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Evaluating Environmental Efficiency: A DEA-Based Analysis of Sectoral Contributions to GHG Emissions

Bruna Salomé da Costa Moreira

Final Version (This version includes the review and suggestions of the examination committee.)

07/2025

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Evaluating Environmental Efficiency: A DEA-Based Analysis of Sectoral Contributions to GHG Emissions

Bruna Salomé da Costa Moreira

Master's Dissertation submitted to the Porto Accounting and Business School (ISCAP) for the attainment of the master's degree in Corporate Finance, under the supervision of Dr. Elif Göksu Öztürk and Dr. Isabel Cristina da Silva Lopes.

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Dedication

I dedicate this dissertation to my grandfather Fernando. Thank you for shaping who I am. I miss you everyday.

Acknowledgements

First and foremost, I would like to express my sincere gratitude to Professor Dr. Elif Göksu Öztürk and Professor Dr. Isabel Cristina da Silva Lopes for their invaluable guidance and support over the past months. Your advice, motivation, and patience have been instrumental throughout this journey. I will never forget your care and constant availability for answering all my doubts and concerns. I feel truly fortunate and grateful to have shared this experience with you and to have learned so much under your mentorship.

To my family, that is always my greatest source of strength and encouragement, thank you for always standing by me. To my mom, brother, grandmother, and dad: I could not have achieved any of this without your unwavering support, love, and belief in me.

I also extend my heartfelt thanks to ISCAP, and to all the professors and colleagues I had the pleasure of meeting during my Master's in Corporate Finance. This institution is home to truly special people, and I have gained valuable insights from each and every one of you. I would also like to extend my special thanks to Professor Dr. Armando Silva and Professor Dr. Ricardo Bahia Machado, whose support and guidance were instrumental in helping me redefine my path at the beginning of this final project.

Last but not least, I am deeply thankful to my friends for always being there and for allowing me to share this journey with you. Your presence and support have meant more than words can say.

And, of course, a heartfelt thanks to myself, for following through and accomplish what I commit myself into.

Resumo:

A presente dissertação avalia a eficiência ambiental de 33 países da OCDE no período 2000 a 2023, utilizando uma estrutura analítica de duas etapas, incluindo uma Análise Envoltória de Dados (DEA), orientada a *inputs*, e Modelos de Regressão Fracionária de uma e duas partes. Esta investigação contribui para a literatura sobre desenvolvimento sustentável e avaliação de eficiência, oferecendo uma análise abrangente entre países e setores de atividade. Os setores selecionados foram obtidos do Banco de Dados de Emissões para Investigação Atmosférica Global (EDGAR), incluindo Agricultura, Energia (Exploração de Combustíveis, Indústria de Energia, Edifícios e Transportes), Indústria (Combustão Industrial e Processos Industriais) e Resíduos. Os resultados fornecem informações para que reguladores possam implementar melhores práticas com vista à melhoria do desempenho ambiental, especialmente através de intervenções direcionadas aos setores mais intensivos em emissões e tendo em conta os efeitos macroeconómicos.

Palavras-chave: Eficiência Ambiental, OCDE, DEA, FRM

Abstract:

This dissertation evaluates the environmental efficiency of 33 OECD countries from 2000 to 2023 using a two-stage analytical framework, including an input-oriented Data Envelopment Analysis (DEA) and One-part and Two-part Fractional Regression Models (FRMs). This research contributes to the growing body of literature on sustainable development and efficiency evaluation by offering a comprehensive cross-country and sectoral analysis. The selected sectors were obtained from the Emissions Database for Global Atmospheric Research (EDGAR), including Agriculture, Energy (Fuel Exploitation, Power Industry, Buildings and Transport), Industry (Industrial Combustion and Industrial Processes) and Waste. The findings provide insights for policymakers aiming to improve environmental performance, particularly through targeted action in emission-intensive sectors and by considering macroeconomic effects.

Key words: Environmental Efficiency, OECD, DEA, FRM

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List of abbreviations

AME – Average Marginal Effects

BCC – Banker, Charnes and Cooper

BRIC – Brazil, Russia, India and China

CC – Climate Change

CCR – Charnes, Cooper and Rhodes

CF – Climate Finance

CGI – Corporate Green Investment

COP21 – 21st United Nations Climate Change Conference

COP28 – 28th United Nations Climate Change Conference

COP29 – 29th United Nations Climate Change Conference

CRS – Constant Returns to Scale

DDF – Directional Distance Function

DEA – Data Envelopment Analysis

DRS – Decreasing Returns to Scale

DMUs – Decision-making units

EDGAR - Emissions Database for Global Atmospheric Research

ESDC – European Sovereign Debt Crisis

ESG – Environmental, Social and Governance

ETSs – Emissions Trading Systems

EU – European Union

E&IC – Energy and Inflation Crisis

FDI – Foreign Direct Investment

FRMs – Fractional Regression Models

GCF – Green Climate Fund

GDP – Gross Domestic Product

GEF – Global Environment Facility

GFC – Global Financial Crisis

GFCF – Gross Fixed Capital Formation

GHGs – Greenhouse gases

GF – Green Finance

GI – Green Investment

GPI – Green Prevention Investments

GTI – Green Treatment Investments

IRS – Increasing Returns to Scale

JRC – Join Research Centre

MtCO2e – Million metric tonnes of CO2 equivalent

OECD – Organisation for Economic Co-operation and Development

QML – Quasi-Maximum Likelihood

ROA – Return on Assets

R&D – Research and Development

RTS – Returns to Scale

SBM – Slacks-based measure

SFA – Stochastic Frontier Analysis

UN – United Nations

UNEP – United Nations Environment Programme

UNFCCC – United Nations Framework Convention on Climate Change

USA – United States of America

VRS – Variable Returns to Scale

WBCSD – World Business Council for Sustainable Development

WHO – World Health Organization

CHAPTER I - INTRODUCTION

1 Introduction

Since the early 1970s, environmentalists, governments, and policymakers have demonstrated a growing awareness of climate change (CC) and environmental protection. Companies have been held accountable and, at the same time, seen as part of the solution to mitigate impacts, facing pressure to reduce the environmental impact of their operations (Monteiro & Aibar-Guzmán, 2010).

Thus, CC is recognized as one of the foremost environmental challenges confronting the world in the 21st century (Chang et al., 2015) and has profoundly affected ecosystems, presenting a significant threat to human existence (Mou & Ma, 2023). Addressing CC demands coordinating global action and efforts through all economic sectors.

Understanding differences in environmental efficiency between countries is essential for policymakers to draw more effective policies. Environmental efficiency core objective is to produce goods and services while at the same time using fewer resources and generating less waste and pollution, including GHG emissions and other pollutants. It follows a resource optimization premise, emphasizing the need to consume the minimum of inputs while at least maintaining or increasing the level of desirable outputs (Moutinho et al., 2017; Woo et al., 2015; Zhu et al., 2022).

The Organisation for Economic Co-operation and Development (OECD) plays a crucial role in supporting its member countries in addressing CC. Through coordinated efforts, the OECD promotes policy alignment, encourages mandatory environmental disclosures, and supports financial mechanisms aimed at mitigating climate risks. It also contributes to major international initiatives, such as the Global Environment Facility (GEF) and the Green Climate Fund (GCF), and helps channel climate finance, particularly toward assisting developing countries in transitioning to low-carbon, climate-resilient economies.

In the present study, the environmental efficiency of OECD countries is analysed, in a two-stage procedure. The first stage involves an application of Data Envelopment Analysis. Furthermore, the second stage implements Fractional Regression Model (FRM) considering two approaches: (i) one-part FRM and (ii) two-part FRM. By implementing these two-stage methodology, the goal is to obtain the relative environmental efficiency scores of all the selected countries through DEA, then, to evaluate the impact of different sectors on efficiency scores through one-part FRM. To gain greater insights also two-part FRM is implemented aiming drawing conclusions on the factors that the countries should pay more attention to improve their efficiency and to draw conclusions on the probability of a country being fully efficient. The selected sectors were obtained from the Emissions Database for Global Atmospheric Research (EDGAR), including Agriculture, Energy (Fuel Exploitation, Power Industry, Buildings and Transport), Industry (Industrial Combustion and Industrial Processes) and Waste.

This study is particularly relevant to the literature, due to allowing for a wider understanding of how the different sectors impact the environmental efficiency instead of focusing on only one, giving insights to policymakers of what sectors and factors they should improve to become more efficient. Some limitations include the lack of data availability for all countries and years, which made the comparison between sectors more challenging.

The remainder of this dissertation is structured as follows: Chapter II presents the Literature Review, Chapter III includes the selected data for DEA and FRM, data bases, definitions and descriptive statistics, Chapter IV introduces the DEA and FRM methodologies in detail and the models that are used in this dissertation. Chapter V draws the main results and includes broad discussion and informed policy recommendations. Finally, Chapter VI concludes.

CHAPTER II – LITERATURE REVIEW AND HYPOTHESIS

2 Literature Review and Hypothesis

This chapter begins by introducing the main impacts of CC and the corresponding mitigation efforts, followed by an outline of the roles that different sectors and companies should play in addressing this global crisis. Next, we present some of the most common Green Investments (GI) currently being implemented, as well as the commitment of major organizations such as the OECD to enhancing countries' positive environmental impact. Finally, the chapter concludes by identifying the main methodologies used in efficiency studies and by formulating our research hypothesis.

2.1 Climate Change and Mitigation

CC is acknowledged as a global, complex and inter-governmental challenge due to its impact on various disciplines such as ecology, environment, socio-economic and socio-political sciences (Adger et al. 2005; Leal Filho et al. 2021; Feliciano et al. 2022, as cited in Abass et al., 2022).

Anthropogenic activities have been the main driver of CC, with several impacts in an economic, social and environmental level, and contributing to the increase of greenhouse gas emissions, which are the primary cause of both greenhouse effect and global warming (Abbass et al., 2022).

Some of the main activities that must adapt and incorporate mitigation policies are agriculture, forestry, transport (international and domestic transportations) and land use (Kärkkäinen et al. 2020; Waheed et al. 2021, as cited in Abass et al., 2022). The agricultural sector, the cornerstone of many economies, has been the most determining for the greenhouse gas (GHG) emissions, representing around 30-40% of all emissions due to its excessive agricultural operations (Abbass et al., 2022), while being at the same time one of the most negatively affected sector. In addition to the well-known effects of CC, such as melting ice caps and subsequent increases in sea levels, farmers have been dealing with issues related to changes in the patterns of precipitation and evaporation as well as extreme weather events, such as droughts, floods, and forest fires, which pose a threat to food security due to decreased agricultural yields and higher food prices and disrupt vital infrastructure, supply chains, and business operations. (Abbass et al., 2022).

Other consequences of CC include the biodiversity loss due to habitats and ecosystems disruption that causes species extinction or changes in its distribution. Human health is also particularly affected, with an increase in respiratory illnesses, infectious diseases, and malnutrition. An estimation by the World Health Organization (WHO) indicates that CC may cause an additional 250,000 deaths per year until 2050 (World Health Organization, 2023).

Governments, international organizations, policymakers as well as the academic community join efforts to mitigate and postpone the negative effects of CC. The Paris Agreement, a major international agreement reached at 21st United Nations Climate Change Conference (COP21) in 2015, was a turning point in the global combat against CC. It aimed to limit global warming to well below 2°C above pre-industrial levels, and encouraged the efforts to limit the increase to 1.5°C. Also, it supported implementing adaptation measures involving "strengthening societies' ability to deal with the effects of climate change" and "continuing and expanding the international assistance for developing nations' adaptation" (Abbass et al., 2022, p.42540). To accomplish these goals, United Nations (UN) indicates the need to mitigate the emissions by 45% until 2030 and achieve net-zero carbon emission goals by 2050 (United Nations, n.d). To help achieving the Paris Agreement, carbon pricing policies, such as emissions trading systems (ETSs) and carbon taxes, are being implemented globally. These policies aim financial compensation and impact mitigation for the emissions created by the governments and companies. Through carbon pricing policies, the total amount of GHGs that certain groups can release (usually heavy and energy industries) are capped. Due to taxes on fossil fuel suppliers, gas, electricity, and other goods and services are served for more expensive prices limiting their use and consumption (World Bank, 2024). In their carbon pricing report, World Bank also remarked that those carbon pricing revenues are used for funding climate and nature-related programmes, supporting the general budget of countries and redistributing to households and businesses.

Companies play a significant role in both driving and addressing carbon emissions. While they are major contributors to the climate crisis, they are also increasingly seen as key agents in the transition to a sustainable future.

2.2 Role of Sectors and Corporates in Climate Mitigation

Companies, as part of their commitment to sustainable development, are obliged to reduce emissions, while also making this information public, through sustainability reporting, especially those in sectors where business activities significantly contribute to CO2 emissions (Wahyuningrum et al., 2024). They may involve measures like auditing direct and indirect carbon emissions, reducing waste, transitioning to renewable energy, decreasing the consumption of energy, converting fleets to electric and hybrid vehicles, and enhancing logistics (Birnik, 2013, as cited in Wright & Nyberg, 2024).

Although the agricultural sector, as referred previously, is one of the most hazardous sectors, the fossil fuel sector is also a significant contributor to GHG emission. Also, given the dependency of many other sectors on fossil fuels as the energy source, its change to "net-zero" emissions bears many challenges (Wright & Nyberg, 2024). These challenges are being addressed by well-known oil and gas companies like Total, BP and Repsol, through substantial investments in renewable and alternative technology pathways as well as exploring and implementing strategic solutions in extraction, processing and distributing (Wright & Nyberg, 2024). Even with these efforts, the world is still highly dependent on the use of energy from coal, oil, and gas (81.5% of total energy), and the share of primary energy consumption from renewables and nuclear energy has risen (Energy Institute, 2024). This dependency clearly indicates that the elimination of fossil fuels is a significant opportunity to mitigate the sector's immediate climate effect and enhance corporate social responsibility (SEI, Climate Analytics, E3G, IISD and UNEP, 2023). For instance, during the 28th UN Climate Change Conference (COP28), the We Mean Business Coalition, including companies like eBay, IKEA and Volvo Cars, assumed their position for a fully decarbonised power sector by 2035 and in emerging economies by 2040. In an open letter to governments and policymakers, the coalition affirmed that they are "setting science-based targets, developing climate transition action plans, investing in net-zero solutions and disclosing their progress". In the same letter, they mentioned that the key steps to decarbonize the global energy system should be "turbocharging the renewables revolution, electrifying key sectors and massively improving efficiency" (*We Mean Business Coalition*, n.d). Also, during COP28, fifty fossil fuel firms signed the Oil and Gas Decarbonization Charter. They pledged to achieve net zero emissions by 2050 and stop gas flaring by 2030, being widely criticised of greenwashing[1], since they made no mention of reducing emissions from global fossil fuel use. In addition, around 130 nations also committed to tripling the global renewable energy capacity to 11,000 GW (REN21, 2024).

CC has also been an opportunity for companies in several sectors to innovate and invest on technology as a solution. The automotive industry experienced a dramatic uptake on electric vehicles. Such change directly affected the oil industry, given major dependency of oil and gas market to transportation (i.e., 60%) (Hunt et al., 2022). Also, the green hydrogen[2] economy is an emergent possibility given its zero-carbon and versatility particularities, since it can be used for commercial, industrial or mobility (e.g., heavy and maritime transport, aviation) purposes, and it is easy to store after its production. The only challenge in implementing this solution is the high generation cost and safety issues related to the volatile and flammable characteristics of hydrogen (Iberdrola, n.d.).

It was also an opportunity for companies to manage reputational risks by disclosing voluntary reporting on corporate environmental performance and Environmental, Social and Governance (ESG) practices, while dealing with the demands of short-term profitability and shareholder value (Wright & Nyberg, 2024).

GIs have emerged as a critical focus in modern finance, with research exploring their efficient allocation and potential to enhance firm value.

2.3 Green Investment: Conceptualization and Empirical Evidence

GI is defined as the investment required to reduce the GHG emissions and air pollutants (Allevi et al., 2019), without substantially lowering down on the manufacturing and consumption of non-energy goods (Barabanov et al., 2021). There is no standard GI practice and all the activities aiming to reduce GHG emission can be considered as GI in the company context. Barabanov et al. (2021, p.1) referred, "renewable energy technologies, environmentally friendly transportation, projects that are committed to preserving natural resources, clean air, water and waste projects, and more generally, the

[1] Greenwashing occurs when companies do misleading GI (like issuing green bonds), claiming they're environmentally responsible but not taking real action, using the income from those investments for other purposes (Hadaś-Dyduch et al., 2022)
[2] Green hydrogen is a clean energy source that, in opposition to coal and oil, only releases water vapor and leaves no residue in the atmosphere (Iberdrola, n.d).

implementation of environmentally conscious business practices" as some examples of GI.

GIs usually have goals for improving corporate environmental performance and reducing environmental risks. In their study, Chen and Feng (2019) classified GIs into two types: (i) Green Prevention Investments and (ii) Green Treatment Investments. The former includes the use of clean energy, renewable technologies, and implementation of Research and Development (R&D) in energy-efficient-green technologies. The latter, on the other hand, aims to include environmental treatments to low emissions, dust removal, waste utilization and regeneration and the maintenance of environmental protection equipment.

Large energy-consuming and polluting businesses need greater assistance from financial institutions, like securities firms and urban banks about GI practices. Green finance (GF) is designed to assist such businesses by investment and financing activities (GI, green securities, green loans and credits, climate insurance, public and private financing). These activities improve the environment and promote sustainable growth. Thus, GF usually offers support for green technology, R&D activities and incentives on the optimal allocation of resources (Zhang & Sun, 2025).

Green bonds are the most well-known form of green securities, and can be issued by governments, local authorities, companies, and financial institutions. They are typically defined as fixed-income securities, in which the money raised is used to finance low-carbon and climate-resilient projects (Hadaś-Dyduch et al., 2022). The Climate Bond Initiative (2022) has given some headlines regarding which projects can be considered as green in the different sectors, and that therefore could be eligible for receiving green bond financing. Some examples of areas and projects are: renewable energy (solar, wind, geothermal, hydro and bioenergy), transport (low-carbon transport, public transport, alternative fuels), waste and pollution (recycling, energy waste, landfills), industry (cement, steel, glass, chemical, fuel production), water (treatment, flood protection) as well as agriculture, forestry and fisheries (Climate Bond Initiative 2022, as cited in Hadaś-Dyduch et al.,2022).

Amolo (2024) explored other widely used GF options. For instance, green equity funds appear to be another type of green securities that are defined as investment vehicles where investors pool their capital to invest in companies based on a commitment to a GI strategy.

Although green leasing is still in its beginnings, it can be used to finance the purchase of planted equipment. Also, it has the ability to finance green assets such as green property leases, green automobile leases, energy efficiency, and green mortgages. Moreover, public and private partnerships are a conceivable financing strategy inside GF, especially considering the need to involve both the public and private sectors in climate mitigation. They have been widely utilized to support infrastructure projects that involve large amounts of capital. Climate insurance is a crucial but underutilized tool for addressing climate-related financial solutions. It can be incorporated into a larger financing strategy to assist make it bankable, such as technology insurance products.

GI plays a pivotal role in corporate environmental sustainability. Still, it faces some challenges such as the perceived risks and uncertainties surrounding new and unproven green technologies. This is due to the shifts in businesses to renewable energy, optimize processes and financial performance by implementing technology and invest on R&D (Amolo, 2024). Furthermore, the absence of consensus in green definitions, lack of infrastructure investment pathways associated with long-term government commitments to low-carbon development and non-standardized projects and cash flow instability contribute such challenges further (L. Chang et al., 2023).

However, several studies proved a positive link between GI and CC mitigation outcomes. GI have been crucial for a shift to a low-carbon economy, with an higher investment in renewable energy sources (Barabanov et al., 2021). Green bonds issuance demonstrated a positive impact on share prices, profitability and environmental improvement (Zhou & Cui, 2019).

2.4 Environmental Efficiency: country and sector-level

Environmental efficiency is a concept of efficiency that demonstrates how much an organization minimizes undesirable production (e.g., carbon emissions) or maximizes desirable production (e.g., electricity generation), taking into account resource scarcity, CC, extreme pollution, and regulations (Woo et al., 2015).

In order to achieve higher scores in environmental efficiency, some recommendations are being made to governments, policymakers and influential organizations. Institutions like OECD, the World Business Council for Sustainable Development (WBCSD), and the UN Environment Programme (UNEP) play a key role in shaping policies and fostering collaboration. Together, they implement strong regulations that support the development of green products and production methods, especially in key sectors (e.g., through labelling, mandatory disclosure of carbon-intensive and green operations, or green public procurement). Financial support is also key, since the transition towards greener industries implies the investment in new technologies and assets (e.g., governments provide subsidies through financing and corporate taxation channels, public-private partnerships to share the risks of big investments) (Sato et al., 2020).

The OECD has 38 member countries and collaborates with different economic agents, including individuals, stakeholders, and governments to tackle social, economic, and environmental issues and set international goals and standards, with the primary objective of establishing norms and facilitating their application. This way, OECD aims to contribute building more resilient, equitable and clean societies (OECD, n.d). Understanding the environmental efficiency in the member countries will be a powerful tool for firms, stakeholders and policymakers.

Figure 1 shows how much each sector contributes to the GHG emission over 20 years in OECD countries. As is seen Electricity and Transportation sectors are the most polluting sectors, responsible for approximately 60% of all emissions by 2021.

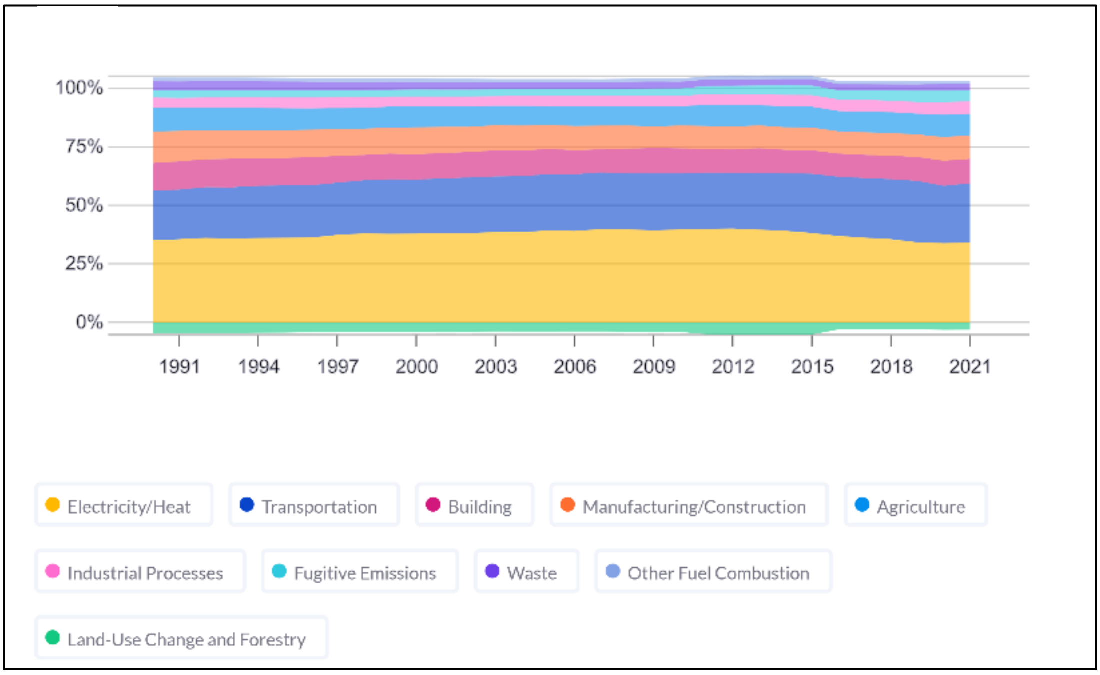

Figure 1. Contribution of each sector on GHG emission (Source: Climate Watch (2024))

Climate Finance (CF) was a prominent topic during 29th UN Climate Change Conference (COP29), where all parties committed to mobilizing at least 1.3 trillion USD annually for climate action by 2035 from public and private sources, and with the developed countries having to pledge at least 300 billion USD annually to support climate action in developing countries by the same year, tripling the previous target of 100 billion USD per year, which was initially set to be achieved by 2020 and was accomplished and exceeded in 2022 with 115.9 billion USD mobilized (United Nations Framework Convention on Climate Change, 2024).

Emerging markets are experiencing a debt crisis because of rising capital costs, making conditions financially worse, especially for developing nations, which are vital in combating CC although they face greater obstacles for investment (REN21, 2024).

The United Nations Framework Convention on Climate Change (UNFCCC), to which OECD member nations in Annex I are signatories, defines CF as the process of mobilizing finances to aid in the reduction of GHG emissions and to prepare for the impacts of CC. As part of the Annex I, OECD countries should assist developing countries and contribute to initiatives like the Global Environment Facility (GEF) and the Green Climate Fund (GCF), which goals are to support environmental programs addressing land degradation, biodiversity loss and CC, and provide grants and concessional loans, prioritizing vulnerable sectors in developing countries through private and public finance, respectively.

Understanding the relevant studies regarding GI and environmental efficiency in sector and country-level is crucial to give further recommendations to governments and policymakers.

2.5 Benchmarking and efficiency in Green Investment

There are various examples of performance evaluation techniques used in the GI and environmental efficiency literature.

Regression analysis is applied in different approaches, such as random effects regressions (Barabanov et al., 2021), Tobit regressions (Chen & Feng, 2019), multivariate analysis (Branco & Rodrigues, 2008; Mahboub, 2024; Monteiro & Aibar-Guzmán, 2010), quantile regression (Moutinho et al., 2017) or static linear regression (Halkos & Bampatsou, 2022). They’re used in several studies as a second-stage procedure to analyse the impact of different independent variables (eg., polluting gases, environmental tax revenues, macroeconomic indicators) related to environmental efficiency (Halkos & Bampatsou, 2022; Moutinho et al., 2017; Moutinho & Madaleno, 2021).

Other methodologies include structural equation modelling, to analyse the relationship between green product development practices and environmental, operational, and market performance (Jabbour et al., 2015). Moreover, event study analysis is employed to examine stock market reactions to corporate events related to GI, such as green bond issuances or announcements of green initiatives (Baulkaran, 2019; Verma & Bansal, 2023). Moreover, meta-analysis is used, adding value to the literature by providing a comprehensive understanding of the overall trends or patterns regarding GI (Amolo, 2024).

Data Envelopment Analysis (DEA), presented by Charnes et al., (1978), is a benchmarking method that is commonly used for GI practices and environmental efficiency on the context of corporates and countries (Cámara-Aceituno et al., 2024; Fazio et al., 2024; Halkos & Petrou, 2019; Woo et al., 2015; Zhu et al., 2022). DEA is particularly relevant given its ability of handle multiple inputs (e.g., energy consumption, labour) and outputs (desirable outputs like GDP and undesirable outputs like CO2 emissions), involving economic, environmental, and social factors (Moutinho & Madaleno, 2021). It can also serve as a guide to policymakers to implement best practices and regulations. DEA is used to assess environmental and energy efficiency, as well as corporate sustainability by evaluating their GI efficiency by considering their GI as inputs and pollutant emissions as undesirable outputs (Almulhim et al., 2024). There are several variations of DEA used in environmental efficiency literature. Most of them are output-oriented, where the goal is to maximise desirable outputs while keeping the inputs constant (Almulhim et al., 2024; Fidanoski et al., 2021; Moutinho et al., 2017; Moutinho & Madaleno, 2021; Pais-Magalhães et al., 2021; Woo et al., 2015).

Regarding our target sample of the OECD countries, there's also some relevant studies that aimed to assess their environmental efficiency. Comparisons between OECD countries and non-OECD countries were made (Chien & Hu, 2007) as well as with BRIC (Brazil, Russia, India and China) nations (Xie et al., 2014). More recent literature include considerations about the highest and lowest ranked countries in environmental and economic efficiency scores (Fidanoski et al., 2021; Mavi et al., 2019; Mehmood et al., 2022; Taleb et al., 2024).

Some studies combined DEA and Fractional Regression Models (FRMs). For instance, Moutinho et al. (2020) implemented an eco-efficiency analysis to observe the effect of urban air pollutants in Germany; Marques and Teixeira (2022) measured the performance of European Union (EU) countries on municipal waste collection; Moutinho and Madaleno (2021) proposed a technical eco-efficiency indicator in EU countries; and Silva et al. (2022) evaluated the social, economic and environmental factors on the technical efficiency in entrepreneurship in European countries.

2.6 Literature gap and justification for the study

The main goal of the study is to evaluate the environmental performance in OECD countries considering the role of sectors using DEA and FRM.

Understanding how the different OECD regions behave in terms of efficiency is still a misused approach in literature. We found those analysis particularly relevant, as regional perspectives can provide valuable insights into the potential influence of geographical, economic, and policy-related factors on environmental performance. A study targeting environmental efficiency of renewable energy conducted by Woo et al. (2015) tried to make the regional comparisons. The authors divided the OECD countries by three regions: OECD Europe (OECD-EU), OECD America (OECD-AM) and OECD Asia and Oceania (OECD-AO), in order to see which region would perform better. Based on their results, we built our first hypothesis.

H1: OECD-AM has the highest average environmental efficiency.

Global instable periods that resulted in financial crises have showed a negative impact in environmental efficiency (Beltrán-Esteve & Picazo-Tadeo, 2017; Cámara-Aceituno et al., 2024; Feng et al., 2017; Halkos & Petrou, 2019; Woo et al., 2015). Covid-19 initially caused a decline in CO2 emissions due to lockdown measures and reducing of economic activity. However, the post-pandemic brought a new rise in energy demand, and CO2 emissions reached in 2021 a new record. The Russia-Ukraine and Israel-Gaza conflicts had caused a short-term reliance on fossil fuels, especially coal, to decrease the dependence on imports from conflict zones (Cámara-Aceituno et al., 2024; Mišík &

Nosko, 2023; Wright & Nyberg, 2024). These two recent crises may also have an impact on environmental efficiency. Thus, it is hypothesised:

H2: Financial/Social crises have a negative impact on environmental efficiency.

Regarding GHG emissions, although most of the studies in the literature focus only on CO2 emissions in sectoral level, other hazardous gasses (i.e., methane, sulphur oxides, nitrogen oxides, etc.) should not be overlooked by firms and policymakers. They should be paying special attention to methane (CH4) emissions, since it is twenty-eight time more hazardous to global warming than CO2 (Cámara-Aceituno et al., 2024). In their study, Cámara-Aceituno et al. (2024), build two DEA methods. The first one treated all undesirable outputs equally, while the second one gave a higher weight to CH4 (97.2 against 2.86% of CO2). The results showed lower efficiency scores in the second method, highlighting the relevant impact of CH4. Regarding methane's emissions across sectors, Agriculture, Waste and Energy had shown a particular relevance (European Environment Agency, 2025). According to European Environment Agency report, Agriculture sector accounts for about 56% of EU's methane emissions, mainly coming from enteric fermentation (e.g., digestion process in ruminants like cows and sheep), and also from the management of livestock manure. Regarding the waste sector, solid waste disposal (primarly landfills) as shown as the biggest contributor, presenting 80% of the Waste sector methane emissions. Also, fugitive emissions from coal mining and handling accounted for 36% of total Energy sector emissions in Europe. Given this evidence and its relevance to this study, adding the need to observe if methane has a particular effect in the already referred and across other sectors, the third hypothesis is defined as:

H3: Methane (CH4) has a negative impact on environmental efficiency across all sectors.

Given the strong impact of emissions and the still highly intensive dependence on fossil fuels to sectoral activity, countries are striving to balance economic development with environmental sustainability. With those concerns, the role of clean energies, namely from renewables and from alternative and nuclear sources, has become a priority. A study targeting 15 OECD countries for the period 1990-2018 conducted by Saidi & Omri (2020), showed that both nuclear and renewable energy consumption reduce carbon emissions, especially when these clean energies are mixed. Other study, targeting 20 OECD countries from 2015-2020 showed that countries with higher shares of renewable energy were consistently ranking amongst the most environmentally efficient (Wang et al., 2023). In Nuclear Power in a Clean Energy System Report by International Energy Agency (IEA), it was stated that “over the past 50 years, the use of nuclear power has reduced CO2 emissions by over 60 gigatonnes” (IEA, 2019, p.1). For these reasons, our fourth hypothesis is:

> **H4:** The production and use of clean energies (renewables and nuclear) improve environmental efficiency.

Finally, the majority of the studies focus solely on the energy sector (Fidanoski et al., 2021; Woo et al., 2015; Zhang & Sun, 2025) and neglect the impact of other sectors on CC. This study aims to provide a deeper analysis of the potentially diverse impacts of several sectors. However, given the shown relevance given to the Energy sector, our last hypothesis is:

> **H5:** The energy sector has the highest impact on environmental efficiency

The following chapters will further explore the proposed hypotheses through the application of Data Envelopment Analysis (DEA) and Fractional Regression Models (FRMs) to the sectoral data, thereby contributing to the broader discourse on environmental accountability and sustainable development.

CHAPTER III – DATA SOURCES AND PREPARATION

3 Data Sources and Preparation

This section presents all the data that is used throughout the analyses. As mentioned before, the analyses are conducted on OECD countries over 24 years (2000-2023). The two-stage strategy – DEA and FRM – requires different data in each stage. Thus, the reminder of this chapter is dedicated to explain the data, definitions, data bases, and some descriptive statistics.

In the present study, 33 OECD countries are included out of 38 due to data availability[3]. Moreover, in Appendices XV-XVI, there is an extensive list of collected environmental and economic data, that can be useful for future research. Some of this data ended up not being used in this study due to missing information.

3.1 DEA Data

Table 1 presents the short definitions and data sources for the variables used in the DEA application, while Table 2 provides the corresponding descriptive statistics.

Table 1. DEA data definitions (Source: World Bank, 2025)

Variable	Definition	Source
	Inputs	
Gross Domestic Product (GDP)	Gross value added by all resident producers in the economy, plus product taxes minus subsidies not included in the value of products. Measured in constant 2015 US dollars.	**World Bank**
Gross Fixed Capital Formation (GFCF)	Include: land improvements (fences, drains, etc.); plant, machinery and equipment purchases; construction of roads, railways, schools, hospitals, etc. Measured in constant 2015 US dollars, expressed as %GDP.	**World Bank**
Labour Force	People ages 15 and older who are currently: employed, unemployed but seeking job, first time job-seekers. Expressed in total persons.	**World Bank**
Research and Development (R&D) Expenditure	R&D comprise creative work to increase knowledge, and the use of this knowledge to devise new applications. This indicator includes R&D carried out by all resident	**World Bank**

[3] Excluded countries are Chile, Colombia, Costa Rica, Mexico and Switzerland.

	companies, research institutes, university, and government laboratories.	
Energy Use GDP	It is the kilogram of oil equivalent of energy use per 1 dollar of GDP generated, measured in constant 2021 PPP dollars.	**World Bank**
	Outputs	
CO2 Emissions	Total Carbon Dioxide (CO_2) emissions, excluding Land Use, Land Use Change and Forestry (LULCF). Expressed in million metric tonnes ($MtCO_2e$).	**World Bank EDGAR**
CH4 Emissions	Total Methane (CH_4) emissions, excluding Land Use, Land Use Change and Forestry (LULCF). Expressed in million metric tonnes ($MtCO_2e$).	**World Bank EDGAR**
Water Stress Level	The proportion of freshwater withdrawn by all major sectors compared to the total renewable freshwater resources available, after accounting for environmental needs. It measures the pressure on a country's water resources and indicates the sustainability challenges in meeting water demand. Higher values reflect greater water scarcity and potential conflicts over water use. **No Stress**: <25% **Low Stress:** 25-50% **Medium Stress:** 50-75% **High Stress:** 75-100% **Critical:** >100%	**World Bank**

All outputs were treated as undesirable since having less of them represent a better situation. To ensure the correct implementation of the DEA model, these undesirable outputs were transformed and incorporated into the model as desirable outputs (i.e., the variables were converted so that higher values reflect better outcomes). This transformation is explained in the next Chapter, subsection 4.1.

Figure 2 shows the diagram of inputs and outputs that will be used in our DEA application.

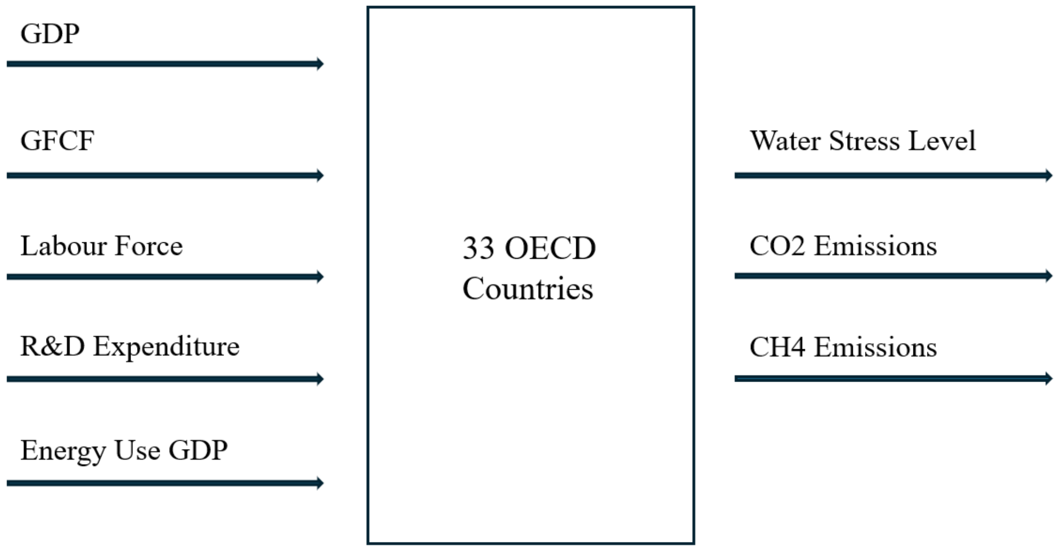

Figure 2. Diagram of Inputs and Outputs for DEA model

The five selected inputs are: (i) GDP, (ii) GFCF, (iii) Labour Force, (iv) R&D Expenditure, (v) Energy Use GDP. In the current study, the GDP is considered as an input, serving as a proxy for the countries' production and economic capacity although it was often used as an output in the literature (Halkos & Bampatsou, 2022; Huang et al., 2018; Mehmood et al., 2022; Zhang & Sun, 2025; Zhu et al., 2022). This choice reflects the premise that higher economic activity may entail greater pressure on environmental resources. For instance, countries with similar GDP levels can exhibit markedly different emission intensities. From an efficiency perspective, the country that generates more output with fewer environmental impacts - despite having comparable economic capacity - demonstrates a more efficient use of its economic resources. Therefore, GDP is included as an input to capture the scale effects in environmental performance assessments. Moreover, GFCF was used in some studies (Halkos & Petrou, 2019; Moutinho & Madaleno, 2021; Reinhard et al., 2000), representing the long-term investments in infrastructure, machinery and equipment. Countries that invest more will probably increase their production capacity, that can result in a higher environmental impact if that increase is not done efficiently. Labour Force is another input that is often used in similar studies (Halkos & Bampatsou, 2022; Halkos & Petrou, 2019; Lin et al., 2025; Mehmood et al., 2022; Taleb et al., 2024). R&D Expenditure is used as a measure of technology innovation following Fidanoski et al. (2021). Expenditures on research and development can improve countries' overall productivity and has a higher chance of reducing their environmental impact when applied efficiently. Energy Use GDP is an indicator represents the energy intensity of the economy, capturing how much primary energy is consumed to generate GDP.

Furthermore, the three outputs that are included in this study are: (i) Water Stress Level, (ii) CO2 emission and (iii) CH4 emission. The Water Stress Level shows how much water resources are being exploited to meet the countries' water demand, challenging the sustainability of water use and increase scarcity propension. The level of water stress is considered low between 25-50% and high between 75-100%. Finally, CO2 and CH4 Emissions are selected as other two outputs to be included in DEA. CO2 is often used in several previous studies (Cámara-Aceituno et al., 2024; Feng et al., 2017; Halkos & Bampatsou, 2022; Taleb et al., 2024; Woo et al., 2015), whereas CH4 is less common, but with a particular relevance given its harmful impacts (Cámara-Aceituno et al., 2024).

Table 2 presents the descriptive statistics of the selected input and output variables. As seen, the table includes variable names, measurement units (Unit), mean, standard deviation (Sd), minimum (Min) and maximum (Max) values.

Table 2. DEA Descriptive Statistics

Data Envelopment Analysis					
Variable	**Unit**	**Mean**	**Sd**	**Min**	**Max**
Inputs					
GDP	Constant 2015 US$	1.303×10^{12}	3.049×10^{12}	1.186×10^{10}	2.206×10^{13}
GFCF	% GDP	22.791	4.126	10.970	53.22
RDExpenditure	% GDP	1.926	1.00	0.38	6.35
LabourForce	Persons	16599440	29273762	167756	171333247
EnergyUseGDP	Kg Oil Eq. per $GDP	90.18076	42.03577	20.87	327.66
Outputs					
WaterStresLevel	%	23.533	25.912	0.22	148.39
CO2Emissions	MtCO2e	367.275	921.945	2.85	5928.97
CH4Emissions	MtCO2e	56.401	138.104	0.55	861.36

Overall, these statistics reveal substantial heterogeneity across OECD countries, highlighting the diversity in their economic size, investment efforts, and environmental performance. For example, the input variable GDP (at constant 2015 US$) presents a mean of 1.303×10^{12} with a substantial standard deviation of 3.049×10^{12}, indicating strong disparities in the economic size of OECD countries over the analysed period. This wide dispersion reflects the inclusion of large economies like the United States of America and smaller ones such as Latvia. Energy Use per GDP shows a mean of 90.18 kilograms of oil equivalent per dollar of GDP and a standard deviation of 42.04, highlighting significant differences in energy intensity across countries. This can happen due to some economies being more energy efficient, while others can still rely on more energy-intensive processes. Regarding outputs, CO_2 Emissions present a mean of 367.28 $MtCO_2e$ and a high standard deviation of 921.95, again pointing to large variations between countries' emissions levels, likely tied to differences in sector predominance and different adoption of climate-related policies and regulation. Similar interpretations can be made for the remaining variables in the model.

Next, we will proceed with FRMs data and descriptive statistics analysis.

3.2 Fractional Regression Models (FRMs) Data

The data used for FRM implementation are described in this section. To measure sector specific effects, the impact of crises and macro indicators, several models are defined. The description tables and descriptive statistics are accordingly separated to avoid confusion. Initially, in Table 3, we presented the selected sectors. The sector level data is collected for these sectors (or subsectors if defined).

Table 3. Descriptions of the selected sectors (Source: IEA et al., 2024)

Sectors	Sub-sectors	Description
Agriculture		Livestock (enteric fermentation, manure management), agricultural soils (fertilisers, lime application, rice cultivation, direct soil emissions, indirect N2O emissions from agriculture), field burning of agricultural residues
Energy	**Fuel Exploitation**	Fuel extraction, transformation and refineries activities, including venting and flaring
	Power Industry	Power and heat generation plants (public and auto-producers)
	Buildings	Small scale non-industrial stationary combustion
	Transport	Road, non-road, domestic and international aviation, inland waterways and international shipping.

Industry	**Industrial Combustion** **Industrial Processes**	Combustion for industrial manufacturing, industrial processes (e.g. iron and steel, cement, aluminium, chemicals, production, solvents, etc.)
Waste		Solid waste disposed on land, solid waste composted and hazardous solid waste processing/storage, wastewater handling, waste incineration.

The impact of external international crises is captured through four global crises. These crises are contextualized in Table 4. Although some crises' duration was longer, the approach chosen was to select the years where the effects were more prevalent. The crises are presented as a dummy variable in the models.

Table 4. Selected International Crises

Crisis	Period Selected (1 = Crisis)	Key Aspects
Global Financial Crisis (GFC)	**2008 - 2009**	Subprime mortgage crisis (started in USA) Bankruptcy of Lehman Brothers (led to stock market crash and bank runs in several countries) Recession Unemployment increase
European Sovereign Debt Crisis (ESDC)	**2010-2012**	Collapse of financial institutions (started with Iceland's banking system collapse) High government debt **Most affected countries:** Portugal, Italy, Ireland, Greece, Spain Intervention of International Monetary Fund (IMF)
Covid19	**2020-2021**	Lockdowns Business restrictions and closures (allowed for temporary decrease in pollution)
Energy And Inflation Crisis	**2022 – 2023**	Post-pandemic recovery Higher energy prices Russia-Ukraine War

Tables 5 and 6 present the variables' definitions and databases. Table 5 shows macro indicators. As is seen, most of the data was retrieved from World Bank database.

Table 5. Macro FRM variables' definition (Source: World Bank (2025))

Macro Indicators		
Independent Variables	**Definition**	**Source**
Population Density	People per square kilometre of land area.	**World Bank**
GDP Growth	Annual % growth rate of GDP at constant 2015 US dollars.	**World Bank**
Foreign Direct Investment (FDI) Inflows	Net inflows of investment from foreign investors into domestic enterprises, aiming for lasting ownership (10% or more of voting stock). It includes equity, reinvested earnings, and other capital. Expressed as %GDP.	**World Bank**
Trade	Sum of exports and imports of goods and services. Expressed as % GDP.	**World Bank**
Renewable Energy Use	Share of renewable energy in total final energy consumption. Expressed as % of total final energy consumption.	**World Bank**
Alternative And Nuclear Energy Use	The share of total energy consumption derived from sources that do not emit carbon dioxide during generation, such as nuclear, hydropower, solar, wind, geothermal, and biomass. This indicator reflects the extent to which a country is transitioning away from fossil fuels toward cleaner energy alternatives.	**World Bank**
Carbon Intensity GDP	Annual emissions of CO2 from agriculture, energy, waste, and industrial sectors, excluding LULUCF, divided by GDP in constant 2021 US dollars.	**World Bank**

Population density and GDP growth were included in this regression to evaluate how the sometimes-fast growth of economy and society patterns can influence efficiency, putting sometimes more pressure on infrastructure but also allowing for development. These two variables were also used in a two-stage DEA paper evaluating socio-economic factors impacts in environmental efficiency (Halkos & Bampatsou, 2022). By including Trade and FDI Inflows we can analyse if the countries' openness to the global economy benefits its efficiency (by being less dependent on itself), and if foreign investment has a positive impact since it could lead to cleaner and technology efficient processes and serve as a proxy of countries' attractiveness. The inclusion of energy consumption by renewables and nuclear aims to assess if the adoption of these cleaner energy sources would affect positively the efficiency scores and, finally, through carbon intensity we wanted to confirm how it could negatively affect efficiencies.

Table 6 represent the sector level data which is collected from EDGAR. The description of the variables are obtained from the 2024 Join Research Centre (JRC) Science for Policy Report (IEA et al., 2024).

Table 6. Sectoral FRMs variables' definitions (Sources: *(EDGAR, 2025; OECD, 2025; World Bank, 2025)*)

Sectors			
Sector	**Independent Variables**	**Definition**	**Source**
Agriculture	**CO_2 & CH_4 Emissions**	Emissions from Livestock (enteric fermentation, manure management), agricultural soils (fertilisers, lime application, rice cultivation, direct soil emissions, field burning of agricultural residues (IPCC 2006 3A+3C1b+3C2+3C3+3C4+3C5+3C6+3C7+5A (only from agricultural activities)). Expressed in Tonnes CO_2e.	**EDGAR**
	Agricultural Land	Share of land used for farming activities, including arable land (temporary crops, meadows, gardens), land under permanent crops (e.g., fruit trees, coffee, rubber), and permanent pastures used for grazing over multiple years. It excludes land abandoned due to shifting cultivation and areas used for timber production. Expressed as % of land area.	**World Bank**
	Employment	Persons working in activities in agriculture, hunting, forestry and fishing. Expressed as a % of total employment.	**World Bank**
	Value Added	Net output of the agriculture, forestry, and fishing sector—covering crop cultivation, livestock production, forestry, hunting, and fishing—as a percentage of a country's gross domestic product (GDP).	**World Bank**
	Energy Use	Energy consumption in agriculture includes deliveries to users classified as agriculture, hunting and forestry by the International Standard Industrial Classification (ISIC). Therefore, it includes energy consumed by such users whether for traction (excluding agricultural highway use), power or heating (agricultural and domestic) [ISIC Rev.4 Divisions 01 and 02].	**OECD**

Energy: Fuel Exploitation	**CO2 & CH4 Emissions**	Emissions from fuel extraction, transformation and refineries activities, including venting and flaring (IPCC 2006 1B + 5B). Expressed in Tonnes CO_2e.	**EDGAR**
	Natural Resources Rents	Sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. Expressed as %GDP.	**World Bank**
	Fuel Exports	Exports of mineral fuels, lubricants and related material (commodities in SITC section 3). Expressed as % of merchandise exports.	**World Bank**
Energy: Power Industry	**CO2 & CH4 Emissions**	Emissions from power and heat generation plants (public and auto-producers) (IPCC 2006 1A1a). Expressed in Tonnes CO_2e.	**EDGAR**
	Elec.Prod. Renewables	Includes geothermal, solar, tides, wind, biomass, and biofuels. Does not include hydroelectric. Expressed as % total electricity production.	**World Bank**
	Elec.Prod. Coal	Includes all coal and brown coal, both primary (including hard coal and lignite-brown coal) and derived fuels (including patent fuel, coke oven coke, gas coke, coke oven gas, and blast furnace gas). Peat is also included in this category. Expressed as % total electricity production.	**World Bank**
	Elec. Prod. Oil	Includes crude oil, condensates, natural gas liquids, refinery feedstocks and additives, other hydrocarbons (including emulsified oils, synthetic crude oil, mineral oils extracted from bituminous minerals such as oil shale, and bituminous sand) and petroleum products (refinery gas, ethane, LPG, aviation gasoline, motor gasoline, jet fuels, kerosene, gas/diesel oil, heavy fuel oil, naphtha, white spirit, lubricants, bitumen, paraffin waxes and petroleum coke). Expressed as % total electricity production.	**World Bank**
	Elec. Prod. Nuclear	Electricity produced by nuclear power plants. Expressed as % total electricity production.	**World Bank**
Energy: Buildings	**CO2 & CH4 Emissions**	Emissions from small scale non-industrial stationary combustion (IPCC 2006 1A4 + 1A5). Expressed in Tonnes CO_2e.	**EDGAR**
	Urban Population	% of total population living in urban areas.	**World Bank**
Energy: Transport	**CO2 & CH4 Emissions**	Emissions from road, non-road, domestic and international aviation, inland waterways and	**EDGAR**

		international shipping (IPCC 2006 1A3). Expressed in Tonnes CO2e.	
	Energy Use	Energy consumption in transport covers all transport activity (in mobile engines) regardless of the economic sector to which it is contributing. Expressed as % total energy consumption.	**World Bank**
Industry	**CO2 & CH4 Emissions**	Emissions from combustion for industrial manufacturing, industrial processes (e.g. iron and steel, cement, aluminium, chemicals, production, solvents, etc.) (IPCC 2006 1A2+2+5A (non-agricultural only)). Expressed in Tonnes CO2e.	**EDGAR**
	Employment	The industry sector consists of mining and quarrying, manufacturing, construction, and public utilities (electricity, gas, and water), in accordance with divisions 2-5 (ISIC 2) or categories C-F (ISIC 3) or categories B-F (ISIC 4). Expressed as % total employment.	**World Bank**
	Value Added	It comprises value added in mining, manufacturing (also reported as a separate subgroup), construction, electricity, water, and gas. Expressed as %GDP.	**World Bank**
	Energy Use	Energy consumption in industry includes the following sub-sectors: iron and steel, chemical and petrochemical, non-ferrous metals, non-metallic minerals, transport equipment, machinery, mining and quarrying, food and tobacco, paper, pulp and print, wood and wood products, construction, textile and leather together with any manufacturing industry not included above. Expressed as % total energy consumption.	**OECD**
Waste	**CO2 & CH4 Emissions**	Emissions from solid waste disposed on land, solid waste composted and hazardous solid waste processing/storage, wastewater handling, waste incineration (IPCC 2006 4). Expressed in Tonnes CO2e.	**EDGAR**

Table 7 shows the descriptive statistics of all the variables that are defined in Tables 5 and 6.

Table 7. FRMs variables' descriptive statistics

Second Stage: Fractional Regression Models (FRM)					
Macro Indicators					
		Mean	Sd	Min	Max
PopulationDensity	People km^2	139.940	137.281	2.477	531.109
GDPGrowth	%	2.421	3.527	-16.040	24.616
FDIInflows	% GDP	4.292	21.649	-440.1307	234.249
Trade	% GDP	98.658	58.827	19.560	394.221
EnergyUseRenewables	% Total Energy Consumption	19.509	16.75561	0.7	82.9
Energy Use Alternative & Nuclear	% Total Energy Consumption	17.19502	17.53131	0.01	89.72
CarbonIntensityGDP	Kg CO2e per constant 2021US$ GDP	0.321	0.198	0.062	1.243
Agriculture					
		Mean	Sd	Min	Max
CO2 Emissions	Tonnes CO2	805234.8	1295160	1571	6801928
CH4 Emissions	Tonnes CO2e	23243128	43943986	276885	263069837
Agricultural Land	% Land Area	39.348	18.636	2.694	73.732
Employment	% Total employment	5.323	4.883	0.682	37.577
Value Added	% GDP	2.370	1.635	0.191	10.191
Energy Use	% Total energy consumption	3.076	2.115	0.08	15.11
Fuel Exploitation					
		Mean	Sd	Min	Max
CO2 Emissions	Tonnes CO2	23600772	53588756	9391	317073715
CH4 Emissions	Tonnes CO2e	18272570	67340606	20696	442042784
Natural Resources Rents	% GDP	0.991	1.950	0	13.35788
Fuel Exports	% Merchandise exports	8.671	12.218	0.024	79.274
Power Industry					
		Mean	Sd	Min	Max
CO2 Emissions	Tonnes CO2	136553397	373003544	1768	2560424211

CH4 Emissions	Tonnes CO2e	148480.2	313445.2	2	1941920
ElecProd Renewables	% Total	12.118	12.968	0	81.558
ElecProd Coal	% Total	25.495	24.365	0	95.710
ElecProd Oil	% Total	2.938	4.824	0	45.508
ElecProd Nuclear	% Total	16.345	21.201	0	79.80362
		Buildings			
		Mean	Sd	Min	Max
CO2 Emissions	Tonnes CO2	48628259	104585200	517528	650829353
CH4 Emissions	Tonnes CO2e	990743.2	1615618	1300	9878400
Urban Population	% Total population	76.649	11.626	50.754	98.189
		Transport			
		Mean	Sd	Min	Max
CO2 Emissions	Tonnes CO2	98577537	290026254	627797	1807722183
CH4 Emissions	Tonnes CO2e	343081.3	1192414	2006	11879944
Energy Use	% Total energy consumption	28.304	8.547	9.83	58.94
		Industry			
		Mean	Sd	Min	Max
CO2 Emissions Industrial Combustion	Tonnes CO2	41384424	85341786	59976	567124876
CH4 Emissions Industrial Combustion	Tonnes CO2e	119087.3	271702.3	80	1825438
CO2 Emissions Industrial Processes	Tonnes CO2	17526632	28242608	159200	163128068
CH4 Emissions Industrial Processes	Tonnes CO2e	75119.21	144931.2	386	1064758
Employment	% Total employment	24.66	6.046	9.192	40.637
Value Added	% GDP	24.362	5.532	10.397	49.158
Energy Use	% Total energy consumption	25.177	7.095	9.45	51.06
		Waste			
		Mean	Sd	Min	Max
CO2 Emissions	Tonnes CO2	459345.5	1027534	1	5024435
CH4 Emissions	Tonnes CO2e	12334073	24839066	44979	177883438

Regarding macro indicators, presented in the beginning of Table 7, GDP Growth shows a mean of 2.42% and extreme values ranging from -16.04% to 24.62%, that can reflect periods of economic recession and expansion. The energy variables like Energy Use from Renewables and Energy Use from Alternative and Nuclear Sources, show a similar mean of 19.5% and 17.2%, respectively. However, the wide difference between the minimum value to the maximum, for example from 0.7% to 82.9% seen in the Energy Use from Renewables, may show that there is still a big difference in OECD countries in terms of adoption of cleaner energies.

When analysing the descriptive statistics across sectors, Power Industry emerges as the largest CO_2 emitter sector, with a mean of over 136 million tonnes emitted and a maximum value superior to 2.5 billion tonnes. This reflects the strong impact of this sector to emissions, associated with energy generation, still highly dependent on fossil fuels. On the other hand, Agriculture sector stands out as the main contributor to CH_4 emissions, with a mean of over 23 million tonnes of CO_2 equivalent emitted and a maximum value of 263 million tonnes.

In addition to sector emissions, other common variables such as Employment, Value Added, and Energy Use show valuable insights about the impact of each sector. The Industry sector showed the highest economic weight, with an average Value added of 24.36% of GDP and 24.66% of total employment, confirming its strong contribution to both output and labour markets across OECD countries. Moreover, it is also one of the most energy-intensive sectors, accounting for approximately 25.18% of total energy consumption. In contrast, the agriculture sector, although environmentally significant due to CH_4 emissions, shows a much lower economic presence, with an average Value Added of only 2.37% and 5.32% of Employment. The Transport sector also emerges as a highly energy-demanding sector, with a mean Energy Use of 28.30%. Similar interpretations can be made also for the other variables.

CHAPTER IV – METHODOLGY

4 Methodology

As mentioned, a two-stage approach is implemented in this study. First, we followed and implemented DEA. Then, we applied two types of FRM, namely, one-part FRM and two-part FRM, with the goal of observing the different interactions between the variables and the efficiency scores, and also to provide insights of how countries could improve their efficiency. These two methodologies will be explained in detail thorough the next subchapters. All methodology was applied using R-studio (version 4.5.0).

4.1 Data Envelopment Analysis (DEA)

The concept of Data Envelopment Analysis (DEA) was originally introduced by Farrell (1957) and subsequently extended by Charnes, Cooper and Rhodes (see Charnes et al., 1978), who addressed limitations in Farrell's model, particularly its failure to account for non-zero slacks[4] (Cooper et al., 2011). DEA is a non-parametric[5], data-driven analytical method, used to evaluate the relative efficiency of comparable decision-making units (DMUs). It operates by calculating the ratio of a weighted sum of outputs to a weighted sum of inputs (Fidanoski et al., 2021; Moutinho & Madaleno, 2021).

There is not a straight definition of efficiency, since it can include economic, environmental or social perspectives (Radu & Dimitriu, 2011). In DEA, efficiency can be perceived as a relative comparison between DMUs, in which the most efficient ones will present a better input-output ratio (Cooper et al., 2011; Sherman & Zhu, 2006). There are different types of efficiency explored in the literature. Technical efficiency is referred to the most primordial one (Cooper et al., 2011), since it does not require much information and presumptions for its implementation. Technical efficiency occurs when it possible to generate more outputs with the actual inputs or to produce the same outputs with fewer inputs, measuring the pure efficiency between inputs and outputs while minimizing waste or excess resource usage (Cooper et al., 2011; Halkos & Petrou, 2019). Allocative (or price) efficiency evaluates how well the prices or costs of the inputs and outputs are blended in the best possible proportions (Cooper et al., 2011; Halkos & Petrou, 2019).

[4] Slacks can be defined as the amount of excess input that an inefficient unit uses to generate its current outputs or as the amount of output that it could generate given its inputs (Halkos & Bampatsou, 2022).
[5] Non-parametric methodologies does not require presumptions on the statistical distribution of the data or the relationship between inputs and outputs (Fidanoski et al., 2021).

Overall efficiency is the combination of technical and allocative efficiency (Cooper et al., 2011). Environmental efficiency and economic efficiency analysis through DEA are used to assess technical efficiency, being widely used due to arising CC and resource depletion concerns (Vlontzos et al., 2014). Taking into account both emissions and pollutants (undesirable outputs), countries, regions and companies aim to achieve the best natural resource optimization and cost allocation, resulting in more goods and services production while having less impact on the environment (Fidanoski et al., 2021; Halkos & Bampatsou, 2022; Huang et al., 2018; Wang et al., 2014; Woo et al., 2015).

This methodology has been used as a decision-making tool in different fields such as schools, hospitals, banks, corporations, etc., and allowing efficiency comparisons between sectors, countries and regions (Cooper et al., 2011; Song et al., 2014). Regarding environmental efficiency studies, DEA has been used in waste management studies (Halkos & Petrou, 2019), energy efficiency studies (Fidanoski et al., 2021; Lin et al., 2025; Woo et al., 2015; Zhang & Sun, 2025), agricultural studies (Song et al., 2012; Vlontzos et al., 2014), industry studies (Moutinho & Madaleno, 2021; Wang et al., 2014), eco-innovation studies (Beltrán-Esteve & Picazo-Tadeo, 2017).

This methodology carries some elementary concepts, which definitions are explored during the next paragraphs: DMUs, radial versus non-radial models; constant returns to scale (CRS) versus variable returns to scale (VRS), input-oriented versus output-oriented and how to deal with undesirable outputs.

A DMU is designed to measure the relative efficiency of several inputs and outputs, without the prior need of knowing the relationship between them (Cooper et al., 2011). DEA identifies best practice scenarios by comparing each DMU to all others and highlighting those that run inefficiently (Sherman & Zhu, 2006). In general, the number of DMUs should be, at least, twice the number of inputs and outputs (Golany & Roll, 1989). The relative efficiency scores range between 0 and 1, being efficient if the efficiency score is 1 or inefficient if the efficiency score < 1. When the efficiency results is 0, it shows total inefficiency. A DMU can be considered “weakly” efficient, since it can have an efficiency score = 1 but have the presence of slacks (potential for input reduction or output increase) (Quan et al., 2022). This means that besides being totally efficient when compared to the other DMUs (relative efficiency), there is still room for improvement. As referred above, these DMUs can represent various entities (hospitals, universities, businesses, etc.), countries or regions. In this study, our DMUs will be the selected OECD countries, which identification can be found in Appendix I.

There are two types of DEA models: (1) radial models, which include constant returns to scale (CRS)[6], developed by Charnes, Cooper and Rhodes (CCR) (see Charnes et al., 1978) and variable returns to scale (VRS), upgraded by Banker, Charnes and Cooper (BCC) (see Banker et al., 1984); (2) non-radial models, that include as the most common examples the Slacks-based measure (SBM) (Tone, 2001) and the Directional Distance Function (DDF) (Chambers et al., 1996). In radial models, inputs and outputs are adjusted proportionally, while in non-radial models these adjustments may be non-proportional (Vlontzos et al., 2014). Thus, while radial models focus on proportionately reduce inputs or expand outputs, depending on the orientation of the model (input-oriented or output-oriented) (Taleb et al., 2022), non-radial models have the ability to decrease or increase them, disproportionally and at the same time, since their relationship is independent of one another (Rashidi et al., 2015). Non-radial models also have the capability of dealing with input and output slacks, and can have three types of orientations: input-oriented, output-oriented and non-oriented (Taleb et al., 2024).

In an extended definition, constant returns to scale (CRS) implies that a change in outputs will be reflected in the same proportion in inputs (Moutinho & Madaleno, 2021; Pais-Magalhães et al., 2021). The CRS model was improved by Banker, Charnes and Cooper (BCC) in 1984 (see Banker et al., 1984), and variable returns to scale (VRS) allowed for increasing returns to scale (IRS) and decreasing returns to scale (DRS) to take part, as they does not assume proportionality (Cooper et al., 2011). CCR constant returns to scale models are more constrained than BCC variable returns to scale models, since fixed returns to scale models usually include fewer efficiency units and the modelled efficiency is lower (Mohtashami & Ghiasvand, 2020). The scheme in Figure 3 displays the radial and non-radial models more commonly used in the literature.

[6] Constant returns to scale (CRS) is one of the three returns to scale (RTS) regions, that also include decreasing returns to scale (DRS) and increasing returns to scale (IRS) (Taleb et al., 2024)

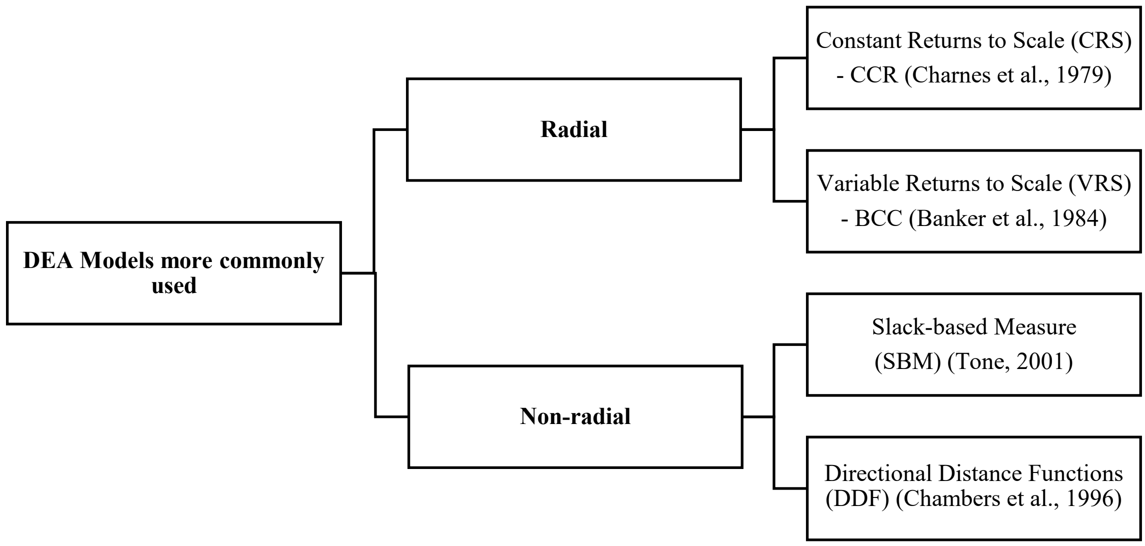

Figure 3. DEA Models more commonly used

Regarding model orientation, traditional DEA models can either be input-oriented or output-oriented. When opting for input-oriented, the goal is to minimize inputs while at least reaching the specified output levels. In the output-oriented models, outputs are maximized without requiring further inputs (Taleb et al., 2024). Therefore, a country will be relatively efficient by reaching the maximum output level with the available inputs (output-oriented) or by using the lowest amount of inputs for the current output level (input-oriented) (Moutinho & Madaleno, 2021; Woo et al., 2015). Non-radial models have the extra possibility of being non-oriented, allowing for a disproportional input and output increase or decrease at the same time (Taleb et al., 2024). The types of DEA orientation are resumed in Figure 4.

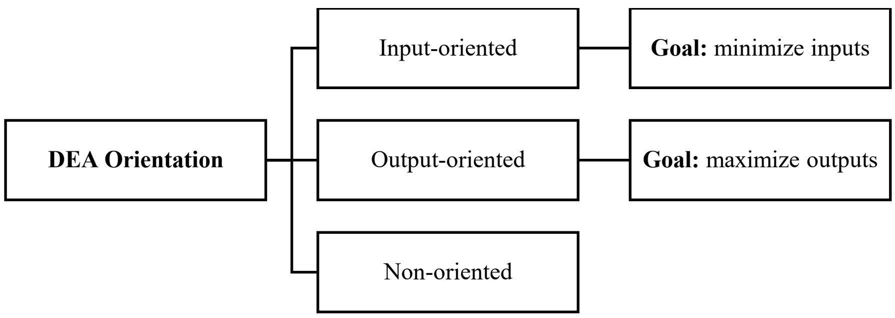

Figure 4. DEA orientation

To understand better the classic model formulation, we follow by introducing the input-oriented and output-oriented CCR and BCC models.

Equation (1) represents the input-oriented CCR and BCC models.

$$\text{Min } \theta \tag{1}$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0}, i = 1,2, \dots, m;$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0}, r = 1,2, \dots, s;$$

$$\lambda_j \geq 0, j = 1,2, \dots, n.$$

If VRS

Add $\sum_{j=1}^{n} \lambda_j = 1$

Where θ represents the input-oriented efficiency score, x_{ij} is the ith input for jth DMU, y_{rj} is the rth output for jth DMU. λ_j is the weights for the jth DMU and s_i^- and s_r^+ are input and output slacks, respectively.

Equation (2) represents the output-oriented CCR and BCC models.

$$\text{Max } \emptyset \tag{2}$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0}, i = 1,2, \dots, m;$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \emptyset y_{r0}, r = 1,2, \dots, s;$$

$$\lambda_j \geq 0, j = 1,2, \dots, n.$$

If VRS

Add $\sum_{j=1}^{n} \lambda_j = 1$

Where $\emptyset$ represents the output-oriented efficiency score, , x_{ij} is the ith input for jth DMU, y_{rj} is the rth output for jth DMU. λ_j is the weights for the jth DMU and s_i^- and s_r^+ are input and output slacks, respectively.

As referred before, environmental studies usually contain undesirable outputs (eg., GHG Emissions, CO2 Emissions, CH4 Emissions, Waste generation, etc.) where the lower the levels refer a better situation. However, in traditional DEA, the efficiency models assume output maximization, they are unable to account for undesirable outputs (Yang et al., 2022). To overcome this limitation, some authors have studied different ways of incorporating undesirable outputs in DEA models. Some possibilities include: (1) simply ignore the undesirable outputs (Seiford & Zhu, 2002); (2) treat the undesirable outputs in the non-linear DEA model (Lewis & Sexton, 2004); (3) treat the undesirable outputs as inputs, having the limitation of not addressing the actual production process (Dyckhoff & Allen, 2001; Hailu & Veeman, 2001; Seiford & Zhu, 2002); (4) apply monotone decreasing transformation (e.g., $1/y^b$) to the undesirable outputs (Seiford & Zhu, 2002); (5) multiply the undesirable outputs by minus one and then sum those values with a translation vector, in order to change all negative undesirable values to positive (Woo et al., 2015). In the present study, we will follow a similar approach as Woo et al. (2015). First, we multiplied the undesirable outputs (water stress level, CO2 emissions and CH4 emissions) by -1. This transformation allowed that countries with the higher water stress level and emissions had now the lower values. After, we added the minimum value (that will correspond to the country that have the highest water stress level and emissions) to each value, resulting that the most polluting country will have a value of 0 and the less polluting will have the highest value. Table 8 displays an example of the procedure followed to transform the undesirable outputs. As seen in Table 8, the three countries presented the most and the least CH4 emissions, in million metric tonnes of CO2 equivalent (MtCO2e). United States of America (USA) is the one with the largest amount of CH4 emissions in all years (861.36 MtCO2e), corresponding to 0 after the transformation. Iceland is the country with less emissions (0.5535 MtCO2e), and when transformed became the country with the highest value. As now the higher represents the better, the output variables are desirable and can be easily used in DEA.

Table 8. Dealing with undesirable outputs

Country	Year	CH4 Emissions	CH4 Emissions * (-1)	- CH4 Emissions + Minimum value (861.3611)
Iceland	2023	0.5535	-0.5535	860.8076
Luxembourg	2023	0.5832	-0.5832	660.7779
Latvia	2000	1.8498	-1.8498	859.5113
….				
Canada	2014	133.142	-133.142	728.2191
Australia	2013	151.4662	-151.4662	709.8949
USA	2023	861.3611	-861.3611	0

Using DEA methodology bears many advantages when comparing with parametric methods (eg., regression, multiple regression analysis, stochastic frontier analysis, etc.), since DEA does not call for presumptions regarding the relationship between inputs and outputs in advance (Song et al., 2014). This fact presented opportunities to solve situations that have proven unresponsive to alternative methods due to the highly complex (often unknown) relationships between the different inputs and outputs that are an integral component of DMUs (Cooper et al., 2011). The authors Vyas and Jha (2017,p.128) have listed other advantages of using DEA: "(1) It allows for the efficient use of multiple inputs and outputs; (2) The weights of inputs and outputs are not required; (3) The efficiency is compared to that of the best operating unit rather than to the average performance".

The environmental efficiency scores obtained through DEA, then used in FRM which is explained in the subsection 4.2.

4.2 Fractional Regression Model (FRM)

Fractional regression models (FRMs) were first proposed by Papke & Wooldridge (1996), and are widely used as a second-stage procedure in efficiency studies using DEA or other methods like the Stochastic Frontier Analysis (SFA) (Marques & Teixeira, 2022; Moutinho et al., 2020; Moutinho & Madaleno, 2021; Silva et al., 2022). This methodology is particularly relevant to efficiency studies, since it is designed to handle dependent variables that are restricted in an interval, as is the case of efficiency scores that usually lay in the interval]0,1[. In the present study we will follow a similar approach as Marques & Teixeira (2022) and apply the Quasi-Maximum Likelihood (QML) based on the Bernoulli log-likelihood function given in Equation (3):

$$l_i(b) = \gamma_i \log[G(x_i b)] + (1-\gamma_i) \log [1 - G(x_i b)] \tag{3}$$

This type of regression implies the usage of functional forms since we are dealing with binary data. The ones that will be explored in this study are Logit, Probit and Cloglog, according to the G function in Equation (3), being the logistic transformation, the standard normal distribution, or the complementary log-log transformation, respectively. These three G functions are able to transform quantitative values into data that lies in the interval]0,1[, as can be seen in Figure 5.

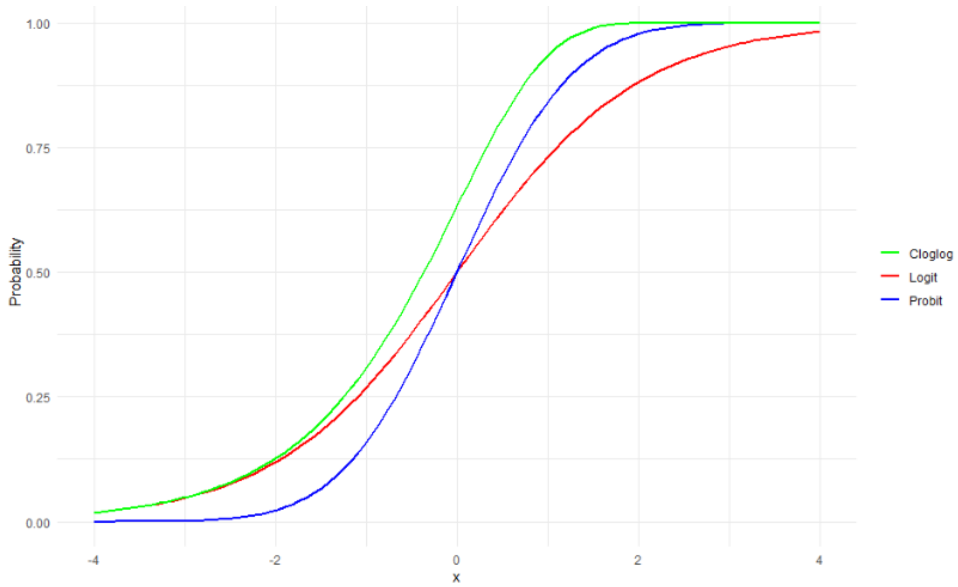

Figure 5. Logit, Probit and Cloglog functions (Source: Mustafa (2023))

We followed the same approach as the studies previously mentioned in the beginning of the subchapter, applying One-Part and Two-Part models. In One-Part Models, there is no distinction between efficient and non-efficient DMUs. The coefficients are determined in a single estimation, with the assumption that the independent variables have the same effect across efficient and non-efficient units. We have decided to apply also the Two-part models, since this technique is recommended when there is a significant amount of DMUs considered totally efficient (efficiency score = 1). However, countries that are fully efficient through each time period is excluded, since they showed no variability. The Two-part model is divided in two components: (i) First Component and (ii) Second Component. The former, we use a binary model, where 0 = inefficient and 1 = efficient, to observe the probability of observing a fully efficient DMU. We include countries that are inefficient through all years, and also countries that show total efficiency in some years and not in others. These last will be the most important, since they will allow to draw conclusions about why are they efficient in some years and not in others. In the latter, we analyse only the relative efficiency of the inefficient DMUs. Here, we can understand "which are the causes of these countries not being on the efficiency frontier", observing which variables can influence positively or negatively their scores, and what they can do to improve their efficiency (Marques & Teixeira, 2022; Moutinho et al., 2020; Moutinho & Madaleno, 2021; Silva et al., 2022).

In this study, we created several FRMs, aiming to give a deeper understanding of how the different sectors impact efficiency scores.

Since we are dealing with countries with different proportions in terms of size and economy, there was a need to apply log+1 transformation to all the variables to try to reduce these disproportions. The decision to apply log+1 instead of log was because there was negative and 0 values in some variables. After estimating each model (logit, probit and cloglog), robust standard errors were computed and clustered at the country level. This was done to account for potential intra-group (within-country) correlation in the error terms, which could bias standard inference procedures.

To analyse which model had the best fit, analysis of pseudo-r^2 and deviance were made. Pseudo R-squared is a goodness-of-fit statistic used instead of R-squared in non-linear models like logit, probit and cloglog, appropriated for methods like quasi-likelihood (QML). We are following the McFadden's pseudo R-squared approach proposed by (McFadden, 1974), which application follows $1 - L_{ur}/L_o$, where L_{ur} is the log-likelihood function for the estimated model and L_o is the log-likelihood function in the model with only an intercept (Wooldridge, 2010). The pseudo R-squared is always between zero and one, and usually presents best fits in one part models and in the second component of two-part models (Moutinho & Madaleno, 2021; Silva et al., 2022). Deviance measures how much the model is far from the perfect model (or saturated model), that is the model that fits perfectly to the sample. Lower deviance indicates a better fit (García-Portugués, 2022). Deviance formulation is represented in Equation (4), and the results from pseudo r-squared and deviance are included in Appendices IV-XIV, joined with models results.

$$D = -2loglik(\hat{\beta}) \quad (4)$$

Average marginal effects (AME) were also calculated to better capture the impact of a change in the explanatory variables on the dependent variable. The marginal effect is calculated for each observation in the sample and then averaged, allowing for more accurate interpretations (Moutinho & Madaleno, 2021). We will be analysing AME for each regression in Chapter V.

Below, there is the FRM regression models that will be used, all accounting for individual (Country) and time (Year) fixed effects, except for Equation (7) that only accounts for individual effects since crisis dummies are already measuring time variations. Remembering that, for crisis dummies, 0 = no crisis and 1= crisis.

In Equations (5) to (15), all the econometric models that are used during the analyses are presented. Here Y is the environmental efficiency scores in country i and year t. β represents the coefficients, α_i the individual (Country) fixed effects, λ_t the time (Year) fixed effects and ε_{it} is the error term.

First, in Equations (5) and (6), we have the regressions for the macro indicators.

In Equation (5), we included all variables previously referred, accounting for individual and time fixed effects.

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 PopulationDensity_{it} + \beta_2 GDPGrowth_{it} \\ + \beta_3 FDIInflows_{it} + \beta_4 Trade_{it} \\ + \beta_5 EnergyUseRenewables_{it} \\ + \beta_6 EnergyUseAlternativeAndNuclear_{it} \\ + \beta_7 CarbonIntensityGDP_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (5)$$

In Equation (6), we added the International Crises dummies, in order to see how they could affect the previous results. For this regression, only individuals fixed effects were taken into consideration, since dummies were already accounting for time effects control.

$$
\begin{aligned}
Y_{it} = \ & \beta_0 + \beta_1 PopulationDensity_i + \beta_2 GDPGrowth_i + \beta_3 FDIInflows_i \\
& + \beta_4 Trade_i + \beta_5 EnergyUseRenewables_i \\
& + \beta_6 EnergyUseAlternativeAndNuclear_i \\
& + \beta_7 CarbonIntensityGDP_i + \beta_8 GlobalFinancialCrisis_i \\
& + \beta_9 EuropeanSovereignDebtCrisis_i + \beta_3 Covid19_i \\
& + \beta_{10} EnergyAndInflationCrisis_i + \alpha_i + \varepsilon_i
\end{aligned} \tag{6}
$$

Before moving to sectors analysis, an isolated regression only containing the International Crises variables was made, as displayed in Equation (7), where we could see how it could affect the efficiency scores separately.

$$
\begin{aligned}
Y_{it} = \ & \beta_0 + \beta_1 GlobalFinancialCrisis_i \\
& + \beta_2 EuropeanSovereignDebtCrisis_i + \beta_3 Covid19_i \\
& + \beta_4 EnergyAndInflationCrisis_i + \alpha_i + \varepsilon_i
\end{aligned} \tag{7}
$$

Moving to the sectoral analysis, Equation (8) shows the model analysed for Agriculture.

$$
\begin{aligned}
Y_{it} = \ & \beta_0 + \beta_1 AgricultureCO2_{it} + \beta_2 AgricultureCH4_{it} \\
& + \beta_3 AgriculturalLand_{it} \\
& + \beta_4 EmploymentAgriculture_{it} \\
& + \beta_5 ValueAddedAgriculture_{it} \\
& + \beta_6 EnergyUseAgriculture_{it} + \alpha_i + \lambda_t + \varepsilon_{it}
\end{aligned} \tag{8}
$$

Regarding the energy sector, all the variables that will be used to evaluate its impacts in efficiency scores are identified in Equation (9).

$$
\begin{aligned}
Y_{it} = \beta_0 + \beta_1 FuelExploitationCO2_{it} + \beta_2 FuelExploitationCH4_{it} \\
+ \beta_3 PowerIndustryCO2_{it} \\
+ \beta_4 PowerIndustryCH4_{it} + \beta_5 BuildingsCO2_{it} \\
+ \beta_6 BuildingsCH4_{it} + \beta_7 TransportCO2_{it} \\
+ \beta_8 TransportCH4_{it} \\
+ + \beta_9 NaturalResourcesRents_{it} \\
+ \beta_{10} FuelExports_{it} + \beta_{11} ElecProdRenewables_{it} \\
+ \beta_{12} ElecProdCoal_{it} + \beta_{13} ElecProdOil_{it} \\
+ \beta_{14} ElecProdNuclear_{it} + \beta_{15} UrbanPopulation_{it} \\
+ \beta_{16} EnergyUseTransport_{it} + \alpha_i + \lambda_t + \varepsilon_{it}
\end{aligned} \tag{9}
$$

The Energy sector will be divided in four subsectors presented in Equations (10) to (13). We have decided to follow this separated division, since the high correlation between variables, especially for emissions, could lead to biased results, as shown in Figure 6. Values closer to 1 or -1 indicates strong linear relationship between variables.

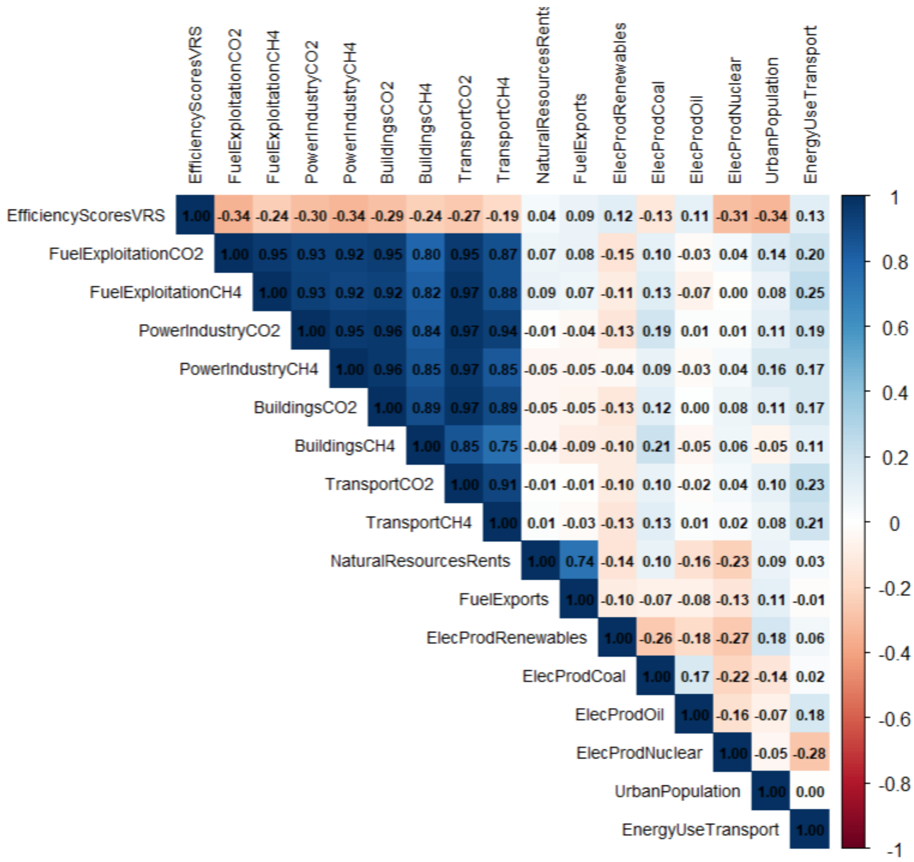

Figure 6. Correlation plot for the Energy sector

All energy subsectors will also include individuals and time fixed effects.

The first Energy subsector analysed will be Fuel Exploitation, as shown in Equation (10).

$$Y_{it} = \beta_0 + \beta_1 FuelExploitationCO2_{it} + \beta_2 FuelExploitationCH4_{it} + \beta_3 NaturalResourcesRents_{it} + \beta_4 FuelExports_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{10}$$

Next, in Equation (11), we have Power Industry subsector, showing how the different sources of electricity production affect the efficiency scores.

$$Y_{it} = \beta_0 + \beta_1 PowerIndustryCO2_{it} + \beta_2 PowerIndustryCH4_{it} + \beta_3 ElecProdRenewables_{it} + \beta_4 ElecProdCoal_{it} + \beta_5 ElecProdOil_{it} + \beta_6 ElecProdNuclear_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{11}$$

In Equation (12) we have the Buildings subsector.

$$Y_{it} = \beta_0 + \beta_1 BuildingsCO2_{it} + \beta_2 BuildingsCH4_{it} + \beta_3 UrbanPopulation_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{12}$$

Finally, the last subsector of Energy is Transport, as displayed in Equation (13).

$$Y_{it} = \beta_0 + \beta_1 TransportCO2_{it} + \beta_2 TransportCH4_{it} + \beta_3 EnergyUseTransport_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{13}$$

The following sector to be analysed is Industry, that includes emissions from Industrial Combustion and Industrial Processes activities, grouped in Equation (14) and controlled for individuals and time fixed effects.

$$
\begin{aligned}
Y_{it} = \beta_0 + \beta_1 IndustrialCombustionCO2_{it} \\
+ \beta_2 IndustrialCombustionCH4_{it} \\
+ \beta_3 IndustrialProcessesCO2_{it} \\
+ \beta_4 IndustrialProcessesCH4_{it} \\
+ \beta_5 EmploymentIndustry_{it} \\
+ \beta_6 ValueAddedIndustry_{t} \\
+ \beta_6 EnergyUseIndustry_{it} + \alpha_i + \lambda_t + \varepsilon_{it}
\end{aligned}
\tag{14}
$$

The last sector is Waste, where a simple model only including emissions and controlled for individuals and time effects was constructed in Equation (15).

$$
Y_{it} = \beta_0 + \beta_1 WasteCO2_{it} + \beta_2 WasteCH4_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{15}
$$

Now that we have all the DEA and FRM models, we will follow through the results section.

CHAPTER V – RESULTS AND DISCUSSION

5 Results and Discussion

In this section, we will present and analyse the results of DEA and FRM models. As referred in Chapter III, we excluded five OECD countries, namely, Chile, Colombia, Costa Rica, Mexico and Switzerland, from both analyses due to data availability.

5.1 DEA results

Appendices II-III display the obtained efficiency scores for all countries and years for VRS and CRS, respectively.

The main conclusions are that in both VRS and CRS we have six countries that are totally efficient (efficiency score = 1) in all the selected period. Those countries are Estonia, Greece, Iceland, Ireland, Latvia and Luxembourg. There is other ten countries that also presented some years with totally efficiency. For both VRS and CRS they were Denmark, Italy, Lithuania, Norway, New Zealand, Poland, Portugal, Slovak Republic, Türkiye and United Kingdom. These countries will be especially determinant in the first component of the Two-Part FRM models, since they achieved efficiency in some years and not in others, and we will draw conclusions of what can make them efficient in some years and not in the others.

Table 9 shows the mean efficiency scores for all countries within the selected period, divided by their geographical regions: Europe (OECD-EU), Asia and Oceania (OECD-AO) and America (OECD-AM), following a similar division approach as Woo et al. (2015). The country with the worst performance in both VRS and CRS was Korea, and the region with the best average performance was OECD-EU, where all the totally efficient countries were inserted.

Table 9. Average efficiency scores and ranking

Region	Country	VRS	CRS	Rank VRS	Rank CRS
OECD-EU	Austria	0.8365	0.8201	22	21
	Belgium	0.7516	0.7474	28	28
	Czechia	0.6820	0.6764	31	30
	Denmark	0.9783	0.9713	9	8
	Estonia	1.0000	1.0000	1	1
	Finland	0.7687	0.7565	27	25
	France	0.7782	0.7528	26	27
	Germany	0.8551	0.8014	18	23
	Greece	1.0000	1.0000	1	1
	Hungary	0.8414	0.8370	21	19
	Iceland	1.0000	1.0000	1	1
	Ireland	1.0000	1.0000	1	1
	Italy	0.9667	0.9392	11	13
	Latvia	1.0000	1.0000	1	1
	Lithuania	0.9979	0.9885	7	7
	Luxembourg	1.0000	1.0000	1	1
	Netherlands	0.8486	0.8363	20	20
	Norway	0.9904	0.8646	8	16
	Poland	0.9120	0.8848	15	14
	Portugal	0.9534	0.9487	13	10
	Slovak Republic	0.9609	0.9473	12	11
	Slovenia	0.9402	0.9396	14	12
	Spain	0.8848	0.8573	17	17
	Sweden	0.8175	0.7747	23	24
	Türkiye	0.9009	0.8710	16	15
	U.K.	0.9774	0.9530	10	9
	Average	0.9093	0.8911		

Region	Country	VRS	CRS	Rank VRS	Rank CRS
OECD-AM	Canada	0.8133	0.7538	24	26
	USA	0.7198	0.6502	29	31
	Average	0.7666	0.7020		
OECD--AO	Australia	0.7151	0.6919	30	29
	Israel	0.8098	0.8015	25	22
	Japan	0.6786	0.6446	32	32
	Korea	0.5329	0.5191	33	33
	New Zealand	0.8545	0.8497	19	18
	Average	0.7182	0.7014		

We followed input-oriented DEA model to assess how efficiently the OECD countries manage environmental impacts given their level of economic and resource utilization. Using this approach was particularly relevant since it aligns with principles of resource optimization and sustainable development, where countries should reduce excessive resource consumption (in inputs).

When opting for the use of VRS or CRS, Halkos and Petrou (2019) have stated that, in most cases, VRS is most appropriate since it can better deal with "imperfect market information, government regulations and constrains on finance". Additionally, (Mohtashami & Ghiasvand, 2020) stated that CRS models are more restrictive and usually present lower efficiency scores. This last affirmation was shown in our results, with CRS efficiency scores being lower than VRS for all countries in Table 9. For these reasons, we decided to follow the VRS approach. The efficiency scores are used as the dependent variable in the regression models as mentioned.

5.2 FRM Results

In this next subsection, we will have a deeper understanding of the One-part and Two-part FRM models results by analysing their average marginal effects (AME). The main goal is to underline the most influential variables, that are not only impacting the efficiency scores but also affecting the probability of each country to be totally efficient or, for the inefficient ones, becoming more or less efficient. Sectors and variables' definitions can be reviewed in Chapter III.

All FRM models include fixed effects for Country and Year, allowing control for unobserved, time-invariant characteristics at the country level. Therefore, the marginal effects should be interpreted as the average within-country variation in efficiency over time, associated with proportional changes in the explanatory variable.

The regression results are presented in Appendices IV-XIV. The current section includes the AME results due to its accuracy in evaluating the real impacts.

First, we will be starting by analysing the two Macro-level regressions. The first one without considering the crises effects in Table 10, and the second one, in Table 11, considering them.

Table 10. Macro-level regression: AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
P_Density	0.0484 **	0.0491 **	0.0496 **	-0.0414	0.3896	0.1736	0.0551 **	0.0562 **	0.0573 **
	(0.0176)	(0.0165)	(0.0151)	(0.3495)	(0.3439)	(0.3158)	(0.0203)	(0.0194)	(0.0182)
GDP_G	-0.0111 ***	-0.0112 ***	-0.0109 ***	-0.0167	-0.0178	-0.0120	-0.0134 ***	-0.0137 ***	-0.0140 ***
	(0.0033)	(0.0032)	(0.0031)	(0.0163)	(0.0159)	(0.0148)	(0.0040)	(0.0040)	(0.0039)
FDI_I	0.0017	0.0016	0.0016	0.0018	0.0078	0.0039	0.0034	0.0033	0.0033
	(0.0017)	(0.0017)	(0.0017)	(0.0149)	(0.0148)	(0.0140)	(0.0021)	(0.0021)	(0.0020)
Trade	0.0525 **	0.0588 **	0.0692 ***	0.4693 *	0.4990 **	0.4457 **	0.0806 ***	0.0857 ***	0.0949 ***
	(0.0201)	(0.0197)	(0.0193)	(0.1897)	(0.1835)	(0.1720)	(0.0239)	(0.0241)	(0.0246)
E_R	0.0054	0.0021	-0.0019	-0.0984	-0.0885	-0.0544	-0.0001	-0.0019	-0.0056
	(0.0077)	(0.0100)	(0.0090)	(0.0616)	(0.0543)	(0.0555)	(0.0131)	(0.0128)	(0.0125)
E_AN	-0.0375 ***	-0.0357 ***	-0.0308 ***	0.0005	-0.0650 *	-0.0399	-0.0202 *	-0.0181 .	-0.0136
	(0.0077)	(0.0073)	(0.0067)	(0.0024)	(0.0298)	(0.0268)	(0.0095)	(0.0095)	(0.0095)
CI_GDP	-0.3406 ***	-0.3589 ***	-0.3630 ***	-0.6403 .	-0.7545 *	-0.6513 .	-0.3578 ***	-0.3736 ***	-0.3859 ***
	(0.0743)	(0.0701)	(0.0641)	(0.3721)	(0.3627)	(0.3405)	(0.0885)	(0.0870)	(0.0842)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. P_density: Population Density; GDP_G: GDP Growth; FDI_I: FDI Inflows; E_R: Energy Use from Renewables; E_AN: Energy Use from Alternative and Nuclear; CI_GDP: Carbon Intensity of GDP.

The results of the regression models that include the macro indicators are displayed in Table 10, revealing significant relationships between macroeconomic and energy variables that were not included in DEA and that affect the efficiency scores.

Showing a positive link, we have Population Density and Trade, that have a strong relevance in One-part and in the 2nd component of the Two-part models, both using the efficiency scores as the dependent variable. These results may imply that densely populated countries may benefit more from economies of scale and infrastructure optimization through shared infrastructure and shorter travel distance, as showed in a recent study that concluded that increasing the population density of an urban area is associated with less CO2 emissions per capita (Monkkonen et al., 2024). As referred before, Trade presents a positive effect in one-part and two-part models. This means that Trade not only improve the probability of countries becoming fully efficient (through its shown significant in the 1st component of the two-part model), but also, inside the inefficient countries' group (2nd component), has proved itself as positive factor to move these countries closer to the efficiency frontier, indicating that higher openness of the countries can help them improve their efficiency scores. This positive Trade relation was shown in a study targeting the impact of international trade on environmental efficiency, where Honma (2015) concluded that countries with higher income per capita, the more they can benefit from Trade. Zhang et al. (2025) also studied the effects of Trade in sustainable energy transition. The authors showed that Trade positively impact Total Factor Renewable Energy Efficiency (TFREE) and that exports and trade in goods had the strongest impact.

On the other hand, GDP growth, Energy Use from Alternative and Nuclear sources and Carbon Intensity of GDP show a significant negative effect in the same one-part and second component of the two-part models. GDP growth's negative effect may be linked to unsustainable growth of the economy as shown in Acheampong & Opoku (2023), that can be related to increase of resource use and poor adoption of sustainability-related procedures, as well as that growth being dependent on sectors with intensive-resource use, like fuel exploitation. The negative impact observed in Energy use from Alternative and Nuclear sources may indicate that there may still exist room of improvement relating with how this energy is being produced and which operational costs it implies. Carbon

Intensity of GDP reinforces that cleaner economic structures are essential for optimizing efficiency scores, as shown in an empirical study of manufacturing industries in Maharashtra, where the results showed that lower carbon intensity correlated with higher technical efficiency (Samal et al., 2024).

The baseline model (without crises dummies) presented in Table 10 reflects average relationships over the full period, while the model including crises dummies in Table 11 accounts for potential shifts in environmental efficiency correlations during the years of crisis.

Differences in coefficient magnitude and sign between models indicate that macroeconomic and energy variables influence efficiency differently in stable versus periods of crises. Some of the crises dummies like ESDC and Covid19 capture a significant direct impact on efficiency, confirming that crises tend to significantly affect environmental performance.

Table 11. Macro regression with international crises dummies: AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
P_Density	-0.0043	-0.0095	-0.0256	-1.1602 ***	-1.0674 ***	-1.1083 ***	-0.0015	-0.0049	-0.0132
	(0.0147)	(0.0157)	(0.0187)	(0.2722)	(0.2744)	(0.2582)	(0.0176)	(0.0187)	(0.0212)
GDP_G	-0.0041	-0.0042 .	-0.0044 .	-0.0151	-0.0162	-0.0076	-0.0039	-0.0041	-0.0046
	(0.0026)	(0.0025)	(0.0025)	(0.0128)	(0.0130)	(0.0125)	(0.0031)	(0.0031)	(0.0031)
FDI_I	0.0027	0.0025	0.0024	-0.0004	-0.0017	-0.0022	0.0039 .	0.0039 .	0.0038
	(0.0020)	(0.0020)	(0.0019)	(0.0152)	(0.0153)	(0.0142)	(0.0023)	(0.0024)	(0.0023)
Trade	0.0069	0.0155	0.0301	0.0347	0.0435	0.0469	0.0208	0.0314	0.0516 .
	(0.0213)	(0.0215)	(0.0218)	(0.1432)	(0.1427)	(0.1381)	(0.0257)	(0.0264)	(0.0276)
E_R	-0.0394 ***	-0.0438 ***	-0.0473 ***	-0.2744 ***	-0.2634 ***	-0.2415 ***	-0.0573 ***	-0.0606 ***	-0.0644 ***
	(0.0113)	(0.0108)	(0.0102)	(0.0654)	(0.0575)	(0.0572)	(0.0140)	(0.0139)	(0.0136)
E_AN	-0.131	-0.0167 *	-0.0200 *	0.0011	0.0009	0.0022	-0.0016 .	-0.0016 .	-0.0014 .
	(0.0086)	(0.0084)	(0.0079)	(0.0021)	(0.0021)	(0.0018)	(0.0008)	(0.0008)	(0.0008)
CI_GDP	0.2778 ***	0.2289 ***	0.1755 **	-0.2519	-0.2256	-0.2240	0.2488 **	0.2257 **	0.2055 **
	(0.0671)	(0.0651)	(0.0621)	(0.3370)	(0.3651)	(0.3511)	(0.0820)	(0.0810)	(0.0792)
GFC	0.0109	0.0109	0.0103	-0.0185	-0.0152	0.0119	0.0183 .	0.0180 .	0.0172 .
	(0.0087)	(0.0085)	(0.0081)	(0.0404)	(0.0407)	(0.0371)	(0.0104)	(0.0103)	(0.0101)
ESDC	-0.0147 *	-0.0137 *	-0.0123 *	0.0127	0.0132	0.0284	-0.0179 *	-0.0180 *	-0.0178 *
	(0.0062)	(0.0062)	(0.0061)	(0.0288)	(0.0296)	(0.0274)	(0.0073)	(0.0075)	(0.0076)
Covid19	-0.0300 ***	-0.0333 ***	-0.0376 ***	-0.0497	-0.0554	-0.0743 .	-0.0356 ***	-0.0391 ***	-0.0441 ***
	(0.0066)	(0.0067)	(0.0068)	(0.0418)	(0.0405)	(0.0435)	(0.0078)	(0.0080)	(0.0082)
E&IC	0.0239 **	0.0208 *	0.0162 *	0.0797 .	0.0890 *	0.0696	0.0239 *	0.0206 *	0.0154
	(0.0081)	(0.0082)	(0.0082)	(0.0432)	(0.0437)	(0.0462)	(0.0097)	(0.0099)	(0.0101)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. P_density – Population Density; GDP_G: GDP Growth; FDI_I: FDI Inflows; E_R: Energy Use from Renewables; E_AN: Energy Use from Alternative and Nuclear; CI_GDP: Carbon Intensity of GDP ; GFC: Global Financial Crisis; ESDC: European Sovereign Debt Crisis ; E&IC: Energy and Inflation Crisis.

Table 11 shows that including crises as dummies revealed several shifts in relationships with environmental efficiency. Population density has lost its previous positive effect and show a negative significant impact on the probability of a country being fully efficient, losing its significance in the other two models (one-part and 2nd component of the two-part model). GDP growth's significance weakens and only became significant in a 10% level in the one-part model for Probit and Cloglog. Trade also lost its significance.

The most notable changes were observed in the variables Energy Use from Renewables and Carbon Intensity of GDP. Energy Use from Renewables became significantly negative, aligning with the negative, but diminished, effect of Energy Use from Alternative and Nuclear Sources. This pattern may reflect the transitional and implementation costs associated with adopting alternative and purportedly cleaner energy sources. Additionally, Carbon Intensity of GDP shifted from a significantly negative effect to a significantly positive one in both the one-part model and the second component of the two-part model, while maintaining a negative but statistically insignificant effect in the first component of the two-part model.

Finally, regarding crises dummies, ESDC and Covid19 showed a negative significant effect on efficiency in one-part and 2nd component of the two-part models, and E&IC showed a positive effect on the environmental efficiency. Such situation may be caused by limited energy consumption due to higher prices.

Table 12 shows the isolated effects of the crises on efficiency scores, confirming the negative and significant effects of ESDC and Covid19. E&IC lost its significance, and GFC shows a positive relationship in one-part and 2nd component of the two-part models, besides not having any significant correlation when mixed with the other macroeconomic and energy variables, as showed in Table 11.

Table 12. International Crises regression: AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
GFC	0.0194 *	0.0196 *	0.0193 *	0.0334	0.0341	0.0488	0.0277 **	0.0277 **	0.0272 **
	(0.0083)	(0.0081)	(0.0076)	(0.0402)	(0.0402)	(0.0364)	(0.0104)	(0.0102)	(0.0099)
ESDC	-0.0173 **	-0.0161 *	-0.0139 *	0.0038	0.0030	0.0173	-0.0204 *	-0.0200 *	-0.0191 *
	(0.0063)	(0.0063)	(0.0062)	(0.0336)	(0.0338)	(0.0319)	(0.0079)	(0.0081)	(0.0082)
Covid19	-0.0560 ***	-0.0581 ***	-0.0599 ***	-0.1340 **	-0.1325 ***	-0.1338 **	-0.0637 ***	-0.0656 ***	-0.0678 ***
	(0.0062)	(0.0063)	(0.0064)	(0.0408)	(0.0386)	(0.0449)	(0.0077)	(0.0079)	(0.0081)
E&IC	-0.0043	-0.0058	-0.0077	0.0027	0.0079	-0.0035	-0.0061	-0.0076	-0.0097
	(0.0077)	(0.0077)	(0.0077)	(0.0456)	(0.0446)	(0.0463)	(0.0095)	(0.0097)	(0.0099)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. GFC: Global Financial Crisis; ESDC: European Sovereign Debt Crisis ; E&IC: Energy and Inflation Crisis.

Next, the seven sectoral regression models are ran, covering Agriculture, Energy (Fuel Exploitation, Power Industry, Buildings, Transport), Industry (Industrial Combustion and Industrial Processes) and Waste. These analysis shows how each sector affect the efficiency scores, allowing informed policy recommendations.

The first sector to be analysed is Agriculture, which results are exhibited in Table 13, and the model regression corresponds to Equation (8) in subchapter 4.2.

Table 13. Agriculture regression: AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
A_CO2	0.0001	-0.0005	-0.0012	-0.1119 ***	-0.1104 ***	-0.1003 ***	0.0008	0.0006	0.0003
	(0.0020)	(0.0019)	(0.0018)	(0.0180)	(0.0159)	(0.0177)	(0.0024)	(0.0024)	(0.0024)
A_CH4	-0.1614 ***	-0.1676 ***	-0.1716 ***	-0.4389 ***	-0.4138 ***	-0.3944 ***	-0.1107 **	-0.1181 **	-0.1277 ***
	(0.0310)	(0.0289)	(0.0262)	(0.0941)	(0.0840)	(0.0882)	(0.0376)	(0.0370)	(0.0358)
A_Land	0.1689 **	0.1791 ***	0.1928 ***	-0.1548	-0.1394	-0.1807	0.1170 .	0.1305 *	0.1526 **
	(0.0516)	(0.0482)	(0.0438)	(0.1990)	(0.1748)	(0.1930)	(0.0618)	(0.0605)	(0.0585)
A_Emp	-0.0195	-0.0235	-0.0280	-0.1156 **	-0.1085 **	-0.1206 **	-0.0625 *	-0.0614 *	-0.0593 *
	(0.0225)	(0.0201)	(0.0173)	(0.0446)	(0.0413)	(0.0439)	(0.0275)	(0.0259)	(0.0237)
A_VA	-0.0079	-0.0004	0.0138	-0.1575 .	-0.1722 **	-0.1078 .	0.0466	0.0517	0.0633 .
	(0.0296)	(0.0276)	(0.0249)	(0.0698)	(0.0650)	(0.0624)	(0.0356)	(0.0348)	(0.0338)
A_Energy	-0.0420 *	-0.0412 *	-0.0383 *	-0.2697 ***	-0.2793 ***	-0.2309 ***	-0.0625 **	-0.0611 **	-0.0562 **
	(0.0190)	(0.0177)	(0.0159)	(0.0699)	(0.0626)	(0.0618)	(0.228)	(0.0221)	(0.0209)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. A_CO2: Agriculture CO2 Emissions; A_CH4: Agriculture CH4 Emissions; A_Land: Agricultural Land; A_Emp: Employment in Agriculture; A_VA: Value Added in Agriculture ; A_Energy: Energy Use in Agriculture

As is seen in Table 13, the CH4 Emissions and Energy Use are the key factors negatively impacting the efficiency scores in Agriculture sector through all one-part and two-part models. These two factors combined with the negative impact of Employment verified in two-part models may suggest the urgent need in this sector for the introduction of new technologies and sources of energy, that cannot only reduce emissions but also make the workforce more efficient. A study targeting Precision Agriculture Technologies showed that implementing technologies like variable-rate nutrient application, GPS-guided equipment and AI-powered systems were able to reduce GHG emissions by 5-30% while maintaining or increasing productivity (Balafoutis et al., 2017).

On the other side, Agricultural Land showed a positive relationship in the one-part and second component of the two-part model. However, its signal changed (even though not being significant) in the first component of the two-part model. This may indicate that Agricultural Land may improve efficiency in general, but it is not a determinant factor for countries' being totally efficient.

Concerning CO2 Emissions, its significant negative association only in the 1^{st} component of the two-part model indicates that they are more relevant in determining the likelihood of reaching full efficiency rather than the level of efficiency itself.

Finally, Value Added showed a negative impact in the first component of the two-part model. This can happen due that higher activity intensity will release more CH4 Emissions, that was already proven having a strong negative impact in efficiency in this particular sector.

Following, the Energy sector is analysed only separately through its subsectors Fuel Exploitation, Power Industry, Buildings and Transport, due to the strong correlations between mainly the emissions, as shown in Figure 6 in the Methodology Chapter. Besides not analysing the Energy sector as a whole, a model including all variables was still built, and it can be found in Appendix VIII.

The first one to be analysed is Fuel Exploitation, as shown in Table 14. Here, we will see how emissions and the intensity of the activity of this sector through the Natural Resources Rents and Fuel Exports affects environmental efficiency.

Table 14. Fuel Exploitation regression AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
FE_CO2	-0.0144	-0.0206 *	-0.0309 ***	-0.0707	-0.0565	-0.0516	-0.0147	-0.0205 .	-0.0313 **
	(0.0096)	(0.0093)	(0.0089)	(0.0444)	(0.0394)	(0.0444)	(0.0113)	(0.0113)	(0.0112)
FE_CH4	-0.0569 ***	-0.0580 ***	-0.0572 ***	-0.0878 **	-0.0965 ***	-0.0793 *	-0.0538 ***	-0.0573 ***	-0.0612 ***
	(0.0104)	(0.0097)	(0.0089)	(0.0316)	(0.0288)	(0.0312)	(0.0129)	(0.0124)	(0.0117)
NRR	0.0197 *	0.0178 .	0.0129	0.0129	0.0074	0.0082	0.0334 **	0.0312 **	0.0261 *
	(0.0095)	(0.0091)	(0.0086)	(0.0333)	(0.0312)	(0.0332)	(0.0111)	(0.0107)	(0.0102)
FuelE	0.0470 ***	0.0470 ***	0.0440 ***	0.1803 **	0.1125 ***	0.0448	0.0349 ***	0.0358 ***	0.0362 ***
	(0.0086)	(0.0084)	(0.0081)	(0.0331)	(0.0309)	(0.0335)	(0.0102)	(0.0101)	(0.0099)

Note: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1. FE_CO2: Fuel Exploitation CO2 Emissions; FE_CH4: Fuel Exploitation CH4 Emissions; NRR: Natural Resources Rents; FuelE: Fuel Exports

The results displayed in Table 14 show that, once again, CH4 Emissions have a consistently negative significant impact across all one-part and two-part models, being one of the by-products resulting from fossil fuel extraction through venting, flaring and unintentional leaks. CO2 Emissions also have some impact on one-part and two-part models, being relevant in worsening the inefficiency gap.

On the other hand, a positive relationship is observed in Natural Resources Rents and Fuel Exports, although with a lower significance in Natural Resources Rents mainly in the 1st component of the two-part model. This may indicate that besides this activity being related with strong environmental damage through emissions, they can improve their processes. For example, countries with advanced fuel sectors export cleaner fuels, using more efficient extraction technologies and benefiting from economies of scale. When efficiently managed, resources rents are reinvested into greener infrastructure and innovation. A good example of implementing better practices in this sector is Norway[7], that is still highly dependent on oil. Norway is the country with the highest fuel exports share from the 33 OECD countries in several years of the selected period, and it is one of the countries with higher efficiency scores (see Table 9 and Appendices II-III). This is related with their Sovereign Wealth Fund (SWF) and strict environmental regulation.

Furthermore, we will follow with Power Industry analysis, which AME results are displayed in Table 15, and corresponds to Equation (11). In this part, we want to see how

[7] Further considerations about Norway can be found in Gasparini (2023).

this sector impacts efficiency in terms of emissions, but also how the different relations when producing electricity from cleaner and pollutant sources.

Table 15. Power Industry regression AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**
PI_CO2	0.0075	0.0028	-0.0051	-0.0210	-0.0204	-0.0262	0.0196	0.0135	0.0032
	(0.0142)	(0.0128)	(0.0112)	(0.0325)	(0.0276)	(0.0323)	(0.0171)	(0.0166)	(0.0160)
PI_CH4	-0.0175	-0.0186	-0.202 .	-0.1448 **	-0.1265 **	-0.1296 **	-0.0212	-0.0188	-0.0159
	(0.0133)	(0.0127)	(0.118)	(0.0496)	(0.0422)	(0.0464)	(0.0161)	(0.0159)	(0.0158)
EP_R	0.0040	0.0041	0.0044	-0.0379 *	-0.0447 *	-0.0312	0.0177 **	0.0184 **	0.0191 **
	(0.0055)	(0.0053)	(0.0051)	(0.0193)	(0.0176)	(0.0191)	(0.0064)	(0.0064)	(0.0063)
EP_Coal	0.0155 .	0.0121 .	0.0074	-0.0184	-0.0190	-0.0185	0.0235 **	0.0204 *	0.0157 *
	(0.0080)	(0.0073)	(0.0063)	(0.0166)	(0.0149)	(0.0168)	(0.0088)	(0.0083)	(0.0076)
EP_Oil	0.0090	0.0094 .	0.0103 *	0.0666 ***	0.0694 ***	0.0619 ***	0.0038	0.0038	0.0038
	(0.0058)	(0.0055)	(0.0050)	(0.0176)	(0.0159)	(0.0139)	(0.0068)	(0.0067)	(0.0066)
EP_N	-0.0200 ***	-0.0200 ***	-0.0185 ***	-0.0464 *	-0.0491 **	-0.0527 **	-0.0157 **	-0.0159 **	-0.0159 *
	(0.0054)	(0.0052)	(0.0048)	(0.0195)	(0.0156)	(0.0174)	(0.0060)	(0.0062)	(0.0062)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. PI_CO2: Power Industry CO2 Emissions; PI_CH4: Power Industry CH4 Emissions; EP_R: Electricity Production from Renewable sources; EP_Coal: Electricity Production from Coal sources; EP_Oil: Electricity Production from Oil sources; EP_N: Electricity Production from Nuclear sources

The results show that CH4 Emissions strongly negatively affect the probability of a country becoming fully efficient, having also a weak significance in other models in the Cloglog one-part model.

Regarding the different types of energy production, Electricity Production from Nuclear sources is the one with the most significantly negative impact on efficiency. Concerning Electricity Production from Renewable sources, the results show that countries that increase the production of this type of source are less likely to be fully efficient (negative significant correlation in 1st component of two-part models). However, among inefficient countries, more renewable production is associated with efficiency score increase (2nd component of two-part models). This may indicate struggles for countries reaching the efficiency frontier due to possible high infrastructure and storage costs and the variability of this type of sources (e.g., solar, wind). These negative effects of so-called "cleaner" energy sources, compared to coal and oil, reveal inconsistencies in the way countries implement them.

Concerning the "dirtiest" sources like Oil and Coal, the positive coefficients in one-part and 2nd component of two-part models for Coal and in one-part and 1st component of two-part models for Oil, may seem counterintuitive environmentally. However, this correlation does not indicate that they are beneficial to the environment, but that countries using these sources of energy may achieve higher relative efficiencies, especially when combining with R&D investments.

Moving on to Buildings subsector, in table 16 and corresponding to Equation (12), we have displayed the AME results from Buildings emissions and also the impact of Urban Population in efficiency scores.

Table 16. Buildings regression: AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**
B_CO2	-0.0451 ***	-0.0510 ***	-0.0576 ***	-0.4311 ***	-0.4239 ***	-0.3623 ***	-0.0178	-0.0222	-0.0283 *
	(0.0114)	(0.0109)	(0.0102)	(0.0523)	(0.0476)	(0.0522)	(0.0142)	(0.0141)	(0.0138)
B_CH4	0.0180 .	0.0183 .	0.0185 *	0.0192	0.0194	0.0067	-0.0032	-0.0022	-0.0002
	(0.0104)	(0.0094)	(0.0082)	(0.0218)	(0.0208)	(0.0216)	(0.0129)	(0.0126)	(0.0120)
Urban_P	-0.1765 .	-0.1775 .	-0.1576 .	-0.8693 *	-0.8345 **	-1.0503 **	-0.0803	-0.0897	-0.0913
	(0.1041)	(0.0965)	(0.0872)	(0.3499)	(0.3159)	(0.3254)	(0.1288)	(0.1244)	(0.1178)

Note: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1. B_CO2: Buildings CO2 Emissions; B_CH4: Buildings CH4 Emissions; Urban_P: Urban Population

In Buildings subsector, CO2 Emissions showed a higher negative impact than CH4 Emissions, substantially reducing the probability of countries being efficient. The sectoral demands, such as heating, cooling and lighting are the main reason of this result. CH4 Emissions present a weakly significant positive correlation, which shows that this is not a decisive factor in buildings’ sector, and that the fact of it not being significant in the 2nd component of the two-part model may indicate that those unexpected results were possibly being influenced by the fully efficient countries.

Urban population shows a weak negative impact in the one-part model and a more moderate impact on the 1st component of the two-part model, suggesting that increases in urban population may, for example, mean higher energy demand or unplanned expansion that led to inefficient buildings.

Finally, we will analyse Transport, the last subsector of Energy, which AME results will be presented in Table 17, corresponding to Equation (13).

Table 17. Transport regression: AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
T_CO2	-0.0238	-0.0275	-0.0427 .	-0.0461	-0.1784	0.0009	-0.0200	-0.0298	-0.0537 .
	(0.0254)	(0.0247)	(0.0238)	(0.2984)	(0.1807)	(0.1693)	(0.0307)	(0.0310)	(0.0313)
T_CH4	-0.0604 ***	-0.0641 ***	-0.0641 ***	-0.1564	-0.1153 .	-0.1391 *	-0.0416 *	-0.0462 **	-0.0506 **
	(0.0144)	(0.0134)	(0.0120)	(0.1068)	(0.0632)	(0.0598)	(0.0180)	(0.0177)	(0.0170)
T_Energy	0.0544	0.0970 *	0.1616 ***	0.6351	0.7661 *	0.4933 .	0.0944 .	0.1345 **	0.2038 ***
	(0.0430)	(0.0411)	(0.0388)	(0.5040)	(0.3054)	(0.2860)	(0.0506)	(0.0505)	(0.0505)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. T_CO2: Transport CO2 Emissions; T_CH4: Transport CH4 Emissions; T_Energy: Energy use from Transport

The results in Table 17 show that higher CH4 Emissions prejudice countries' environmental efficiency, while higher Energy Use enhances it. CO2 Emissions does not have a significant impact (only showed in 10% significance in Cloglog in one-part and 2nd component of two-part model).

Those prejudicial CH4 emissions typically arise from incomplete fuel combustion, leakage in natural gas systems and use of outdated or poorly maintained vehicles, which ends up burning fuel and wasting energy. On the other hand, the good impact of energy in efficiency may link with modernization of transport activities, making them more efficient. Some examples include the introduction of electric vehicles and fossil-free public transportation.

Moving on to the next sector, we have Industry, which AME results are presented in Table 18, corresponding to Equation (14). Industry include emissions from Industrial Combustion and Industrial Processes, and Employment, Value Added and Energy include Construction.

Table 18. Industry regression AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
IC_CO2	-0.0021	-0.0036	-0.0048	-0.1363	-0.1568 .	-0.1267	0.0151	0.0122	0.0087
	(0.0187)	(0.0179)	(0.0168)	(0.0931)	(0.0831)	(0.1002)	(0.0212)	(0.0207)	(0.0197)
IC_CH4	0.0155	0.0160	0.0164	-0.0663	-0.0648	-0.0515	0.0217	0.0242	0.0281
	(0.0154)	(0.0151)	(0.0144)	(0.0605)	(0.0553)	(0.0623)	(0.0178)	(0.0177)	(0.0174)
IP_CO2	-0.0588 *	-0.0456 *	-0.0318	-0.0170	-0.0075	-0.0442	-0.0777 **	-0.0680 **	-0.0556 *
	(0.0243)	(0.0223)	(0.0195)	(0.0580)	(0.0537)	(0.0616)	(0.0273)	(0.0256)	(0.0232)
IP_CH4	0.0164	0.0093	-0.0009	0.0204	0.0147	0.0333	0.0129	0.0067	-0.0031
	(0.0116)	(0.0112)	(0.0107)	(0.0451)	(0.0410)	(0.0509)	(0.0132)	(0.0130)	(0.0126)
I_Emp	-0.2390 ***	-0.2298 ***	-0.2103 ***	0.1451	0.1809	0.1272	-0.2759 ***	-0.2758 ***	-0.2694 ***
	(0.0546)	(0.0522)	(0.0482)	(0.2106)	(0.1921)	(0.2090)	(0.0639)	(0.0622)	(0.0593)
I_VA	0.0994 *	0.0981 *	0.0902 *	0.3912 *	0.3676 *	0.4218 *	0.1256 *	0.1208 *	0.1066 *
	(0.0447)	(0.0439)	(0.0421)	(0.1641)	(0.1434)	(0.1644)	(0.0508)	(0.0511)	(0.0511)
I_Energy	-0.0492	-0.0428	-0.0343	0.6012 ***	0.6774 ***	0.5157 **	-0.1274 **	-0.1235 **	-0.1157 **
	(0.0416)	(0.0402)	(0.0379)	(0.1756)	(0.1613)	(0.1822)	(0.0475)	(0.0466)	(0.0449)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. IC_CO2: Industrial Combustion CO2 Emissions; IC_CH4: Industrial Combustion CH4 Emissions; IP_CO2: Industrial Processes CO2 Emissions; IP_CH4: Industrial Processes CH4 Emissions; I_Emp: Employment in Industry; I_VA: Value Added in Industry; I_Energy: Energy Use in Industry

Emissions in Industry does not represent a significant impact, except for CO2 Emissions in Industrial Processes that have a negative impact in one-part and in 2nd component of two-part models.

The negative impact of Employment, as shown in Agriculture in Table 13, may reinforce that labour-intensive and poor innovation investments reduces countries' efficiency.

The positive correlation of Value Added indicate that countries that depend more on Industry sector to generate income can achieve higher efficiency levels, even though this effect is only significant at a 5% level.

Finally, Energy Use presents mixed effects in the two-part model, indicating that, for one side, in the 1st component, an increase in energy use increases the probability of the country being fully efficient, but when considering the 2nd component with only the inefficient countries, it shows that higher energy use will worsen their efficiency scores.

To end the regressions' analysis, we have the last sector results presented in Table 19, corresponding to Waste (Equation (15)). For this sector we will only analyse emissions impacts, since it was difficult to find available data.

Table 19. Waste regression AME results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
W_CO2	0.0047 *	0.0027	0.0006	-0.0019	-0.0004	-0.0039	0.0030	0.0017	-0.0001
	(0.0024)	(0.0021)	(0.0018)	(0.0060)	(0.0054)	(0.0068)	(0.0028)	(0.0027)	(0.0025)
W_CH4	-0.0200 .	-0.0205 *	-0.0223 *	0.0097	0.0058	0.0204	-0.0112	-0.0138	-0.0185
	(0.0111)	(0.0101)	(0.0089)	(0.0265)	(0.0232)	(0.0252)	(0.0143)	(0.0140)	(0.0137)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. W_CO2 – Waste CO2 Emissions; W_CH4 - Waste CH4 Emissions.

CO2 emissions reported in Table 19 exhibit no statistically significant results, with the exception of the Logit model in the one-part specification. In the case of CH4 emissions, a modest negative correlation is observed solely within the one-part model.

These were the main results obtained by the DEA implementation and FRM models. The main conclusions and policy recommendations will be further developed in the next subsection.

5.3 Discussion and Hypothesis Validation

In this subchapter, we will draw the main results' conclusions regarding the previous interactions between sectors and efficiency scores, as well as give considerations about our hypothesis formulation, contextualized in the end of Chapter II.

Before moving to more sector-specific conclusions, we will start by giving the considerations for Hypothesis 1 and Hypothesis 2, targeting DEA scores and crises effects.

For our first Hypothesis, claiming that H1: "OECD-America has the highest average environmental efficiency", based on Woo et al. (2015), we can, based on our results showed in Table 9, refute this Hypothesis. For our input and output selection, not only Europe presented the highest average environmental efficiency by a large difference but also contained all the fully efficient countries from our sample. The average results are showed in Table 20, serving as a reminder from Table 9.

Table 20. Average VRS Efficiency Scores by world region

	OECD-EU	OECD-AM	OECD-AO
Average VRS Efficiency Scores	0.9093	0.7666	0.7182

In addition, regarding our second hypothesis that H2: "Financial/Social crises have a negative impact on efficiency" supported by several studies (Beltrán-Esteve & Picazo-Tadeo, 2017; Cámara-Aceituno et al., 2024; Feng et al., 2017; Halkos & Petrou, 2019; Woo et al., 2015), we can partially validate this hypothesis. In one hand, based on our results obtained in the mixed macro-economic level regression and in the solo regression only including crises dummies presented in Tables 11 and 12, respectively, we can assume that European Sovereign Debt Crisis and Covid19 had a strong negative impact on efficiency scores. However, the effects of Global Financial Crisis and Energy and Inflation Crisis need for better investigation and interpretation. The inconsistency of Energy and Inflation Crisis may be justified by it being relatively recent starting in 2022, and that it is still happening and producing its effects.

Moving on to our third hypothesis regarding H3: "Methane (CH4) has a negative impact on environmental efficiency across all sectors", we created the Tables 21 and 22. Table 21 displays the CO2 emissions aggregate from all sectors, and Table 22 shows the same for the CH4 Emissions.

Table 21. CO2 Emissions: AME aggregate

		One-part Models			Two-part Models					
					First Component			Second Component		
		Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
CO2 Emissions	Agriculture	0.0001	-0.0005	-0.0012	-0.1119 ***	-0.1104 ***	-0.1003 ***	0.0008	0.0006	0.0003
		(0.0020)	(0.0019)	(0.0018)	(0.0180)	(0.0159)	(0.0177)	(0.0024)	(0.0024)	(0.0024)
	Fuel Exploitation	-0.0144	-0.0206 *	-0.0309 ***	-0.0707	-0.0565	-0.0516	-0.0147	-0.0205 .	-0.0313 **
		(0.0096)	(0.0093)	(0.0089)	(0.0444)	(0.0394)	(0.0444)	(0.0113)	(0.0113)	(0.0112)
	Power Industry	0.0075	0.0028	-0.0051	-0.0210	-0.0204	-0.0262	0.0196	0.0135	0.0032
		(0.0142)	(0.0128)	(0.0112)	(0.0325)	(0.0276)	(0.0323)	(0.0171)	(0.0166)	(0.0160)
	Buildings	-0.0451 ***	-0.0510 ***	-0.0576 ***	-0.4311 ***	-0.4239 ***	-0.3623 ***	-0.0178	-0.0222	-0.0283 *
		(0.0114)	(0.0109)	(0.0102)	(0.0523)	(0.0476)	(0.0522)	(0.0142)	(0.0141)	(0.0138)
	Transport	-0.0238	-0.0275	-0.0427 .	-0.0461	-0.1784	0.0009	-0.0200	-0.0298	-0.0537 .
		(0.0254)	(0.0247)	(0.0238)	(0.2984)	(0.1807)	(0.1693)	(0.0307)	(0.0310)	(0.0313)
	Industrial Combustion	-0.0021	-0.0036	-0.0048	-0.1363	-0.1568 .	-0.1267	0.0151	0.0122	0.0087
		(0.0187)	(0.0179)	(0.0168)	(0.0931)	(0.0831)	(0.1002)	(0.0212)	(0.0207)	(0.0197)
	Industrial Processes	-0.0588 *	-0.0456 *	-0.0318	-0.0170	-0.0075	-0.0442	-0.0777 **	-0.0680 **	-0.0556 *
		(0.0243)	(0.0223)	(0.0195)	(0.0580)	(0.0537)	(0.0616)	(0.0273)	(0.0256)	(0.0232)
	Waste	0.0047 *	0.0027	0.0006	-0.0019	-0.0004	-0.0039	0.0030	0.0017	-0.0001
		(0.0024)	(0.0021)	(0.0018)	(0.0060)	(0.0054)	(0.0068)	(0.0028)	(0.0027)	(0.0025)

We can see in Table 21 that some sectors had a strong impact, with the predominance of Buildings emissions, and that, on the other side, sectors like Power Industry, Transport, Industrial Combustion and Waste showed weak or insignificant relationships.

For CH4 Emissions the results behaved a little differently, as we can see in Table 22.

Table 22. CH4 Emissions: AME aggregate

		One-part Models			Two-part Models					
					First Component			Second Component		
		Logit	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**
CH4 Emissions	**Agriculture**	-0.1614 ***	-0.1676 ***	-0.1716 ***	-0.4389 ***	-0.4138 ***	-0.3944 ***	-0.1107 **	-0.1181 **	-0.1277 ***
		(0.0310)	(0.0289)	(0.0262)	(0.0941)	(0.0840)	(0.0882)	(0.0376)	(0.0370)	(0.0358)
	Fuel Exploitation	-0.0569 ***	-0.0580 ***	-0.0572 ***	-0.0878 **	-0.0965 ***	-0.0793 *	-0.0538 ***	-0.0573 ***	-0.0612 ***
		(0.0104)	(0.0097)	(0.0089)	(0.0316)	(0.0288)	(0.0312)	(0.0129)	(0.0124)	(0.0117)
	Power Industry	-0.0175	-0.0186	-0.202 .	-0.1448 **	-0.1265 **	-0.1296 **	-0.0212	-0.0188	-0.0159
		(0.0133)	(0.0127)	(0.118)	(0.0496)	(0.0422)	(0.0464)	(0.0161)	(0.0159)	(0.0158)
	Buildings	0.0180 .	0.0183 .	0.0185 *	0.0192	0.0194	0.0067	-0.0032	-0.0022	-0.0002
		(0.0104)	(0.0094)	(0.0082)	(0.0218)	(0.0208)	(0.0216)	(0.0129)	(0.0126)	(0.0120)
	Transport	-0.0604 ***	-0.0641 ***	-0.0641 ***	-0.1564	-0.1153 .	-0.1391 *	-0.0416 *	-0.0462 **	-0.0506 **
		(0.0144)	(0.0134)	(0.0120)	(0.1068)	(0.0632)	(0.0598)	(0.0180)	(0.0177)	(0.0170)
	Industrial Combustion	0.0155	0.0160	0.0164	-0.0663	-0.0648	-0.0515	0.0217	0.0242	0.0281
		(0.0154)	(0.0151)	(0.0144)	(0.0605)	(0.0553)	(0.0623)	(0.0178)	(0.0177)	(0.0174)
	Industrial Processes	0.0164	0.0093	-0.0009	0.0204	0.0147	0.0333	0.0129	0.0067	-0.0031
		(0.0116)	(0.0112)	(0.0107)	(0.0451)	(0.0410)	(0.0509)	(0.0132)	(0.0130)	(0.0126)
	Waste	-0.0200 .	-0.0205 *	-0.0223 *	0.0097	0.0058	0.0204	-0.0112	-0.0138	-0.0185
		(0.0111)	(0.0101)	(0.0089)	(0.0265)	(0.0232)	(0.0252)	(0.0143)	(0.0140)	(0.0137)

Through the analysis of Tables 21 and 22, emissions across sectors reveals distinct patterns in how CO2 and CH4 emissions influence OECD countries' efficiency. CO2 Emissions presents its stronger impact in Buildings, across all one-part and two-part models, reducing substantially the probability of countries being fully efficient and demanding for better urban planning and building efficiency. CH4 emissions consistently show a strong negative impact, particularly in Agriculture, Fuel Exploitation and Transport, where they significantly reduce both the likelihood of a country being efficient (1st component) and the degree of that efficiency (2nd component). This reflects the high global warming potential of CH4, confirming in part our H3: "Methane (CH4) has a negative impact in environmental efficiency across all sectors". However, this relation was not observed, in sectors, such as Buildings and Industry (Industrial Combustion and Industrial Processes). This situation made "across all sectors" of the affirmation refuted.

Figure 7 summarizes these conclusions, reflecting some of the anthropogenic activities causing CH4 emissions, mainly happening in Agriculture, Energy and Waste.

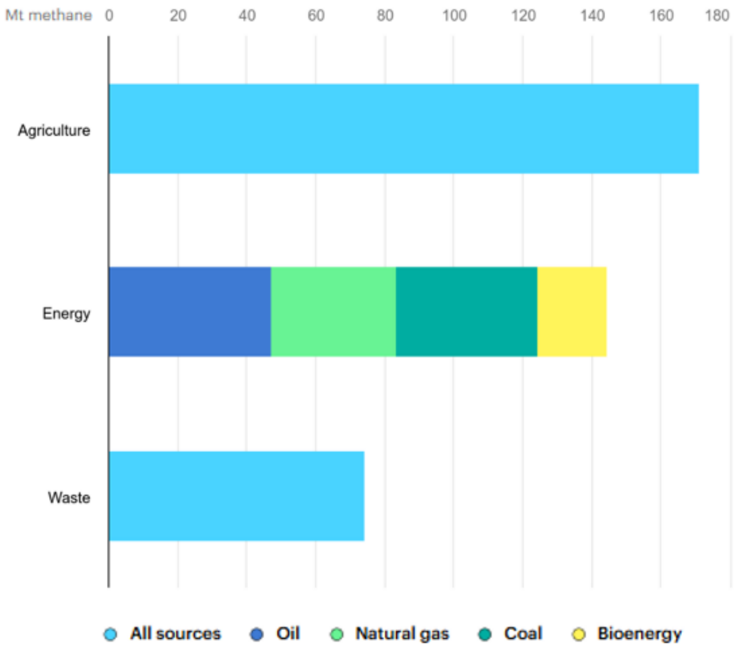

Figure 7. Methane Emissions from Anthropogenic activities (Source: IEA (2022))

Before we follow through the next hypothesis analysis, we joined in Table 23 the common variables between sectors, in order to make fair comparisons. For macroeconomic variables, only Agriculture, Industry and Transport allowed for these comparisons, contrarily to what happened in CO2 and CH4 emissions.

Table 23. Employment, Value Added and Energy Use comparison

		One-part Models			Two-part Models					
					First Component			Second Component		
		Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
Employment	Agriculture	-0.0195	-0.0235	-0.0280	-0.1156 **	-0.1085 **	-0.1206 **	-0.0625 *	-0.0614 *	-0.0593 *
		(0.0225)	(0.0201)	(0.0173)	(0.0446)	(0.0413)	(0.0439)	(0.0275)	(0.0259)	(0.0237)
	Industry	-0.2390 ***	-0.2298 ***	-0.2103 ***	0.1451	0.1809	0.1272	-0.2759 ***	-0.2758 ***	-0.2694 ***
		(0.0546)	(0.0522)	(0.0482)	(0.2106)	(0.1921)	(0.2090)	(0.0639)	(0.0622)	(0.0593)
Value Added	Agriculture	-0.0079	-0.0004	0.0138	-0.1575 .	-0.1722 **	-0.1078 .	0.0466	0.0517	0.0633 .
		(0.0296)	(0.0276)	(0.0249)	(0.0698)	(0.0650)	(0.0624)	(0.0356)	(0.0348)	(0.0338)
	Industry	0.0994 *	0.0981 *	0.0902 *	0.3912 *	0.3676 *	0.4218 *	0.1256 *	0.1208 *	0.1066 *
		(0.0447)	(0.0439)	(0.0421)	(0.1641)	(0.1434)	(0.1644)	(0.0508)	(0.0511)	(0.0511)
Energy Use	Agriculture	-0.0420 *	-0.0412 *	-0.0383 *	-0.2697 ***	-0.2793 ***	-0.2309 ***	-0.0625 **	-0.0611 **	-0.0562 **
		(0.0190)	(0.0177)	(0.0159)	(0.0699)	(0.0626)	(0.0618)	(0.228)	(0.0221)	(0.0209)
	Transport	0.0544	0.0970 *	0.1616 ***	0.6351	0.7661 *	0.4933 .	0.0944 .	0.1345 **	0.2038 ***
		(0.0430)	(0.0411)	(0.0388)	(0.5040)	(0.3054)	(0.2860)	(0.0506)	(0.0505)	(0.0505)
	Industry	-0.0492	-0.0428	-0.0343	0.6012 ***	0.6774 ***	0.5157 **	-0.1274 **	-0.1235 **	-0.1157 **
		(0.0416)	(0.0402)	(0.0379)	(0.1756)	(0.1613)	(0.1822)	(0.0475)	(0.0466)	(0.0449)

As shown in Table 23, Employment has a strongly negative significance in both Agriculture and Industry sectors, that usually are those with the most extensive workforce. These sectors must invest in R&D and in the implementation of new technologies, as proved already in Agriculture that the implementation of technologies like variable-rate nutrient application, GPS-guided equipment and AI-powered systems were able to reduce GHG emissions by 5-30% while maintaining or increasing productivity (Balafoutis et al., 2017).

Regarding Value Added, Industry shows a positive relationship through all three model specifications, while Agriculture only presents some negative significance in the 1st component of the two-part model.

Finally, Energy Use shows a negative significant relationship in the Agriculture sector and a positive link in Transport and in the two-part model of the Industry sector, that may reflect distinct energy use sources between sectors.

Our fourth hypothesis claimed that H4: "The production and use of clean energies (renewables and nuclear) improve environmental efficiency" as shown, for example, in Wang et al. (2023). However, the results obtained in this dissertation makes us practically refuting this hypothesis. In Table 10, we could see that both Energy Use from Renewables as Energy Use from Alternative and Nuclear had a significant negative effect on efficiency, especially for the last one. Also, when analysing Power Industry Electricity Production variables, we saw that same negative effect, and surprisingly the most pollutant sources like Coal and Oil had a positive influence in efficiencies. This may reflect allocation inefficiencies of this cleaner sources, that may be related with high costs of implementation and storage. Countries and companies should pay special attention to these results, since the potential of sustainable development through these cleaner sources is undeniable.

Regarding our last modelled hypothesis that H5: "The energy sector has the most negative impact in efficiency", our findings can assume that, in fact, energy sector has a strong impact mainly in their emissions contribution to global GHG emissions. Fuel Exploitation exhibits the most pronounced negative impact, as it shows strong negative correlations with both CO_2 and CH_4 emissions. Within CO_2 emissions, the Buildings subsector also demonstrates a significant negative effect, while Transport and Power Industry contribute notably to CH_4 emissions. Among other variables within the energy sector, Energy

Production from Nuclear Sources and Urban Population are negatively associated with efficiency, whereas Natural Resource Rents, Fuel Exports, and Energy Use in Transport show positive associations. Despite these contrasting effects, it is not entirely accurate to characterize the energy sector as having the most negative overall impact. For instance, the Agriculture sector emerges as particularly relevant, especially regarding CH4 emissions, where it constitutes the largest contributing sector.

After this discussion, there are important recommendations for policymakers and companies that should be made. The findings presented in this study highlight the importance of strengthening environmental regulations and drive initiatives that promote sustainable growth and resource efficiency. Countries should collaborate to achieve their goals, mainly inside the Paris Agreement and Net-zero commitments by applying stricter carbon tax policies and mandatory disclosing of information, as well as orientate their efforts to the most concerning sectors, giving companies support they need to contribute to sector and country efficiency. No sector should be forgotten, however, there are some sectors that need stronger vigilance and action. Policies should be drawn to incentivise CH4 Emissions reduction mainly in Energy and Agriculture sectors. Governments should support firms' operations in these sectors, giving them financial support for cleaner extraction methods and agriculture technology, like the precision technology example showed earlier about Agriculture, that showed a positive impact in emissions. Cleaner Energy Use should be improved and implemented especially in Agriculture and Industry, encouraging renewable energy and nuclear infrastructure investments. In Buildings, countries should invest in better urban planning, in order to build more efficient buildings that reduce their emission impact. Companies should enhance their GI and transparent reporting, and play a more proactive role close to governments, that should give them better conditions to R&D and technology implementation. Companies operating in densely populated urban areas should invest in smart building technologies, energy management systems, and digital solutions that optimize resource use and reduce emissions. Firms in fast-growing economies must also balance expansion with sustainability by adopting green technologies, ensuring that growth does not come at the expense of environmental efficiency.

CHAPTER VI – CONCLUSION

6 Conclusion

In this dissertation, the main goal was to evaluate the environmental efficiency OECD countries for the 2000-2023 period.

This study followed a two-stage procedure. First, through an input-oriented Data Envelopment Analysis (DEA), we have analysed countries' environmental efficiency, in a relation of five inputs to three undesirable outputs. Next, we implemented ten Fractional Regression Models (FRMs), where the goal was to evaluate how different macro-economic and sector variables would affect the countries' efficiency. Crises' dummies from four of the biggest global crises were included, were the results show that two of them, namely, European Sovereign Debt Crisis and Covid19, negatively affected the efficiencies.

The results showed that OECD-EU have higher efficiency-score levels, and that was the world's region where all the totally efficient countries through all years were located. Those fully efficient countries were Estonia, Greece, Iceland, Ireland, Latvia, Luxembourg. Concerning the FRMs results, the Agriculture and Energy sectors are the ones showing a more negative impact in emissions and environmental efficiency, showing that policymakers and firms should pay special attention to them. Investment in regulation, technology and R&D should be the key factors to improve countries and sectors efficiency, and to mitigate negative effects induced by excessive labour-dependence. Governments and policymakers should work closely to firms, considering their important role.

Some limitations of the study include data constraints for all countries and years, as well as between sectors, which made comparisons challenging. For future research, effects from most recent crises should be analysed, and hopefully being able to access more complete databases concerning more countries and years. It would also be interesting to do the same analysis in corporate level to, for example, see the impact of the main companies of each sector on emissions and efficiency.

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APPENDICES

APPENDIX I – Selected OECD countries and corresponding DMUs

DMU-1	Australia	**DMU-12**	Hungary	**DMU-23**	New Zealand
DMU-2	Austria	**DMU-13**	Iceland	**DMU-24**	Norway
DMU-3	Belgium	**DMU-14**	Ireland	**DMU-25**	Poland
DMU-4	Canada	**DMU-15**	Israel	**DMU-26**	Portugal
DMU-5	Czechia	**DMU-16**	Italy	**DMU-27**	Slovak Republic
DMU-6	Denmark	**DMU-17**	Japan	**DMU-28**	Slovenia
DMU-7	Estonia	**DMU-18**	Korea	**DMU-29**	Spain
DMU-8	Finland	**DMU-19**	Latvia	**DMU-30**	Sweden
DMU-9	France	**DMU-20**	Lithuania	**DMU-31**	Türkiye
DMU-10	Germany	**DMU-21**	Luxembourg	**DMU-32**	United Kingdom
DMU-11	Greece	**DMU-22**	Netherlands	**DMU-33**	United States of America

APPENDIX II – VRS Results (2000-2023)

Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Australia	0.7762	0.8292	0.8054	0.7605	0.7510	0.7315	0.7022	0.7028	0.6962	0.6479	0.6205	0.6468
Austria	0.9866	0.9454	0.9350	0.9143	0.9169	0.8937	0.8836	0.9162	0.9055	0.8894	0.8427	0.8343
Belgium	0.8652	0.8665	0.9331	0.9174	0.9096	0.8641	0.8290	0.8190	0.8233	0.7860	0.7571	0.6855
Canada	0.9972	0.9572	0.9609	0.9337	0.9277	0.8876	0.8159	0.8158	0.8569	0.8034	0.7203	0.7557
Czechia	0.7222	0.7318	0.7355	0.7406	0.7634	0.7546	0.7820	0.7542	0.7810	0.6941	0.6493	0.6573
Denmark	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9983	1.0000	1.0000	1.0000	0.9842	1.0000
Estonia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Finland	0.8622	0.8813	0.9111	0.9100	0.9116	0.8400	0.7993	0.7802	0.8164	0.7683	0.7218	0.7313
France	0.8937	0.8607	0.8951	0.8737	0.8692	0.8507	0.8196	0.8143	0.8042	0.8054	0.7608	0.7169
Germany	0.8644	0.8708	0.9326	0.9372	0.9378	0.9376	0.9162	0.9275	0.9080	0.9079	0.8450	0.7955
Greece	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hungary	0.9068	0.9154	0.8914	0.9392	0.9882	0.9523	0.9580	0.9678	0.9764	0.8238	0.8410	0.8764
Iceland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Ireland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Israel	0.8365	0.8673	0.8690	0.8977	0.9413	0.8742	0.8075	0.8083	0.8740	0.8316	0.7774	0.7655
Italy	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9898	1.0000
Japan	0.6914	0.6890	0.7185	0.7303	0.7239	0.7106	0.6903	0.7172	0.7180	0.7095	0.7084	0.6580
Korea	0.6425	0.5891	0.6167	0.6101	0.6099	0.6110	0.5998	0.6148	0.6469	0.5644	0.5370	0.4871
Latvia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Lithuania	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Luxembourg	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Netherlands	0.8810	0.8649	0.9080	0.9074	0.9515	0.9323	0.8832	0.8575	0.9085	0.8454	0.8562	0.7728
New Zealand	1.0000	1.0000	0.9907	0.9466	0.9548	0.9507	0.9347	0.9254	0.9696	0.9446	0.8818	0.8943
Norway	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Poland	0.8668	0.9185	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9363	0.8565	0.8967
Portugal	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9489	0.9758	0.9640	0.9524
Slovak Republic	0.8780	0.8520	0.8300	0.9530	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Slovenia	0.8308	0.8829	0.8918	0.8972	0.9122	0.9094	0.9240	0.9344	0.8812	0.8407	0.8452	0.9484
Spain	0.9060	0.9076	0.8826	0.8547	0.8565	0.8614	0.8504	0.8527	0.8877	0.9116	0.9115	0.8822
Sweden	0.9060	0.8768	0.8934	0.8921	0.9159	0.9104	0.8337	0.8400	0.8495	0.8078	0.7586	0.7888
Türkiye	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9134	0.9426	0.9029	0.9137	0.9722
UK	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9583
USA	0.7693	0.7870	0.8227	0.8099	0.7899	0.7671	0.7739	0.8132	0.8310	0.8528	0.8610	0.7401

APPENDIX II – VRS Results (2000-2023) (Cont.)

Country	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Australia	0.6375	0.5987	0.6373	0.6617	0.6745	0.7246	0.6540	0.7691	0.7600	0.7956	0.7512	0.8283
Austria	0.8251	0.7776	0.8028	0.7626	0.7715	0.7829	0.7666	0.7265	0.6979	0.6733	0.6850	0.9395
Belgium	0.7141	0.6674	0.6821	0.6670	0.6462	0.6696	0.6486	0.6314	0.6318	0.6374	0.6726	0.7133
Canada	0.7069	0.7285	0.7440	0.7305	0.7585	0.7870	0.7519	0.8125	0.7326	0.7606	0.7628	0.8108
Czechia	0.6376	0.6266	0.6330	0.5910	0.6376	0.6520	0.6120	0.6138	0.6122	0.6228	0.6100	0.7528
Denmark	1.0000	0.9762	0.9970	0.9647	0.9956	1.0000	0.9493	0.9926	0.9559	0.8435	0.8212	1.0000
Estonia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Finland	0.7074	0.7166	0.7684	0.7598	0.7227	0.7275	0.6305	0.6866	0.6428	0.7109	0.6829	0.7587
France	0.7446	0.7195	0.7418	0.7357	0.7392	0.7580	0.7172	0.7124	0.6999	0.6908	0.7097	0.7447
Germany	0.8400	0.8029	0.8263	0.8163	0.8183	0.8473	0.8092	0.8005	0.7692	0.7858	0.7790	0.8471
Greece	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hungary	0.8364	0.7884	0.7904	0.7702	0.8548	0.7714	0.7028	0.7010	0.6622	0.6548	0.6959	0.9294
Iceland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Ireland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Israel	0.7487	0.7772	0.8183	0.7809	0.7764	0.8294	0.7853	0.7801	0.7317	0.7382	0.6972	0.8207
Italy	1.0000	0.9792	0.9950	0.9546	0.9597	0.9768	0.9329	0.9193	0.8777	0.8206	0.7951	1.0000
Japan	0.6839	0.6473	0.6537	0.6526	0.6611	0.6790	0.6466	0.6424	0.6279	0.6355	0.6308	0.6616
Korea	0.4901	0.4707	0.4775	0.4793	0.4781	0.4836	0.4495	0.4497	0.4653	0.4709	0.4743	0.4716
Latvia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Lithuania	1.0000	1.0000	1.0000	1.0000	0.9555	1.0000	1.0000	1.0000	0.9953	1.0000	1.0000	1.0000
Luxembourg	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Netherlands	0.8345	0.8350	0.8823	0.7628	0.8297	0.8746	0.8038	0.7737	0.7525	0.8263	0.8279	0.7953
New Zealand	0.8082	0.8198	0.7975	0.7584	0.7258	0.7483	0.7277	0.7412	0.7430	0.7255	0.7067	0.8128
Norway	1.0000	1.0000	1.0000	0.9686	0.9416	0.9768	1.0000	0.9727	0.9511	0.9956	1.0000	0.9642
Poland	0.8425	0.8672	0.8606	0.8329	0.8343	0.8921	0.8567	0.8206	0.8596	0.9071	0.9494	0.8913
Portugal	1.0000	1.0000	0.9957	0.9612	0.9518	0.9692	0.9159	0.8860	0.8453	0.8467	0.8403	0.8280
Slovak Republic	1.0000	0.9988	0.9949	0.8148	0.8819	0.9363	0.9761	0.9795	1.0000	1.0000	1.0000	0.9671
Slovenia	0.9713	0.9787	1.0000	1.0000	1.0000	1.0000	0.9842	1.0000	1.0000	0.9996	0.9332	1.0000
Spain	0.9434	0.9394	0.9267	0.9117	0.9228	0.9383	0.8993	0.8850	0.7991	0.8313	0.8280	0.8450
Sweden	0.8066	0.8254	0.8298	0.7577	0.7348	0.7390	0.7171	0.7850	0.7099	0.7398	0.7019	1.0000
Türkiye	1.0000	1.0000	1.0000	0.8522	0.8052	0.8141	0.7609	0.7823	0.7476	0.7030	0.7585	0.7529
UK	1.0000	0.9811	0.9690	0.9478	0.9496	0.9741	0.9713	0.9274	0.9301	0.9665	0.9551	0.9272
USA	0.6637	0.6137	0.6112	0.6167	0.6237	0.6349	0.6067	0.6125	0.6185	0.6480	0.6986	0.7099

APPENDIX III – CRS Results (2000-2023)

Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Australia	0.7740	0.8279	0.8016	0.7560	0.7458	0.7313	0.6972	0.6949	0.6960	0.6462	0.6180	0.6106
Austria	0.9796	0.9369	0.9224	0.9032	0.9097	0.8912	0.8767	0.9110	0.9000	0.8849	0.8043	0.7551
Belgium	0.8608	0.8643	0.9315	0.9159	0.9090	0.8605	0.8256	0.8116	0.8179	0.7806	0.7495	0.6797
Canada	0.9931	0.9522	0.9553	0.9266	0.9249	0.8865	0.8157	0.8152	0.8474	0.7871	0.7124	0.6639
Czechia	0.7170	0.7292	0.7302	0.7367	0.7613	0.7516	0.7805	0.7522	0.7738	0.6878	0.6427	0.6506
Denmark	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9975	1.0000	1.0000	1.0000	0.9647	0.9164
Estonia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Finland	0.8606	0.8799	0.9081	0.9079	0.9107	0.8377	0.7923	0.7743	0.8137	0.7652	0.7165	0.7253
France	0.8836	0.8426	0.8951	0.8627	0.8689	0.8492	0.7778	0.7839	0.8020	0.7817	0.7336	0.6792
Germany	0.7831	0.8055	0.8776	0.8848	0.9277	0.9300	0.8475	0.8680	0.8750	0.8558	0.7975	0.7394
Greece	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hungary	0.9051	0.9152	0.8894	0.9387	0.9862	0.9519	0.9553	0.9665	0.9743	0.8237	0.8386	0.8764
Iceland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Ireland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Israel	0.8341	0.8664	0.8675	0.8968	0.9409	0.8701	0.8023	0.8038	0.8711	0.8286	0.7732	0.7216
Italy	1.0000	1.0000	1.0000	1.0000	1.0000	0.9873	0.9872	0.9875	0.9839	0.9748	0.9477	0.9671
Japan	0.6542	0.6551	0.6910	0.6951	0.7210	0.6930	0.6482	0.6885	0.7059	0.6887	0.6823	0.6202
Korea	0.6281	0.5890	0.6155	0.6086	0.6079	0.5998	0.5810	0.5944	0.6310	0.5513	0.5202	0.4747
Latvia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Lithuania	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Luxembourg	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Netherlands	0.8641	0.8592	0.9042	0.9023	0.9502	0.9266	0.8679	0.8397	0.9024	0.8311	0.8420	0.7669
New Zealand	1.0000	1.0000	0.9907	0.9465	0.9545	0.9306	0.9335	0.9246	0.9695	0.9070	0.8662	0.8827
Norway	1.0000	1.0000	1.0000	1.0000	1.0000	0.9957	0.9929	0.8993	0.9326	0.8430	0.8797	0.8348
Poland	0.8382	0.8915	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9863	0.8947	0.8212	0.8580
Portugal	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9464	0.9589	0.9429	0.9327
Slovak Republic	0.8591	0.8441	0.8296	0.9523	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Slovenia	0.8298	0.8825	0.8909	0.8963	0.9116	0.9088	0.9232	0.9331	0.8803	0.8397	0.8443	0.9478
Spain	0.9047	0.8975	0.8726	0.8415	0.8470	0.8330	0.8289	0.8312	0.8566	0.8809	0.8772	0.8520
Sweden	0.9054	0.8762	0.8930	0.8919	0.9159	0.9031	0.8101	0.8066	0.8350	0.8058	0.7585	0.7209
Türkiye	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9833	0.8837	0.9097	0.8722	0.8779	0.9313
UK	1.0000	0.9868	1.0000	0.9816	1.0000	1.0000	0.9412	0.9674	1.0000	1.0000	0.9780	0.9580
USA	0.6909	0.6990	0.7269	0.7033	0.7150	0.6917	0.6518	0.7026	0.7454	0.7587	0.7508	0.6996

APPENDIX III – CRS Results (2000-2023) (Cont.)

Country	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Australia	0.6174	0.5753	0.5965	0.6144	0.6298	0.6673	0.6441	0.6713	0.7084	0.7560	0.7439	0.7806
Austria	0.8112	0.7602	0.7886	0.7554	0.7646	0.7773	0.7620	0.7192	0.6915	0.6677	0.6789	0.8320
Belgium	0.7136	0.6672	0.6798	0.6603	0.6401	0.6636	0.6408	0.6257	0.6256	0.6335	0.6677	0.7124
Canada	0.5881	0.5486	0.5494	0.5978	0.6060	0.6711	0.6774	0.6790	0.6782	0.7026	0.7406	0.7713
Czechia	0.6308	0.6209	0.6273	0.5846	0.6307	0.6456	0.6046	0.6070	0.6043	0.6161	0.6018	0.7467
Denmark	1.0000	0.9525	0.9786	0.9618	0.9922	1.0000	0.9471	0.9895	0.9534	0.8413	0.8196	0.9976
Estonia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Finland	0.7061	0.7081	0.7442	0.7202	0.6816	0.6877	0.6094	0.6545	0.6290	0.6932	0.6789	0.7503
France	0.7045	0.6811	0.7072	0.6980	0.7005	0.7177	0.6792	0.6765	0.6680	0.6568	0.6749	0.7416
Germany	0.7773	0.7442	0.7713	0.7511	0.7538	0.7806	0.7474	0.7419	0.7138	0.7325	0.7263	0.8007
Greece	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hungary	0.8330	0.7866	0.7793	0.7573	0.8251	0.7653	0.6984	0.6966	0.6580	0.6513	0.6911	0.9257
Iceland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Ireland	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Israel	0.7486	0.7608	0.8018	0.7750	0.7695	0.8235	0.7807	0.7727	0.7252	0.7323	0.6908	0.7798
Italy	0.9526	0.9348	0.9596	0.9073	0.9127	0.9275	0.8858	0.8750	0.8361	0.7828	0.7579	0.9740
Japan	0.6411	0.6075	0.6178	0.6082	0.6164	0.6331	0.6027	0.6009	0.5869	0.5964	0.5911	0.6261
Korea	0.4752	0.4556	0.4648	0.4625	0.4609	0.4664	0.4320	0.4332	0.4477	0.4524	0.4544	0.4514
Latvia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Lithuania	1.0000	1.0000	1.0000	1.0000	0.9554	0.9884	0.9662	0.9677	0.9388	0.9429	0.9646	1.0000
Luxembourg	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Netherlands	0.8225	0.8232	0.8755	0.7451	0.8108	0.8540	0.7847	0.7582	0.7371	0.8104	0.8118	0.7820
New Zealand	0.8080	0.8182	0.7974	0.7573	0.7244	0.7429	0.7268	0.7359	0.7400	0.7239	0.7034	0.8079
Norway	0.8294	0.8018	0.8271	0.7586	0.7367	0.7712	0.7891	0.7158	0.6924	0.7890	0.8895	0.7706
Poland	0.8153	0.8294	0.8221	0.7953	0.7951	0.8489	0.8141	0.7822	0.8189	0.8639	0.9050	0.8542
Portugal	1.0000	1.0000	0.9865	0.9579	0.9488	0.9637	0.9095	0.8823	0.8408	0.8435	0.8363	0.8188
Slovak Republic	0.9889	0.9579	0.9426	0.7848	0.8381	0.8957	0.9690	0.9600	1.0000	1.0000	0.9925	0.9217
Slovenia	0.9708	0.9780	0.9998	1.0000	1.0000	1.0000	0.9831	1.0000	1.0000	0.9986	0.9322	1.0000
Spain	0.9045	0.9032	0.8915	0.8757	0.8841	0.8960	0.8592	0.8489	0.7710	0.8011	0.7976	0.8181
Sweden	0.7473	0.7177	0.7460	0.6887	0.6757	0.6822	0.6500	0.6951	0.6564	0.6887	0.6776	0.8457
Türkiye	1.0000	1.0000	0.9477	0.8019	0.7542	0.7570	0.7081	0.7289	0.6955	0.6497	0.7039	0.6992
UK	1.0000	0.9656	0.9671	0.8965	0.8974	0.9192	0.9187	0.8784	0.8819	0.9226	0.9052	0.9062
USA	0.6223	0.5724	0.5652	0.5595	0.5670	0.5801	0.5477	0.5547	0.5638	0.6101	0.6577	0.6683

APPENDIX IV – Macro regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**
(Intercept)	0.4678	0.2089	-0.3053	-42.7902 *	-34.0416	-43.4677 *	-0.2724	-0.1782	-0.5571
	(0.844)	(0.498)	(0.462)	(18.826)	(23.2941)	(18.919)	(0.725)	(0.426)	(0.396)
P_Density	0.5079 ***	0.2911 ***	0.2560 ***	-0.7913	4.3112	2.6009	0.4409 ***	0.2543 ***	0.2261 ***
	(0.137)	(0.071)	(0.053)	(6.506)	(4.776)	(4.637)	(0.105)	(0.056)	(0.045)
GDP_G	-0.1167 **	-0.0662 **	-0.0563 **	-0.3201	-0.1965	-0.1791	-0.1070 ***	-0.0619 ***	-0.055 ***
	(0.037)	(0.021)	(0.019)	(0.324)	(0.180)	(0.1978)	(0.032)	(0.019)	(0.017)
FDI_I	0.0177	0.0096	0.0082	0.0338	0.0861	0.0583	0.0269	0.0151	0.0130
	(0.017)	(0.010)	(0.009)	(0.263)	(0.159)	(0.179)	(0.017)	(0.010)	(0.009)
Trade	0.5510 *	0.3489 **	0.3571 **	8.9784 *	5.5231 **	6.6771 **	0.6448 ***	0.3878 ***	0.3743 ***
	(0.222)	(0.131)	(0.120)	(3.644)	(2.091)	(2.353)	(0.188)	(0.110)	(0.102)
E_R	0.0564	0.0123	-0.0099	-1.8835 .	-0.9795 *	-0.8157	-0.0005	-0.0088	-0.0221
	(0.116)	(0.065)	(0.055)	(1.086)	(0.493)	(0.705)	(0.099)	(0.044)	(0.050)
E_AN	-0.3938 ***	-0.2115 ***	-0.1592 ***	0.0100	-0.7191	-0.5978	-0.1617 *	-0.0819 .	-0.0535
	(0.093)	(0.052)	(0.043)	(0.058)	(0.466)	(0.460)	(0.078)	(0.044)	(0.039)
CI_GDP	-3.5755 ***	-2.1275 ***	-1.8746 ***	-12.2519 .	-8.3498 *	-9.7572 *	-2.8640 ***	-1.6909 ***	-1.5226 ***
	(0.898)	(0.537)	(0.478)	(7.411))	(3.920)	(4.697)	(0.6969)	(0.415)	(0.380)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8665	0.8713	0.8767	0.6751	0.6733	0.6867	0.8056	0.8081	0.8115
Deviance	19.1131	18.42971	17.65188	207.4339	208.5510	200.0150	9.8885	9.7617	9.5880

APPENDIX V – Macro with crisis regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	1.0523	0.6635	0.2741	13.4153	11.2146	0.5751	0.8594	0.4414	-0.0750
	(1.080)	(0.673)	(0.733)	(14.216)	(8.567)	(8.841)	(0.933)	(0.570)	(0.575)
P_Density	-0.0446	-0.0558	-0.1296	-18.6352 ***	-9.7939 **	-12.6802 ***	-0.0117	-0.0219	-0.0505
	(0.295)	(0.202)	(0.267)	(5.461)	(3.593)	(3.161)	(0.255)	(0.164)	(0.184)
GDP_G	-0.0428	-0.0248	-0.0222	-0.2427	-0.1485	-0.0871	-0.0303	-0.0183	-0.0178
	(0.027)	(0.016)	(0.014)	(0.229)	(0.143)	(0.155)	(0.023)	(0.014)	(0.012)
FDI_I	0.0280	0.0147	0.0123	-0.0064	-0.0160	-0.0255	0.0309	0.0172	0.0146
	(0.020)	(0.012)	(0.010)	(0.252)	(0.144)	(0.162)	(0.019)	(0.011)	(0.010)
Trade	0.0717	0.0906	0.1524	0.5572	0.3989	0.5370	0.1634	0.1393	0.1979 .
	(0.243)	(0.144)	(0.135)	(2.234)	(1.337)	(1.513)	(0.197)	(0.118)	(0.113)
E_R	-0.4092 ***	-0.2566 ***	-0.2396 ***	-4.4069 ***	-2.4169 ***	-2.7625 ***	-0.4506 ***	-0.2685 ***	-0.2472 ***
	(0.123)	(0.070)	(0.059)	(1.157)	(0.540)	(0.650)	(0.104)	(0.060)	(0.053)
E_AN	-0.1366	-0.0980 .	-0.1012 *	0.0175	0.0080	0.0257	-0.0126 *	-0.0070 *	-0.0056 .
	(0.091)	(0.054)	(0.049)	(0.0424)	(0.026)	(0.021)	(0.006)	(0.004)	(0.003)
CI_GDP	2.8885 **	1.3397 *	0.8895	-4.0465	-2.070	-2.5629	1.9570 *	1.0004 *	0.7887 .
	(0.944)	(0.580)	(0.552)	(6.731)	(3.886)	(4.241)	(0.799)	(0.468)	(0.425)
GFC	-0.1135	0.0638	0.0523	-0.2974	-0.1390	0.1362	0.1438 *	0.0798 *	0.0661 .
	(0.078)	(0.045)	(0.039)	(0.631)	(0.370)	(0.417)	(0.072)	(0.041)	(0.035)
ESDC	-0.1525 *	-0.0804 **	-0.0621 *	0.2043	0.1207	0.3251	-0.1406 **	-0.0798 **	-0.0684 **
	(0.050)	(0.029)	(0.0267)	(0.414)	(0.243)	(0.283)	(0.049)	(0.029)	(0.026)
Covid19	-0.3118 ***	-0.1950 ***	-0.1905 ***	-0.7985	-0.5085	-0.8502	-0.2801 ***	-0.1733 ***	-0.1694 ***
	(0.076)	(0.045)	(0.042)	(0.908)	(0.531)	(0.638)	(0.064)	(0.037)	(0.034)
E&IC	0.2487 **	0.1218 *	0.0823	1.2798	0.8170	0.7967	0.1879 *	0.0914	0.0591
	(0.096)	(0.057)	(0.054)	(0.867)	(0.538)	(0.637)	(0.081)	(0.048)	(0.045)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8290	0.8308	0.8331	0.6136	0.6104	0.6149	0.7320	0.7317	0.7316
Deviance	24.4844	24.2247	23.8890	246.7053	248.8386	245.8386	13.6311	13.6469	13.6499

APPENDIX VI – Crisis regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	1.0109 ***	0.6168 ***	0.2624 ***	-20.4840 ***	-5.9381 ***	-20.4310 ***	0.9950 ***	0.6087 ***	0.2577 ***
	(0.091)	(0.054)	(0.049)	(3.404)	(0.062)	(2.719)	(0.087)	(0.052)	(0.047)
GFC	0.2002 **	0.1139 **	0.0966 **	0.4154	0.2543	0.4331	0.2146 **	0.1208 **	0.1025 **
	(0.086)	(0.039)	(0.034)	(0.442)	(0.259)	(0.275)	(0.066)	(0.037)	(0.032)
ESDC	-0.1786 ***	-0.0933 **	-0.0696 **	0.04784	-0.0223	0.1538	-0.1578 **	-0.0874 **	-0.0719 **
	(0.049)	(0.029)	(0.025)	(0.379)	(0.223)	(0.253)	(0.048)	(0.028)	(0.025)
Covid19	-0.5778 ***	-0.3373 ***	-0.3003 ***	-1.6677 **	-0.9888	-1.1882 **	-0.4937 ***	-0.2863 ***	-0.2556 ***
	(0.063)	(0.037)	(0.034)	(0.592)	(0.339)	(0.429)	(0.052)	(0.030)	(0.028)
E&IC	-0.0447	-0.0337	-0.0388	0.0336	0.0589	-0.0309	-0.0476	-0.0330	-0.0366
	(0.082)	(0.050)	(0.046)	(0.667)	(0.0410)	(0.461)	(0.065)	(0.038)	(0.035)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No	No
Pseudo R^2	0.8021	0.8041	0.8064	0.5203	0.5204	0.5222	0.6754	0.6770	0.6788
Deviance	28.3264	28.0398	27.7158	306.2372	306.1871	305.0395	16.5136	16.4312	16.3360

APPENDIX VII – Agriculture Regression results

	One-art Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	26.2339 ***	15.2905 ***	13.0817 ***	213.5394 *	120.5755 **	132.7190 *	14.5734 **	8.5889 **	7.4447 **
	(6.788)	(3.890)	(3.436)	(84.326)	(45.945)	(55.090)	(5.370)	(3.000)	(2.567)
A_CO2	0.0013	-0.0027	-0.0064	-2.3689 ***	-1.3312 ***	-1.5267 ***	0.0065	0.0029	0.0010
	(0.016)	(0.009)	(0.008)	(0.623)	(0.323)	(0.422)	(0.016)	(0.009)	(0.008)
A_CH4	-1.6944 ***	-0.9932 ***	-0.8851 ***	-9.2939 *	-4.9889 *	-6.0033 *	-0.8831 **	-0.5316 **	-0.4999 ***
	(0.397)	(0.220)	(0.185)	(4.353)	(2.339)	(2.792)	(0.320)	(0.178)	(0.150)
A_Land	1.7724 **	1.0607 **	0.9942 ***	-3.2769	-1.6801	-2.7511	0.9336 .	0.5876 *	0.5975 *
	(0.601)	(0.345)	(0.300)	(4.870)	(2.500)	(3.348)	(0.498)	(0.286)	(0.253)
A_Emp	-0.2043	-0.1394	-0.1443	-2.4472	-1.3081	-1.8355 .	0.3714	-0.2763	-0.2324
	(0.384)	(0.213)	(0.177)	(1.562)	(0.868)	(1.068)	(0.301)	(0.181)	(0.154)
A_VA	-0.0829	-0.0026	0.0711	-3.3338	-2.0756 .	-1.6408	-0.4989	0.2329	0.2477 .
	(0.370)	(0.205)	(0.167)	(2.177)	(1.230)	(1.258)	(0.323)	(0.170)	(0.146)
A_Energy	-0.4408 **	-0.2443 **	-0.1974 *	-5.7096 **	-3.3670 ***	-3.5138 ***	-0.4989 **	-0.2752 **	-0.2200 **
	(0.171)	(0.095)	(0.079)	(1..925)	(0.981)	(1.045)	(0.152)	(0.084)	(0.071)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8620	0.8671	0.8735	0.6966	0.6969	0.7013	0.7941	0.7960	0.7989
Deviance	19.7531	19.0306	18.1139	193.6893	193.4944	190.7221	10.4747	10.3744	10.2268

APPENDIX VIII – Energy Regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	34.6137 ***	18.3239 ***	14.4687 ***	120.596	66.1810	95.0923	22.1823 *	13.0048 **	11.8777 **
	(9.696)	(5.221)	(4.320)	(140.504)	(75.6700)	(570.689)	(8.914)	(4.037)	(4.101)
FE_CO2	0.1173	0.0362	-0.0158	-0.4471	-0.0929	-0.5786	-0.0691	-0.0578	-0.0840
	(0.151)	(0.082)	(0.066)	(2.092)	(1.011)	(1.639)	(0.115)	(0.063)	(0.052)
FE_CH4	-0.3848 **	-0.2280 **	-0.1939 ***	0.9257	0.4437	0.8110	-0.3647 **	-0.2263 ***	-0.2083 ***
	(0.135)	(0.070)	(0.055)	(1.396)	(0.784)	(0.940)	(0.119)	(0.066)	(0.057)
PI_CO2	0.8166 ***	0.4127 ***	0.2916 ***	0.1040	0.1260	0.0652	0.5527 ***	0.2906 ***	0.2107 **
	(0.197)	(0.104)	(0.082)	(1.153)	(0.575)	(0.924)	(0.159)	(0.088)	(0.073)
PI_CH4	-0.3754 *	-0.1978 *	-0.1638 *	-2.6714 .	-1.5895 *	-1.9399 .	-0.1493	-0.0719	-0.0606
	(0.159)	(0.087)	(0.073)	(1.511)	(0.808)	(1.056)	(0.136)	(0.076)	(0.065)
B_CO2	-0.8639 ***	-0.4569 ***	-0.3506 ***	-8.2411 **	-4.8346 ***	-5.1433 **	-0.3027 *	-0.1613 *	-0.1237 .
	(0.181)	(0.096)	(0.078)	(2.533)	(1.258)	(1.658)	(0.145)	(0.081)	(0.069)
B_CH4	0.2388	0.1235	0.0909	0.5211	0.3305	0.1614	0.0470	0.0134	-0.0061
	(0.154)	(0.082)	(0.065)	(0.822)	(0.467)	(0.627)	(0.138)	(0.078)	(0.068)
T_CO2	-0.2270	-0.1024	-0.1014	6.8154	3.9486	5.1950	-0.3871	-0.2233	-0.2144
	(0.378)	(0.209)	(0.178)	(5.435)	(2.655)	(4.108)	(0.305)	(0.172)	(0.149)
T_CH4	-0.9572 ***	-0.5197 ***	-0.4022 ***	-1.2516	-0.5946	-1.2790	-0.4966 **	-0.2898 **	-0.2522 **
	(0.198)	(0.110)	(0.092)	(2.187)	(0.614)	(1.500)	(0.164)	(0.091)	(0.077)
NRR	0.2148 *	0.1262 *	0.1037 *	1.2797	0.6508	1.0913	0.2814 ***	0.1590 **	0.1296 **
	(0.109)	(0.062)	(0.052)	(1.144)	(0.614)	(0.735)	(0.084)	(0.049)	(0.043)
FuelE	0.3225 ***	0.1830 ***	0.1504 **	1.4658	0.8005	0.8082	0.2315 **	0.1328 **	0.1117 **
	(0.096)	(0.054)	(0.049)	(1.434)	(0.752)	(1.143)	(0.079)	(0.045)	(0.041)

EP_R	0.0267	0.0234	0.0330	0.1588	0.0715	0.2845	0.1261 **	0.0746 **	0.0704 **
	(0.071)	(0.040)	(0.034)	(0.723)	(0.384)	(0.470)	(0.047)	(0.027)	(0.024)
EP_Coal	0.0916	0.0354	0.01363	-0.8384	-0.4779 .	-0.4406	0.1440 *	0.0680 .	0.0442
	(0.085)	(0.046)	(0.036)	(0.525)	(0.283)	(0.357)	(0.064)	(0.035)	(0.029)
EP_Oil	0.0571	0.0177	0.0060	0.9635	0.5206	0.6612 *	-0.0179	-0.0215	-0.0301
	(0.063)	(0.033)	(0.027)	(0.719)	(0.410)	(0.321)	(0.053)	(0.030)	(0.027)
EP_N	-0.1250 *	-0.0677 *	-0.0494 *	-0.5010	-0.3608	-0.3555	-0.0644	-0.0328	-0.0225
	(0.053)	(0.029)	(0.025)	(0.506)	(0.267)	(0.328)	(0.041)	(0.024)	(0.022)
Urban_P	-4.0407 **	-1.9757 **	-1.3132 *	-20.2333	-10.2340	-19.7985	-2.4712 *	-1.2771 .	-0.9303 .
	(1.391)	(0.751)	(0.626)	(26.843)	(14.380)	(20.379)	(1.248)	(0.678)	(0.560)
T_Energy	1.1912 *	0.7639 *	0.7846 **	-3.386	-1.9390	-3.8020	1.3831 **	0.8591 **	0.8446 ***
	(0.607)	(0.341)	(0.291)	(7.262)	(3.847)	(5.068)	(0.491)	(0.273)	(0.236)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8828	0.8880	0.8936	0.7152	0.7174	0.7163	0.8232	0.8259	0.8296
Deviance	16.7807	16.0346	15.2323	181.8327	180.4130	181.1208	8.9936	8.8580	8.6684

APPENDIX IX – Fuel Exploitation regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	12.7873 ***	8.0189 ***	7.6096 ***	23.8876	17.4763	8.0510	9.7125 ***	6.2748 ***	6.2139 ***
	(2.895)	(1.571)	(1.269)	(19.552)	(10.656)	(14.142)	(2.545)	(1.449)	(1.260)
FE_CO2	-0.1512	-0.1222 .	-0.1594 **	-1.2747	-0.5743	-0.6737	-0.1178	-0.0931	-0.1235 *
	(0.119)	(0.067)	(0.057)	(1.2107)	(0.6469)	(0.8542)	(0.103)	(0.060)	(0.053)
FE_CH4	-0.5973 ***	-0.3437 ***	-0.2951 ***	-1.5826 **	-0.9815 **	-1.0352 *	-0.4315 ***	-0.2599 ***	-0.2417 ***
	(0.113)	(0.060)	(0.047)	(0.5971)	(0.328)	(0.445)	(0.098)	(0.055)	(0.048)
NRR	0.2070	0.1053	0.0666	0.2318	0.0755	0.1072	0.2675 *	0.1416 *	0.1032 *
	(0.131)	(0.073)	(0.060)	(0.913)	(0.533)	(0.631)	(0.105)	(0.060)	(0.051)
FuelE	0.4941 ***	0.2784 ***	0.2267 ***	1.9515 .	1.1438 .	0.5855	0.2795 ***	0.1622 ***	0.1431 **
	(0.097)	(0.058)	(0.057)	(1.069)	(0.591)	(0.740)	(0.078)	(0.046)	(0.044)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8645	0.8696	0.8755	0.6484	0.6461	0.6563	0.7978	0.8005	0.8045
Deviance	19.3952	18.6670	17.8151	224.4766	225.9031	219.3968	10.2836	10.1470	9.9419

APPENDIX X – Power Industry regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**
(Intercept)	1.0517	1.3127	1.8141	19.1371	13.5651	8.4715	-0.7660	-0.0655	0.506
	(2.815)	(1.550)	(1.316)	(21.576)	(11.211)	(15.552)	(2.277)	(1.315)	(1.201)
PI_CO2	0.0784	0.0164	-0.0264	-0.4013	-0.2189	-0.3762	0.1560	0.0607	0.0123
	(0.178)	(0.097)	(0.076)	(0.789)	(0.411)	(0.669)	(0.144)	(0.082)	(0.071)
PI_CH4	-0.1840	-0.1102	-0.1037	-2.7648	-1.3581	-1.8586 .	-0.1693	-0.0844	-0.0624
	(0.162)	(0.089)	(0.073)	(1.722)	(0.928)	(1.000)	(0.128)	(0.073)	(0.065)
EP_R	0.0420	0.0243	0.0225	-0.7234	-0.4797	-0.4481	0.1412 **	0.0830 **	0.0747 **
	(0.071)	(0.039)	(0.033)	(0.638)	(0.371)	(0.468)	(0.048)	(0.027)	(0.024)
EP_Coal	0.1628 .	0.0717	0.0529 .	-0.3512	-0.2034	-0.2659	0.1874 **	0.0920 *	0.0615 .
	(0.091)	(0.052)	(0.027)	(0.430)	(0.250)	(0.315)	(0.069)	(0.040)	(0.034)
EP_Oil	0.0949	0.0557 .	0.0379	1.2728 **	0.7451 **	0.8873 **	0.0304	0.0169	0.0149
	(0.058)	(0.032)	(0.042)	(0.481)	(0.263)	(0.281)	(0.041)	(0.023)	(0.020)
EP_N	-0.2095	-0.1180 ***	-0.0953 ***	-0.8862 *	-0.5275 **	-0.7556 **	-0.1247 ***	-0.0716 ***	-0.0623 **
	(0.063)	(0.034)	(0.027)	(0.349)	(0.203)	(0.262)	(0.036)	(0.021)	(0.019)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8619	0.8652	0.8688	0.6622	0.6609	0.6780	0.8018	0.8009	0.7991
Deviance	19.7619	19.2977	18.7833	215.6518	216.5142	205.5950	10.0795	10.1295	10.2184

APPENDIX XI – Buildings Regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**	**Logit**	**Probit**	**Cloglog**
(Intercept)	15.1289 *	9.1463 *	7.7576 *	197.496 **	114.3027 **	135.1089 **	6.8928	4.3952	3.8691
	(6.519)	(3.594)	(3.090)	(65.565)	(35.933)	(43.035)	(5.468)	(3.031)	(2.590)
B_CO2	-0.4735 ***	-0.3016 ***	-0.2967 ***	-8.6763 ***	-4.8644 ***	-5.3532 ***	-0.1425	-0.1004 .	-0.1113 *
	(0.124)	(0.071)	(0.063)	(2.167)	(1.219)	(1.411)	(0.103)	(0.060)	(0.054)
B_CH4	0.1889	0.1083 .	0.0953 .	0.3871	0.2221	0.0983	-0.0255	-0.0099	-0.0010
	(0.123)	(0.065)	(0.052)	(0.711)	(0.405)	(0.479)	(0.118)	(0.068)	(0.060)
Urban_P	-1.8521	-1.0507	-0.8115	-17.4956 .	-9.5760 .	-15.5180 *	-0.6412	-0.4048	-0.3587
	(1.393)	(0.758)	(0.644)	(10.009)	(5.400)	(6.720)	(1.179)	(0.651)	(0.556)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8601482	0.8649576	0.8706358	0.6840	0.6837	0.6920	0.7871	0.7883	0.7898
Deviance	20.01957	19.33111	18.51829	201.7396	201.9126	196.6186	10.8287	10.7668	10.6936

APPENDIX XII – Transport Regression Results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	12.1338 **	6.6642 **	5.7451 ***	-7.7378	14.9236	-18.8842	5.8334 .	3.7596 *	3.9505 **
	(3.808)	(2.090)	(1.726)	(43.842)	(35.804)	(25.413)	(3.118)	(1.755)	(1.510)
T_CO2	-0.2501	-0.1632	-0.2205	-0.8740	-1.8640	0.0122	-0.1598	-0.1345	-0.2111 .
	(0.278)	(0.160)	(0.141)	(4.313)	(3.527)	(2.464)	(0.219)	(0.125)	(0.111)
T_CH4	-0.6337 ***	-0.3799 ***	-0.3310 ***	-2.9640	-1.2043	-1.9711 .	-0.3325 *	-0.2085 *	-0.1989 **
	(0.169)	(0.095)	(0.080)	(1.951)	(1.404)	(1.095)	(0.142)	(0.082)	(0.072)
T_Energy	0.5711	0.5749 .	0.8341 ***	12.034 *	8.0027 *	6.9880 *	0.7551 .	0.6073 **	0.8009 ***
	(0.544)	(0.305)	(0.252)	(5.066)	(3.604)	(3.397)	(0.414)	(0.235)	(0.203)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8617	0.8669	0.8745	0.6650	0.6584	0.6771	0.7907	0.7941	0.8002
Deviance	19.8040	19.0478	17.9705	213.8933	218.0894	206.1650	10.6467	10.4755	10.1639

APPENDIX XIII – Industry Regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	14.6252 ***	7.2583 ***	5.1137 ***	-30.8599 .	-12.8143	-25.1082 *	13.5821 ***	7.3640 ***	5.7729 ***
	(3.558)	(1.928)	(1.513)	(17.462)	(10.030)	(11.965)	(3.092)	(1.709)	(1.405)
IC_CO2	-0.0222	-0.0216	-0.0249	-2.4526	-1.5978	-1.7268	0.1206	0.0551	0.0342
	(0.180)	(0.103)	(0.089)	(2.313)	(1.346)	(1.574)	(0.1617)	(0.090)	(0.075)
IC_CH4	0.1632	0.0946	0.0841	-1.1921	-0.6605	-0.7022	0.1735	0.1093	0.1103 .
	(0.145)	(0.082)	(0.070)	(1.340)	(0.759)	(0.925)	(0.130)	(0.072)	(0.062)
IP_CO2	-0.6170 .	-0.2700	-0.1633	-0.3058	-0.0767	-0.6025	-0.6211 *	-0.3066 *	-0.2181 .
	(0.319)	(0.184)	(0.153)	(1.434)	(0.840)	(0.975)	(0.264)	(0.151)	(0.128)
IP_CH4	0.1722	0.0553	-0.0045	0.3670	0.1499	0.4543	0.1031	0.0303	-0.0123
	(0.131)	(0.075)	(0.065)	(1.134)	(0.634)	(0.887)	(0.117)	(0.067)	(0.057)
I_Emp	-2.5096 ***	-1.3605 ***	-1.0811 ***	2.6098	1.8432	1.7330	-2.2048 ***	-1.2441 ***	-1.0569 ***
	(0.591)	(0.346)	(0.309)	(5.154)	(2.917)	(3.119)	(0.529)	(0.304)	(0.268)
I_VA	1.0433 *	0.5809 *	0.4639 *	7.0378 .	3.7461 .	5.7477 *	1.0037 *	0.5449 *	0.4181 *
	(0.455)	(0.261)	(0.227)	(4.157)	(2.214)	(2.746)	(0.394)	(0.228)	(0.207)
I_Energy	-0.5164	-0.2532	-0.1765	10.8168 *	6.9040 *	7.0271 *	-1.0183 *	-0.5571 *	-0.4541 *
	(0.426)	(0.242)	(0.212)	(4.681)	(2.755)	(3.077)	(0.406)	(0.227)	(0.193)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8642	0.8673	0.8708	0.6461	0.6446	0.6633	0.8049	0.8061	0.8077
Deviance	19.4426	18.9939	18.4980	225.9499	226.8972	214.9791	9.9262	9.8635	9.7828

APPENDIX XIV – Waste Regression results

	One-part Models			Two-part Models					
				First Component			Second Component		
	Logit	Probit	Cloglog	Logit	Probit	Cloglog	Logit	Probit	Cloglog
(Intercept)	4.3727 *	2.6580 *	2.2785 *	-22.1730 **	-6.8754	-23.7068 ***	2.5530	1.7344 .	1.5909 .
	(2.082)	(1.121)	(0.888)	(7.628)	(4.225)	(5.144)	(1.716)	(0.990)	(0.892)
W_CO2	0.0493	0.01608	0.0032	-0.0322	-0.0037	-0.0495	0.0241	0.0076	-0.0002
	(0.038)	(0.020)	(0.016)	(0.173)	(0.100)	(0.140)	(0.033)	(0.018)	(0.015)
W_CH4	-0.2095 .	-0.1209 .	-0.1146 *	0.1646	0.0550	0.2623	-0.0894	-0.0623	-0.0723
	(0.127)	(0.068)	(0.054)	(0.435)	(0.238)	(0.289)	(0.106)	(0.061)	(0.055)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.8575	0.8608	0.8646	0.6291	0.6250	0.6483	0.7870	0.7876	0.7885
Deviance	20.3979	19.9316	19.3774	236.7900	239.3827	224.5390	10.8368	10.8044	10.7590

APPENDIX XV – Data Collection (Country-level)

Population: Population, total | Data

Population Density (people per sq. km of land area): Population density (people per sq. km of land area) | Data

Employment: OECD Data Explorer • Employment and unemployment by five-year age group and sex - levels

GDP growth (anual %): GDP growth (annual %) | Data

Annual GDP and components - output approach: OECD Data Explorer • Annual GDP and components - output approach

GDP (constant 2015 US$ & current prices): GDP (constant 2015 US$) - OECD members | Data & GDP (current US$) | Data

Gross Fixed Capital Formation (current 2015 US$ & % GDP): Gross fixed capital formation (constant 2015 US$) - OECD members | Data & Gross fixed capital formation (% of GDP) - OECD members | Data

Current Health Expenditure (% GDP): Current health expenditure (% of GDP) - OECD members | Data

Government Expenditure on Education, total (%GDP): Government expenditure on education, total (% of GDP) - OECD members | Data

Foreign Direct Investment, Net (BoP, current US$): Foreign direct investment, net (BoP, current US$) - OECD members | Data

Adjusted savings (net florest depletion, energy depletion & mineral depletion): Adjusted savings: net forest depletion (% of GNI) - OECD members | Data & Adjusted savings: energy depletion (% of GNI) - OECD members | Data & Adjusted savings: mineral depletion (% of GNI) - OECD members | Data

Electricity production: Electricity production from renewable sources, excluding hydroelectric (% of total) - OECD members | Data & Electricity production from nuclear sources (% of total) - OECD members | Data & Electricity production from oil, gas and coal sources (% of total) - OECD members | Data & Electricity production from coal sources (% of total) - OECD members | Data & Electricity production from oil sources (% of total) - OECD members | Data

Energy Use - KG of oil equivalent per capita: Energy use (kg of oil equivalent per capita) - OECD members | Data

Energy Use – Kg Oil Equivalent per 1000$GDP at Constant 2021 PPP: Energy use (kg of oil equivalent) per $1,000 GDP (constant 2021 PPP) - OECD members | Data

Types Energy Use

Alternative & Nuclear Energy (% Total Energy Use): Alternative and nuclear energy (% of total energy use) - OECD members | Data

Fossil fuel energy consumption (% of total energy): Fossil fuel energy consumption (% of total) - OECD members | Data

Combustible renewables & waste (% of total energy): Combustible renewables and waste (% of total energy) - OECD members | Data

Renewable energy consumption (% total final energy consumption): Renewable energy consumption (% of total final energy consumption) - OECD members | Data

Total natural resources rents (% of GDP): Total natural resources rents (% of GDP) - OECD members | Data

R&D expenditure (% of GDP): Research and development expenditure (% of GDP) - OECD members | Data & Gross domestic spending on R&D | OECD (What we are using)

Labor force, total: Labor force, total - OECD members | Data

Environmental Protection Expenditure Accounts: OECD Data Explorer • Environmental Protection Expenditure Accounts

Green Growth - Production-based GHG productivity: OECD Data Explorer • Green Growth

Demand-based GHG productivity: OECD Data Explorer • Green Growth

Production-based GHG emissions: OECD Data Explorer • Green Growth

Demand-based GHG emissions: OECD Data Explorer • Green Growth

Forest Area (% Total Land Area): Forest area (% of land area) - OECD members | Data

Forest resource stocks (m3): OECD Data Explorer • Green Growth

Naturally regenerating forests: OECD Data Explorer • Green Growth

Level of water stress: freshwater withdrawal as a proportion of available freshwater resources: Level of water stress: freshwater withdrawal as a proportion of available freshwater resources - OECD members | Data

Threatened mammal, bird and vascular plant species, % of total species: OECD Data Explorer • Green Growth

Mean population exposure to PM2.5: OECD Data Explorer • Green Growth

Mortality from exposure to ambient PM2.5: OECD Data Explorer • Green Growth

Mortality from exposure to ambient ozone (O3): OECD Data Explorer • Green Growth

Renewable energy public RD&D budget, % total energy public RD&D: OECD Data Explorer • Green Growth

Development of environment-related technologies: % all technologies, % inventions worldwide & inventions per capita: OECD Data Explorer • Green Growth

Environmentally related tax revenue: % GDP & % total tax revenue: OECD Data Explorer • Green Growth

Energy related tax revenue, % total environmental tax revenue: OECD Data Explorer • Green Growth

Labour tax revenue, % GDP & % Total tax revenue: OECD Data Explorer • Green Growth

Total GHG emissions per capita (TCO2e/capita): Total greenhouse gas emissions excluding LULUCF per capita (t CO2e/capita) - OECD members | Data

GHG emissions by country: OECD | Agriculture, Bunker Fuels, Energy, Industrial Processes, Land-Use Change and Forestry, Waste | Greenhouse Gas (GHG) Emissions | Climate Watch

CO2 emissions per capita (TCO2/capita): Carbon dioxide (CO2) emissions excluding LULUCF per capita (t CO2e/capita) - OECD members | Data

CO2 emissions by country: OECD | Agriculture, Bunker Fuels, Energy, Industrial Processes, Land-Use Change and Forestry, Waste | Greenhouse Gas (GHG) Emissions | Climate Watch

CH4 emissions by country: OECD | Agriculture, Bunker Fuels, Energy, Industrial Processes, Land-Use Change and Forestry, Waste | Greenhouse Gas (GHG) Emissions | Climate Watch

Total waste generated, tonnes: OECD Data Explorer • Waste - Waste by sector: generation, recovery and recycling

Environmental Policy Stringency (EPS) index: OECD Data Explorer • OECD Environmental Policy Stringency Index

Market based policies: OECD Data Explorer • OECD Environmental Policy Stringency Index

Non-market based policies: OECD Data Explorer • OECD Environmental Policy Stringency Index

Technology support policies: OECD Data Explorer • OECD Environmental Policy Stringency Index

Wastewater – connection rates to treatment: OECD Data Explorer • Wastewater - connection rates to treatment

APPENDIX XVI – Data Collection (Sector-Level)

Employed population by economic activity: OECD Data Explorer • Employed population by economic activity

Annual capital formation by economic activity: OECD Data Explorer • Annual capital formation by economic activity

Business enterprise R&D expenditure by industry: OECD Data Explorer • Business enterprise R&D expenditure by industry

Green Growth - Energy consumption by sector: OECD Data Explorer • Green Growth

Greenhouse gas footprint (Production-based) by sector: OECD Data Explorer • Greenhouse Gas Footprints (GHGFP): Principal indicators

Greenhouse gas footprint (Demand-based) by sector: OECD Data Explorer • Greenhouse Gas Footprints (GHGFP): Principal indicators

Value added by sector (% GVA): OECD Data Explorer • Green Growth

Value added by sector (% GDP)

Agriculture, forestry, and fishing, value added (% of GDP) - OECD members | Data

Manufacturing, value added (% of GDP) - OECD members | Data

Industry (including construction), value added (% of GDP) - OECD members | Data

Services, value added (% of GDP) - OECD members | Data

Greenhouse Gas Footprints (GHGFP): OECD Data Explorer • Greenhouse Gas Footprints (GHGFP): Emissions embodied in final demand by expenditure category

GHG emissions by sector: OECD | Agriculture, Bunker Fuels, Energy, Industrial Processes, Land-Use Change and Forestry, Waste | Greenhouse Gas (GHG) Emissions | Climate Watch

CO2 emissions by sector: OECD | Agriculture, Bunker Fuels, Energy, Industrial Processes, Land-Use Change and Forestry, Waste | Greenhouse Gas (GHG) Emissions | Climate Watch

CO2 emissions

Carbon dioxide (CO2) emissions (total) excluding LULUCF (Mt CO2e) - OECD members | Data

Carbon dioxide (CO2) emissions from Industrial Processes (Mt CO2e) - OECD members | Data

Carbon dioxide (CO2) emissions from Transport (Energy) (Mt CO2e) - OECD members | Data

Carbon dioxide (CO2) emissions from Industrial Combustion (Energy) (Mt CO2e) - OECD members | Data

Carbon dioxide (CO2) emissions from Power Industry (Energy) (Mt CO2e) - OECD members | Data

Carbon dioxide (CO2) emissions from Fugitive Emissions (Energy) (Mt CO2e) | Data

Carbon dioxide (CO2) emissions from Building (Energy) (Mt CO2e) | Data

Carbon dioxide (CO2) emissions from Waste (Mt CO2e) - OECD members | Data

CO2 emissions (% change from 1990): Carbon dioxide (CO2) emissions (total) excluding LULUCF (% change from 1990) - OECD members | Data

Carbon Intensity of GDP (kg CO2 per 2021 PPP$ of GDP & kg CO2 per constant 2015 US$ of GDP): Carbon intensity of GDP (kg CO2e per 2021 PPP $ of GDP) - OECD members | Data & Carbon intensity of GDP (kg CO2e per constant 2015 US$ of GDP) - OECD members | Data

CH4 emissions by sector: OECD | Agriculture, Bunker Fuels, Energy, Industrial Processes, Land-Use Change and Forestry, Waste | Greenhouse Gas (GHG) Emissions | Climate Watch

CH4 emissions

Methane (CH4) emissions (total) excluding LULUCF (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Agriculture (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Industrial Processes (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Transport (Energy) (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Industrial Combustion (Energy) (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Power Industry (Energy) (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Fugitive Emissions (Energy) (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Building (Energy) (Mt CO2e) - OECD members | Data

Methane (CH4) emissions from Waste (Mt CO2e) - OECD members | Data

CH4 emissions (% change from 1990): Methane (CH4) emissions (total) excluding LULUCF (% change from 1990) - OECD members | Data

Generation of waste by economic activity: Statistics | Eurostat

Annual freshwater withdrawals

Annual freshwater withdrawals, total (billion cubic meters) - OECD members | Data

Annual freshwater withdrawals, total (% of internal resources) - OECD members | Data

Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal) - OECD members | Data

Annual freshwater withdrawals, industry (% of total freshwater withdrawal) - OECD members | Data

Annual freshwater withdrawals, domestic (% of total freshwater withdrawal) - OECD members | Data

GHG by sector and by Gas

GHG data from UNFCCC | UNFCCC