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Eco-innovation and determinants of GHG emissions in OECD countries

1. Introduction

The consequences of global warming are a clear reality. As such, all countries must commit to international agreements to establish common lines of action allowing them to take advantage of synergies and tackle this situation as effectively as possible. From the United Nations Framework Convention on Climate Change in 1992 to Cop25-Chile in 2019, international consensus has been sought to address the problem of climate change. The aim is to combat an increasingly widespread scourge that threatens to destroy the planet and does not discriminate on the basis of economics, affecting all territories equally (Kahn et al., 2019). Issues such as resource scarcity, pollution, desertification and, ultimately, environmental imbalance are endangering the health of the population (Watts et al., 2018).

The search for solutions to climate change and sustainability gives experimentation a prominent role (Hildén et al., 2017). Technology transfer and innovation can effectively respond to climate change, ensuring sustainable economic growth (Ferreira et al., 2020). However, the transition to sustainable development also involves a shift in the behaviour of society, and cultural differences should not represent an obstacle to such a change (Soyez, 2012; Sreen et al., 2018). According to an extensive literature, sustainability is grounded in the conjunction of three pillars: the economy, society and the environment (Barbier, 1987; Moldan et al., 2012; Boyer et al., 2016). Though, authors such as Purvis et al. (2019) call for a theoretical basis for this conception, to be able to apply it to specific contexts. Returning to the original definition, sustainable development is aimed at meeting current needs without compromising the resources and opportunities of future generations (United Nations, 1987). Wang and Li (2012) argue that it is possible to achieve this if economic growth can be reconciled with environmental quality.

There is a certain scientific consensus on the need to mitigate greenhouse gas (GHG) emissions to ensure compliance with the targets set in international agreements (Hickmann, 2017). The Kyoto Protocol signed in 1997 was the first international agreement aimed at GHG emissions, which are the primary cause of climate change. Population, growth and economic structure are factors that have a two-way relationship with trends in GHG emissions (Romero and Gramkow, 2021). In the absence of countervailing measures, climate change has adverse effects on economic activity, the costs of which are estimated to range between 5% and 15% of GDP (IPCC, 2014). In turn, economic growth can also intensify emissions, although the relationship is not always linear but rather depends on the income level of the country (Dietz et al., 2018; Stoerk et al., 2018).

Over the last two decades, changes to production processes have been fostered in an effort to reduce GHG emissions, with calls for the introduction of innovative technologies in sectors such as construction (Yu et al., 2018), industry (Frigon et al., 2020), the food trade (Mylan et al., 2015; Galera-Quiles et al., 2021) and in the circular economy (de Jesus et al., 2018). Thus, emphasis is placed on the concept of eco-innovation, which is in line with the definition of innovation provided by the Oslo Manual (OECD, 2005): both concepts incorporate the application of new technologies developed by another institution.

Eco-innovation is sometimes primarily driven by purposes other than environmental ones. For example, innovation in waste management may be aimed at cutting costs, while additionally leading to a reduction in GHG emissions. The numerous papers on this concept all focus on the introduction of know-how that avoids adverse effects on the environment, fostering more efficient use of available resources (European Commission, 2013; Hojnik and Ruzzier, 2016; Tamayo-Obergozo et al., 2017). The search for forms of production compatible with environmental quality is encouraging companies and leaders to implement eco-innovation in sectors that have a major impact on all issues related to climate change; these include agriculture (FAO, 2017), tourism (Reyes-Santiago et al., 2017) and industry (Maldonado-Guzmán and Garza-Reyes, 2020). Innovation in the environmental sphere seeks to prevent the negative impacts of economic and social activity on the environment, by reducing energy consumption, waste or excessive use of natural resources.

In this context, the empirical analysis in this study is aimed at identifying the connection between eco-innovation and GHG emissions using a panel data sample of developed countries. The research is conducted in two stages. The first stage quantifies the eco-innovation by OECD countries during the period 2011-2018, using an extension of data envelopment analysis, DEA-Bootstrap. An intertemporal analysis is carried out to help ensure the stability of the findings. In addition, the calculation of the Malmquist Index

(MI) supports the consistency of the previous results and reveals the changes in productivity. In the second stage, the two-step Generalized Method of Moments (GMM) is used to examine the determinants of GHG emissions, including the calculated eco-innovation and other factors that a priori could also be expected to affect emissions, such as environmental and resource productivity and environmental policies and management.

There are numerous papers in the literature that focus on analysing the environmental implication of new technologies. For example, Balsalobre et al. (2015) and Álvarez-Herránz et al. (2017) examine the effect of energy innovation on GHG emissions. Others study the connection between environmental regulation and technological innovation (Guo et al., 2017; Yuan and Xiang, 2018; Feng et al., 2018), as well as the possible link between financial development, energy innovation and environmental quality (Baloch et al., 2021) or internationalization and eco-innovation (Hojnik et al., 2018; Šūmakaris et al., 2020). Within this sphere, the results of the present research represent a novel contribution to this paradigm, where environmental innovation plays an important role in halting climate change. First, the length of the period analysed means that conclusions can be drawn that are immediately applicable by decision-makers. Secondly, the intertemporal efficiency analysis makes it possible to establish a ranking of countries and extract a performance profile of those at the top of the ranking. Thirdly, the functions estimated with GMM shed light on the factors that need to be enhanced in order to reduce emissions, and can help guide forthcoming international agreements.

The rest of the paper is structured as follows. Section 2 reviews the literature on environmental innovation and the issues surrounding GHG emissions. Section 2 presents the methods applied and the samples used. Section 4 analyses the results of the research. Lastly, Section 5 summarizes the conclusions of the study, the contribution it makes and the limitations.

2. Literature review

2.1. Eco-innovation, green innovation or environmental innovation

There is a fairly widespread belief about the positive effects that innovation and technology transfer can have on the environment. According to the OECD, GHG emissions decreased by around 7% during the period 2008-2017, while at the same time the patents it classifies as environment-related technologies rose by over 18%. However, a rebound in emissions was detected in 2018, along with a decline in patents aimed at tackling climate change. That said, a specific type of innovation must be encouraged: the introduction of new, environmentally-friendly technologies aimed at achieving socially desirable results (Voegtlin and Scherer, 2017; Lee and Trimi, 2018). Mongo et al. (2021) show that the effects of environmental innovation do not emerge in the short term; a longer time horizon is needed to reduce emissions.

The transformation towards a green economy involves promoting innovative processes aimed at mitigating climate change. In recent decades, the literature has proposed concepts such as eco-, green or environmental innovation, all of which centre on preventing the negative impact of human actions (Shin et al., 2018). The concept of eco-innovation can be attributed to the works of Fussler and James (1996) and James (1997), who addressed the emergence of new products and processes that provide added value to the customer and the company while simultaneously lessening the impact on ecosystems. Green innovation encompasses the introduction of technologies related to energy saving, pollution prevention, recycling, green product design or firms' environmental management (Chen et al., 2006). Lastly, environmental innovation centres on promoting economic development while reducing adverse effects on the environment (Polzin et al., 2016). These three concepts, which have very similar purposes, have sparked the interest of the scientific community, prompting it to approach innovation as a key factor for achieving economic and social objectives in a way that respects the planet (Läple et al., 2015).

International organizations need quantitative information that allows them to assess the results of eco-innovation and identify its key drivers (Arundel and Kemp, 2009). In short, governments and companies need a paradigm of knowledge for the implementation of sustainable plans that mitigate global warming (García-Granero et al., 2018).

All the measurement instruments developed to quantify eco-innovation have been based around the four categories originally established by Acs and Audretsch (1993): input measures, including research and development (R&D) expenditure, R&D personnel and innovation expenditure; intermediate output measures, relating to patents and scientific articles; direct output measures, such as the number of innovations or the increase in sales of new products; and indirect impact measures, such as changes in resource efficiency and productivity. In this research, inputs and intermediate output measures are used to measure the eco-innovation by OECD countries. A broad literature supports the use of DEA for measuring efficiency in relation to environmental issues (Beltrán-Esteve and Picazo-Tadeo, 2017; Feng et al., 2017; Mavi et al., 2019; Mavi and Mavi, 2021).

2.2. Mitigation of GHG emissions

The various international agreements on climate change adopted in recent decades have been aimed at reducing GHG emissions, driving new strategies that act in different directions, from land use and infrastructure to industry as a whole (Han and Zhu, 2020; Liu et al., 2020; Zhang et al., 2020). A large amount of economic resources has been targeted at promoting the use of clean technologies to facilitate the achievement of this objective (IPCC, 2018). The scientific community needs information on specific production processes and technology in order to propose an effective treatment; as yet there is no sectoral classification associated with emissions (Romero and Gramkow, 2021).

The implementation of climate policies requires solid theoretical foundations and sound statistical information to ensure the success of the efforts made. Under the Paris Agreement, which set emission reduction as a priority in order to curb climate change, a wide-ranging scientific paradigm was developed aimed at clearly identifying the economic and social factors responsible for GHG emissions. Sectors such as transport (Andrés and Padilla, 2018), agriculture (Rotz, 2018) and energy (Xu et al., 2019) have been extensively analysed. Nevertheless, the conclusions drawn cannot always be generalized to all territories or periods of time. According to Picazo-Tadeo et al. (2014), improving energy efficiency is the most effective way of cutting emissions. Sadik-Zada and Gatto (2021) show that there is a monotonically increasing relationship between oil rents and the quantigy of GHG. Other authors such as Liobikienė and Butkus (2017) or

Jin and Kim (2018) argue that improved energy efficiency must be combined with the use of renewable energies in order to curb global warming and ensure sustainable growth.

There is also a fairly large stream of research in which innovation is considered to have a notable impact on emission reduction (Kahouli, 2018; Yu and Xu, 2019). However, some contradictions have been detected: Fernández et al. (2018) show that R&D expenditure reduces CO_2 emissions in the EU and US, but raises them in China. Koçak and Ulucak (2019) find evidence that certain types of R&D expenditure in OECD countries, such as renewable energy R&D and nuclear energy R&D, are not achieving their intended objectives.

Three research methods have been used to analyse the determinants of GHG emissions: IPAT (Impact, Population, Affluence, Technology), Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA). IPAT, originally proposed by Ehrlich and Holdren (1971), is a mathematical function that explains the impact of population, affluence and technology on the environment. The introduction of the extended Input-Output framework (Isard et al., 1968; Leontief, 1970) allowed the application of SDA and IDA to be extended to energy and emissions. Both of these methods examine the determinants of the change in ~~aggregate~~ energy consumption, GHG emissions and energy efficiency. The difference between them lies in the scope of the results: IDA only captures direct effects, while SDA also identifies indirect impacts. Authors such as Hu et al (2017), Wang and Feng (2018a, 2018b) propose decomposition analysis to study the determinants of GHG in China, however when using a panel sample composed of different countries, econometric models are more appropriate. Therefore, this research proposes the use of the extended IPAT, which consists of using two-step GMM to estimate a stochastic model that includes technology and GDP per capita along with other aspects such as environmental productivity, management and policies.

3. Methods and materials

The research was conducted on a panel data sample of 28 OECD countries[1]. The study was carried out for a time period of eight years, 2011-2018, in order to ensure the consistency of the analysis and accurately estimate the effect of innovation on emission

[1] Chile, Israel, Korea, Luxembourg, Mexico, New Zealand, the Slovak Republic and Switzerland were eliminated due to a lack of complete statistical data.

reduction. Both the proposed efficiency analysis methods and GMM are supported by an extensive literature in the field of climate change (Luo et al., 2019; Mavi and Mavi, 2021; Hakimi and Inglesi-Lotz, 2020; Chen et al., 2021).

3.1. Stage 1: Eco-innovation, DEA and MI

The measurement of efficiency dates back to the original paper by Farrell (1957), which gave rise to stochastic frontier analysis (SFA) and DEA. The former applies econometric techniques to estimate the production frontier, while DEA uses linear programming to determine the efficient frontier.

DEA is a non-parametric model developed by Charnes, Cooper and Rhodes (1978) under the assumption that production generates constant returns to scale, whereby any change in the inputs produces a proportional change in the outputs (CCR model). In order to avoid this assumption of proportionality, DEA was subsequently extended by Banker, Charnes and Cooper (1984) to account for the existence of variable returns to scale (BCC model). Both models can be either input- or output-oriented, that is, they can seek to minimize the resources needed to obtain a given output, or vice versa, to maximize the output obtained from the available inputs. The efficiency levels calculated by solving the linear programming problem are bounded between 0 and 1, with 1 being the maximum efficiency level. The degree of inefficiency is measured by the distance of the efficiency score from unity, resulting from a sub-optimal combination of inputs and outputs.

There are two major advantages of DEA. First, it allows a relationship to be established between the inputs and outputs that characterize the decision-making units (DMUs) of the sample without having to specify a functional form. Second, it can provide additional information on how to improve the performance of inefficient DMUs (He et al., 2016). These advantages have led to the extensive use of this method in the field of sustainability. Covering a long period from 1996 to 2016, Zhou et al. (2018) conduct a review of the literature that uses DEA in the field of sustainability. Tsaples and Papathanasiou (2021) recently brought the analysis up to date by covering the period 2017-2020, noting that the vast majority of applications study Asian territories, with far less focus on European nations.

Despite the popularity of the DEA technique among the scientific community, it does have some important limitations: the presence of outliers can distort the results; the exclusion of variables can lead to inefficiencies being identified; and as it is a non-parametric technique, it is not possible to formulate hypotheses to test to confirm its suitability. All this justifies the appropriateness of using DEA-Bootstrap, an extension of DEA that enables the researcher improve the robustness of the estimates by providing confidence intervals for the efficiency scores (Simar and Wilson, 1999). DEA-Bootstrap generates a numerical simulation of the DMUs in the original sample. Efficiency scores can then be calculated for a large number of simulated samples, thus minimizing data contamination.

Given the objective of this research, the output-oriented BCC model is used, with 2000 bootstrap replications as suggested by Simar and Wilson (2000). Furthermore, an intertemporal analysis is conducted to ensure that isolated distortions occurring in a particular year do not lead to erroneous conclusions (Cruz-Cázares et al., 2013; Puertas et al., 2020).

The MI is then used to calculate the evolution of the performance of a DMU in different periods of time. The MI was originally proposed by Caves et al. (1982), with Färe et al. (1992) later adapting DEA to measure it. The MI measures possible changes in productivity-over time, that is, it performs a vertical comparison using panel data with distance functions. These changes in productivity can be broken down according to their source: technical efficiency change (TEC) and the change resulting from technological progress (TC). In turn, TEC can be a result of different values of the distance to the frontier due to better use of the available technology (pure technical efficiency change, PTEC) or changes in scale efficiency (SEC). TC, on the other hand, corresponds to a shift in the frontier itself, that is, technological improvements as a result of progress (Appendix 1). If TEC>1, the analysed DMU has improved its technical efficiency, and if in addition TC>1, it has undergone technological development. However, a DMU may become more technologically advanced (TC>1) while also suffering from technical inefficiency (TEC<1), with the latter due to worse use of available technology (PTEC<1) and/or errors in the scale of production (SEC<1).

In the first stage of the empirical analysis, the two methods, DEA-Bootstrap and MI, are applied to a production function composed of two inputs and two outputs (Table 1). Inputs are expressed in constant USD to prevent price changes or currency rates from distorting the results. R&D expenditure includes personnel costs and any other costs associated with the activity. The literature presented in Table 1 supports the choice of variables in the field of eco-innovation.

Table 1. Variable used in DEA-Bootstrap and MI analysis

Variable	Role	Unit	Source	Literature sources
Business Enterprise R&D expenditure by industry* (BERD)	Input	millions constant USD	OECD	Yang and Yang (2015); Steinert et al (2020); Mavi and Mavi (2021)
Government budget allocations for R&D in environment** and energy*** (GBARD)	Input	millions constant USD	OECD	Yang and Yang (2015); Mavi and Mavi (2021); Steinert et al (2020)
Patents on environment-related technologies	Output	Number	OECD	Yang and Yang (2015); Steinert et al (2020)
Scientific Publications on environmental science	Output	Number	Scimago Journal	Yang and Yang (2015); Steinert et al (2020)

*Electricity, gas, steam, air conditioning and water supply; sewerage, waste management and remediation.
**Environment: control, measuring, elimination and prevention pollution; climate protection; solid wastes; water protection; noise and vibrations; radioactive pollution; protecting the air; etc.
***Energy: production, storage, transportation, distribution and rational usage is any type of energy; energy efficiency; capture and storage of CO_2; sources of renewable energies; hydrogen and gas; etc.

~~The literature on eco-innovation supports the choice of the proposed variables, as suggested by Steinert et al. (2020) and Mavi and Mavi (2021)~~. As the focus is on output-oriented efficiency, the result indicates whether the countries analysed have been able to use their inputs properly to maximize outputs. Table 2 shows the main descriptive statistics of the variables.

Table 2. Descriptive statistics for inputs and outputs (2011-2018).

	$GBARD_{t-1}$	$BERD_{t-1}$	Patents	Scientific Publications
Mean	652	120	1,638	3,970
SD	1,175	180	3,666	6,021
Max	5,851	903	17,147	35,927
Min	0.3	0.1	2	67

The inputs are lagged one year to allow for the maturity process of the research. The statistics reveal greater involvement by the public sector in promoting environmental R&D, with Japan, the USA and Germany being the countries with the largest budget. In the business sector, it is in France, Japan and the USA where the largest amounts are allocated to environmental research. Regarding the outputs, the countries that stand out for their number of patents are the USA, Japan and Germany, while in terms of scientific publications it is the USA, the United Kingdom and Germany that register the highest volumes of research in this field.

3.2. Stage 2: Determinants of GHG emissions , two-step GMM

The second stage of the research involves estimating dynamic panel models using two-step GMM. This method is applied to three models to assess the determinants of GHG emissions (equations 1, 2 and 3). GMM was originally put forward by Arellano and Bond (1991) to address the problem of endogeneity, proposing the use of lags as instruments for the endogenous variable. Roodman (2006) later suggested that in panel data samples of only a few years, and therefore with a small number of instruments, it is more appropriate to apply the two-step GMM. This extension uses the heteroscedastic weight matrix and the instruments in levels in the estimation, which reduces the loss of information but introduces the risk of overidentification.

In all the specified models, GHG emissions, the efficiency score (EFF) and GDP per capita are included as independent variables. In addition, Model 1 analyses the impact of variables related to waste generation (Disposal) and treatment (Recovery), as well as resource consumption (Material footprint). Model 2 includes productivity indicators (CO_2 productivity, Energy productivity, and Non-energy productivity) and Model 3 examines the environmental policies adopted (Taxes, Terrestrial protected area, and DParis).

Model 1

$$GHG_{it} = \beta_0 + \beta_1 GHG_{it-1} + \beta_2 EFF_{it-1} + \beta_3 GDP_{it} + \beta_4 Disposal_{it} + \beta_5 Recovery_{it} + \beta_6 MFootprint_{it} + \varepsilon_{it} \quad (1)$$

$\beta_1, \beta_4,\ \beta_6 > 0;\ \ \beta_2, \beta_5 < 0;\ \beta_3$ could be positive or negative

Model 2 $$GHG_{it} = \beta_0 + \beta_1 GHG_{it-1} + \beta_2 EFF_{it-1} + \beta_3 GDP_{it} + \beta_4 CO_2\ productivity_{it} + \beta_5 Energy\ productivity_{it} + \beta_6 Non - energy\ productivity_{it} + \varepsilon_{it} \quad (2)$$

$\beta_1 > 0$; $\beta_2, \beta_4, \beta_5, \beta_6 < 0$; β_3 could be positive or negative

Model 3 $$GHG_{it} = \beta_0 + \beta_1 GHG_{it-1} + \beta_2 EFF_{it-1} + \beta_3 GDP_{it} + \beta_4 CO_2 Environmental\ taxes_{it} + \beta_5 Protected\ area_{it} + \beta_6 DParis_{it} + \varepsilon_{it} \quad (3)$$

$\beta_1 > 0$; $\beta_2, \beta_4, \beta_5, \beta_6 < 0$; β_3 could be positive or negative

i = 1,2, …, 28 countries and t = 2011, 2012, …, 2018

Table 3 presents the definitions of the variables used in each model and their unit of measurement. They are all sourced from the official statistics published by the OECD.

Table 3. Description of the determinants of GHG emissions

Model 1: Waste and Material footprint		
Variables	**Definition**	**Unit**
Disposal	Any waste management operation serving or carrying out the final treatment and disposal of waste	Kilograms, Thousands per capita
Recovery	Any waste management operation that diverts a waste material from the waste stream and which results in a certain product with a potential economic or ecologic benefit	Tonnes, Thousands per capita
Material footprint	Global allocation of used raw material extracted to meet the final demand of an economy.	Kilograms, Thousands per capita
Model 2: Environmental and resource productivity		
CO_2 productivity	Reflects the economic value generated per unit of CO_2 emitted	USD per kilogram, 2015
Energy productivity	Reflects efforts to improve energy efficiency and to reduce carbon and other atmospheric emissions	USD, 2015
Non-energy productivity	Monetary value generated per unit of non-energy materials used	USD per kilogram, 2015
Model 3: Environmental policies		
Environmental taxes	An important instrument for governments to shape relative prices of goods and services. Environmental domain: Air pollution and Climate Change	Millions USD 2015 PPP per capita
Terrestrial protected area	Political regulation to determine the protected area	% land area
DParis	The effect of the Paris Agreement	Dummy[2] (1 in 2018, 0 otherwise)
Common variables		
GHG emissions	Total emissions of CO_2, CH_4, N_2O, HFCs, PFCs, SF_6 and NF_3	Tonnes of CO_2 equivalent, Thousands per capita
EFF-Bootstrap	Eco-innovation of OECD countries	Index
GDP	Gross Domestic Product	USD 2015 per capita

[2] The possible delay between the adoption of the Paris Agreement and the introduction of specific measures for countries to comply with it has been taken into account.

GHG emissions has been used as a dependent variable and lagged independent variable, reflecting the trend in emissions over time. Likewise, the efficiency score calculated using DEA-Bootstrap has been lagged to account for the maturation period required by investments and the implementation of patents in production processes. The dummy capturing the effects of the Paris Agreement identifies the possible influence of the agreement two years after its signing, the time frame needed for countries to begin to introduce changes in their economies. Table 4 presents the main statistics of these variables.

Table 4. Descriptive statistics for independent variables (2011-2018).

	Mean	**S.D.**	**Max**	**Min**
GHG	0.011	0.005	0.024	0.005
EFF-Bootstrap	0.571	0.192	0.937	0.149
GDP	40,571	11,252	81,394	21,033
Disposal	0.183	0.163	0.717	0.002
Recovery	0.314	0.176	0.810	0.002
Material footprint	26.372	6.796	43.400	12.645
CO_2 productivity	6.016	2.270	14.884	1.962
Energy productivity	11,202	3,841	28,602	2,473
Non-energy productivity	3.576	1.843	9.662	1.305
Environmental taxes	1,680	681	3,568	225
Terrestrial protected	22.742	9.572	53.530	9.850

Some of the descriptive statistics show dispersion in variables such as disposal, recovery and non-energy productivity. All the variables included are a priori related in some way to global warming, except GDPpc because the level of income does not necessarily reflect the efforts made in this regard. All variables have been log transformed to help ensure stability and lessen the effect of outliers and units of measurement, thus limiting the variability of the variables. Appendix 2 (Table A1) presents the correlation matrix confirming the absence of severe multicollinearity among the variables (Gujarati, 2004).

4. Results and Discussion

The first stage of the research was to analyse the eco-innovation of OECD countries. Although they are in different continents, they are all classified as high-income by the World Bank, except Turkey, which is among the upper-middle-income economies. They also have similar social standards. As a consequence, the sample is fairly homogeneous, which is a requisite for the proper application of DEA.

DEA-Bootstrap can be used to identify countries whose spending on environmental innovation has been adequately converted into technology, measured by the number of patents and research papers. An eight-year period has been analysed with both the DEA-Bootstrap and the MI, yielding consistent results. The first and second columns of Table 5 show the mean efficiency (EFF mean) and its standard deviation (EFF SD), respectively. The following columns present the MI, TC, PTEC and SEC, allowing an assessment of the source of the productivity changes occurring during the analysed period.

Table 5. Efficiency scores of the intertemporal DEA-Bootstrap and MI (2011-2018)

	EFF mean	EFF SD	MI	TC	PTEC	SEC
UK	0.859	0.060	0.932	1.036	1	0.900
Netherlands	0.847	0.087	1.014	1.070	1.005	0.943
USA	0.829	0.025	1.028	1.080	1	0.952
Australia	0.767	0.134	1.065	1.096	1.034	0.940
Portugal	0.741	0.116	1.129	1.093	1.006	1.027
Slovenia	0.672	0.182	1.027	1.027	1	1
Poland	0.649	0.110	0.880	0.952	0.985	0.938
Sweden	0.634	0.056	0.916	1.055	0.955	0.910
Ireland	0.625	0.218	1.256	1.112	1.109	1.018
Japan	0.612	0.089	0.930	1.234	0.950	0.793
Italy	0.600	0.085	0.916	0.956	0.985	0.972
Denmark	0.599	0.186	1.084	1.057	1.057	0.970
Greece	0.577	0.127	0.841	1.005	0.877	0.954
Turkey	0.564	0.088	0.965	1.031	0.965	0.970
Germany	0.555	0.064	1.008	1.167	0.971	0.889
Iceland	0.551	0.172	2.065	1.903	1	1.085
Spain	0.545	0.150	1.126	1.077	1.094	0.955
Czech Rep.	0.525	0.118	1.082	0.999	1.106	0.979
Belgium	0.516	0.119	1.086	1.141	1.022	0.932
Lithuania	0.496	0.231	1.171	1.034	1	1.133
Canada	0.489	0.106	1.036	1.058	1.055	0.928
Norway	0.481	0.075	1.025	1.027	1.029	0.969
Austria	0.472	0.050	0.978	1.130	0.926	0.935
Latvia	0.421	0.158	0.945	1.065	0.887	1
Hungary	0.405	0.146	1.009	1.030	0.998	0.982
Finland	0.365	0.118	1.114	1.128	1.072	0.921
Estonia	0.323	0.237	1.268	1.144	1.142	0.970
France	0.269	0.045	1.001	1.168	1.006	0.852

The results reveal that, for the defined production function, the United Kingdom, the Netherlands and the USA are the countries that have achieved the highest levels of efficiency (0.859, 0.847 and 0.829, respectively), although there are some differences in the progress they have made in productivity. All three show a decline in scale efficiency (SEC<1), however, the Netherlands and the USA have been able to offset this through technological advances of 7% and 8%, respectively (TC= 1.070 and 1.080). The United Kingdom has registered an advance of only 3.6%, which is not enough to compensate for the adverse result of the SEC; hence the evolution of its productivity shows a drop of 6.8% (MI= 0.932).

Generally speaking, efficiency levels are not very high with a wide dispersion between the maximum registered by the United Kingdom (EFF mean = 0.859) and the minimum by France (EFF mean = 0.269). This can be attributed to the intrinsic features of the sample analysed, as they are all highly developed countries with a strong commitment to international agreements on climate change. As such, small variations in inputs/outputs are probably behind these differences. Furthermore, the performance of each country should be compared only with the other members of the sample.

Iceland has a level of inefficiency of 45% (EFF mean = 0.551) but has achieved an improvement in productivity of over 200% (MI = 2.065), while Greece has a similar efficiency level but has registered a decline of more than 25% (MI = 0.841). However, almost all countries show progress in productivity resulting from the introduction of technological improvements. This has translated into advances of, for example, 90.3% in Iceland, 23.4% in Japan or more than 16% in France and Germany.

In the second stage of the research, the determinants of GHG emissions have been analysed, using the efficiency levels along with other variables. Table 6 shows the results of the three models estimated using two-step GMM. The coefficients have been standardized in order to determine the relative weight of each in determining the volume of emissions. For all the models, the applied tests confirm the adequacy of the results: the Hansen test confirms that the instruments used are valid and there is no overidentification problem (Prob>chi2 is greater than 0.05); the Arellano-Bond test confirms the absence of second-order serial correlation in the error [AR(2)] (Prob>z is greater than 0.05); the number of instruments is smaller than the number of groups (21 instruments and 28 groups); and the Wald test, with a Prob>chi2 of less than 0.05, indicates that they are correctly specified and the set of indicators explain the dependent variable.

Table 6. Two-step GMM estimation results

	Model 1	Model 2	Model 3
lnGHG(-1)	0.1504^{***}	0.1418^{***}	0.1458^{***}
lnEFF(-1)	-0.0117^{***}	-0.0067^{***}	-0.0083^{***}
lnGDP	0.0163^{***}	0.0178^{***}	0.0148^{***}
lnDisposal	0.0091^{***}		
lnRecovery	-0.0037^{**}		
lnMFootprint	0.0054^{**}		
lnCO_2Productivity		-0.0230^{***}	
lnEnergy Productivity		0.0003	
lnNon-Energy Productivity		-0.0031^{**}	
lnEnvironamental Taxes			-0.0076^{***}
lnProtected area			-0.0081^{***}
DParis18			-0.0007
Hansen chi2(Prob>chi2)	18.19(0.198)	20.87(0.105)	18.42(0.188)
ABond AR(1) z(Prob>z)	-3.30(0.001)	-3.30(0.001)	-3.15(0.002)
Abond AR(2) z(Prob>z)	-0.72(0.470)	-0.78(0.436)	-0.80(0.426)
Wald chi2 (Prob>chi2)	1.24e+06(0.000)	8.69e+06(0.000)	1.35e+06(0.000)
Observations/groups	196/28	196/28	196/28
Instruments	21	21	21

Note: ***p<0.01, **p<0.05, *p<0.1. Hansen, A-Bond and Wald tests report p-values in parentheses

In all three models the variable GHG (-1) turns out to have a significant and positive coefficient, reflecting the carry-over effect of the previous situation and how difficult it is for countries to break this trend. According to official OECD statistics, emissions are in decline, yet they continue to have a significant impact on subsequent emissions. These results are in line with the conclusions of the study by Koçak and Ulucak (2019), which analyses the effect of energy R&D expenditure on CO_2 emissions, also introduced as a lagged independent variable.

The eco-innovation calculated in the first stage of the research through the efficiency indicator also presents a significant coefficient with the expected sign, demonstrating that innovation enables a reduction in GHG emissions, unlike the wealth of the country. There is no consensus on these two variables in the literature (Grunewald and Martínez-Zarzoso, 2011; Kahn et al., 2019; Ferreira et al., 2020). However, economic growth is often associated with increased production and, consequently, more pollution, while innovation represents the introduction of new technologies fostering environmental quality into production processes.

In Model 1 it can be seen that the other three variables analysed have significant coefficients: while recovery has an inverse relationship with GHG emissions, disposal and material footprint lead to an increase in emissions. Recovery includes the actions of recycling, reusing fuel or composting, all of which help mitigate climate change and therefore global warming. Disposal understood as overall waste management produces environmental pollution, however, if official statistics permitted such an analysis, we would very likely find that not all waste treatments yield the same results. Regarding material footprint, it is confirmed that the extraction and excessive use of raw materials increases emissions, harming the environment and therefore the health of the population. This challenging goal could be achieved by promoting the use of autonomous vehicles (Hoekstra, 2019), second generation biofuels produced from forest residues (Soimakallio et al., 2009) or increasing recovery rates of raw material (Altay et al., 2011). In short, GHG (-1) is the factor that has the greatest impact on emissions, followed by GDP and eco-innovation.

In Model 2, both carbon and non-energy productivity are found to have significant coefficients with the expected sign. Moreover, the former has a greater impact on emissions than eco-innovation or GDP, pointing to a possible line of action for future agreements. Lastly, the environmental policies analysed in Model 3 reduce pollution, with an influence very similar to that of eco-innovation. However, with regard to the Paris Agreement, captured by the dummy variable, it is not found to have led to a reduction in emissions by the analysed countries. In this respect, Chen et al. (2017) conclude that the authorities should boost investment in environmental protection, and adopt fiscal policies that facilitate the development of green projects.

While some of the results are in line with the existing literature, they are not directly comparable. For example, in this empirical study the impact of innovation is analysed by means of eco-innovation rather than directly with the number of patents or R&D expenditure, as in Mongo et al. (2021) or Petrović and Lobanov (2020). In addition, the proposed empirical approach includes other variables such as waste management, measures of environmental productivity and environmental policies, which have not previously been analysed in this field.

5. Conclusions

Using a panel data sample of 28 OECD countries over the period 2011-2018, this research has two objectives: to measure eco-innovation, and to analyse the determinants of GHG emissions, thereby identifying the factors that have the greatest impact on climate change. The methods used to do so are strongly supported by the existing literature.

In the first stage, it is shown that the countries under analysis have implemented new technologies and achieved improvements in productivity during the eight years analysed. Iceland stands out with technological change of more than 90%. In the second stage, the estimations carried out reveal the significant impact of eco-innovation, carbon productivity and environmental policies on emission reduction.

The results shed light on the aspects that need to be strengthened by the authorities in order to be able to comply with the increasingly demanding series of international agreements. The European Union recently set itself the goal of eliminating emissions by 2050, entailing the introduction of countless changes to its constituent economies. According to this research, eco-innovation should be promoted to help ensure that technological advances and scientific studies are oriented towards the achievement of a clean society. Complemented by public policies to establish environmental taxes and protected areas, this will foster environmental productivity, the introduction of improvements in waste management, and will encourage less demand for raw materials.

This study is not without its limitations, which point to avenues for future research. Although environmental agreements have been ratified by a large number of countries, the existing literature focuses mostly on developed economies. Therefore, the logical continuation of this analysis would be to extend it to other territories with different levels of development to determine the behaviour of the analysed variables, along with others such as different types of waste management and generation, or the use of environmentally-friendly resources.

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Appendix 1. Calculation and decomposition process of MI

The MI is defined and decomposed as follows:

$$MI(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \tag{1}$$

$$= \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} x \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right]^{1/2}$$

$$= TEC \; x \; TC$$

Färe et al (1994b) redefined one component. They decomposed the TEC component to obtain:

$$TEC = \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\right] x \left\{\frac{D_c^{t+1}(x^{t+1}, y^{t+1})/D^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)/D^t(x^t, y^t)}\right\} \tag{2}$$

$$= PTEC \; x \; SEC$$

sub-index c refers to constant returns to scale.

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Appendix 2. Table A1. Correlation matrix of the variables used in the three models

	GHG(-1)	EFF(-1)	GDP	Disposal	Recovery	Material Footprint	CO_2 Productivity	Energy Productivity	Non-energy Productivity	Environmental Taxes	Protected area
GHG(-1)	1										
EFF(-1)	0.163	1									
GDP	0.416	0.245	1								
Disposal	0.407	0.008	-0.231	1							
Recovery	0.052	0.107	0.731	-0.605	1						
Material Footprint	0.586	0.040	0.440	0.126	0.215	1					
CO_2 Productivity	-0.581	0.000	0.324	-0.354	0.365	-0.084	1				
Energy Productivity	-0.431	0.240	0.145	-0.277	0.225	-0.485	0.389	1			
Non-energy Productivity	-0.142	0.332	0.225	-0.296	0.243	-0.247	0.029	0.299	1		
Environmental Taxes	-0.222	0.085	0.313	-0.515	0.577	-0.048	0.254	0.379	0.221	1	
Protected area	-0.409	0.014	-0.102	-0.152	0.012	-0.177	0.244	0.173	0.203	-0.091	1