D.3 - Variables Summary | Southern Region

Variables	Observations	Mean	Standard Deviation	Min	Max
lENER_PROD	110	9.3443	.1969	8.7840	9.6261
lCO2_PROD	110	1.5692	.2325	1.0223	1.9527
lINOV	110	.9839	.9263	1.3863	2.5079
lENER_INT	110	1.0018	.1663	.6796	1.3437
lRGDP	110	10.3479	.1606	9.9091	10.6295

Table D. 4 - Variables Summary | Western Region

Variables	Observations	Mean	Standard Deviation	Min	Max1
lENER_PROD	110	9.2759	.1486	8.9627	9.7252
lCO2_PROD	110	1.6529	.2284	1.2229	2.2014
lINOV	110	3.1471	.4855	1.9081	4.0760

lENER_INT	110	1.5566	.2735	1.2108	2.2596
lRGDP	110	10.8269	.3303	10.4091	11.5875

Table D.5 - Variables Correlation with Energy Productivity | Eastern Region

	lENER_PROD	lINOV	lENER_INT	lRGDP
lENER_PROD	1			
lINOV	0.6781	1		
lENER_INT	-0.1204	0.3772	1	
lRGDP	0.7697	0.8123	0.5408	1

Table D. 6 - Variables Correlation with Energy Productivity | Northern Region

	lENER_PROD	lINOV	lENER_INT	lRGDP
lENER_PROD	1			
lINOV	-0.2261	1		
lENER_INT	-0.9180	0.3721	1	
lRGDP	0.6853	0.1644	-0.3405	1

Table D.7 - Variables Correlation with Energy Productivity | Southern Region

	lENER_PROD	lINOV	lENER_INT	lRGDP
lENER_PROD	1			
lINOV	0.1888	1		
lENER_INT	-0.6154	0.4599	1	
lRGDP	0.5870	0.6882	0.2751	1

Table D. 8 - Variables Correlation with Energy Productivity | Western Region

	lENER_PROD	lINOV	lENER_INT	lRGDP
lENER_PROD	1			
lINOV	0.5835	1		
lENER_INT	0.1332	-0.1248	1	
lRGDP	0.5767	0.1810	0.8855	1

Table D. 9 - Variables Correlation with Emissions Productivity | Eastern Region

	lCO2_PROD	lINOV	lENER_INT	lRGDP
lCO2_PROD	1			
lINOV	0.7126	1		
lENER_INT	-0.0845	0.3772	1	
lRGDP	0.6741	0.8123	0.5408	1

Table D.10 - Variables Correlation with Emissions Productivity | Northern Region

	lCO2_PROD	lINOV	lENER_INT	lRGDP
lCO2_PROD	1			
lINOV	0.3525	1		
lENER_INT	-0.1971	0.3721	1	
lRGDP	0.5775	0.1644	-0.3405	1

Table D.11 - Variables Correlation with Emissions Productivity | Southern Region

	lCO2_PROD	lINOV	lENER_INT	lRGDP
lCO2_PROD	1			
lINOV	0.3985	1		
lENER_INT	-0.3627	0.4599	1	
lRGDP	0.5769	0.6882	0.2751	1

Table D.12 - Variables Correlation with Emissions Productivity | Western Region

	lCO2_PROD	lINOV	lENER_INT	lRGDP
lCO2_PROD	1			
lINOV	0.0145	1		
lENER_INT	-0.3308	-0.1248	1	
lRGDP	-0.1422	0.1810	0.8855	1