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Patent now, benefit later: Lagged relationships between green innovation, GHG emissions and efficiencies in the EU-27

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HIGHLIGHTS

- Green patents reduce GHG emissions with delayed but measurable effects.
- Energy efficiency rises after a one-year lag from green innovation.
- Material efficiency gains emerge with a two-year lag from green patents.
- Joint framework assesses emissions and efficiency simultaneously.
- Models uncovers heterogeneous temporal green innovation effects.

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ABSTRACT

Green innovation plays a key role in reducing emissions and increasing resource efficiencies, as suggested by pioneering definitions. However, there are still some gaps in the literature as few studies consider the effects of green innovation on emissions and resource efficiencies simultaneously, while also considering lagged effects by explicitly modelling the temporal lags between patent filing and observable environmental benefits. To address these gaps, this study analyses this relationship by incorporating greenhouse gas (GHG) emissions, various measures of resource efficiency (energy and materials) and green patents across the 27 EU Member States for the period 1993–2017, using data from the European Patent Office (EPO) and other secondary sources. The results show that green innovation, captured through lagged associations of green patents, reduces emissions and increases resource efficiency. However, the relationships are not immediate and differ depending on the type of indicator. Policy implications should consider the differentiated effects of green technologies on these indicators in order to effectively address climate change.

1. Introduction

Climate change is an urgent global problem that affects people and regions. Extreme temperatures, rising sea levels, biodiversity loss, and water scarcity require policies to address these devastating effects (Intergovernmental Panel on Climate Change, 2023). In response, international organisations have developed various policies to combat climate change. In this vein, Goal 13 of the United Nations 2030 Agenda encourages countries to implement actions to mitigate climate change by reducing their emissions and increasing their resource efficiency (Caiado et al., 2018). Green innovations have become a powerful tool in this fight (Ghimire et al., 2023; Wang and Yang, 2024; Li et al., 2024).

Previous papers have analysed the effects of green innovations on reducing emissions (Du et al., 2019; Chen et al., 2021; Luo et al., 2023) and on increasing resource efficiency (Sun et al., 2019; Liu et al., 2024). However, none of these papers examines various measures of emissions and resource efficiency jointly (Ghimire et al., 2023), and they are generally focused on individual countries or cities rather than on a regional context, such as the EU-27. Furthermore, within the field of resource efficiency, the evidence is more limited than in the case of

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emissions. Indeed, most studies focus mainly on energy efficiency, while material efficiency has received considerably less attention (Sun et al., 2023; Cainelli et al., 2020; Wang et al., 2023) -Gap 1-. In addition, the analysis of lagged effects is also largely absent from this body of literature, as recognized by Li et al. (2024). In this sense, existing literature provides limited understanding of whether the lagged effects of green innovation differ across environmental dimensions and how these heterogeneous temporal dynamics may affect the design and evaluation of environmental policies -Gap 2-. This is particularly relevant given that emissions reduction and resource efficiency improvements may emerge over different time horizons due to differences in technological diffusion and structural adjustment processes (Jaffe et al., 2005; Acemoglu et al., 2012; Popp, 2019; Li et al., 2024). As a result, policymakers may underestimate the long-term environmental benefits of green innovation if policy evaluation is based only on short-term outcomes.

Consequently, the gaps mentioned in the previous paragraph form the basis for this study, the aim of which is to examine the role of green innovation in shaping environmental performance across the EU-27, with a particular focus on its dynamic (delayed) effects on emissions and resource efficiency. To this end, the study pursues two main objectives: 1) to analyse the association between green innovations and emissions and resource efficiencies jointly, using different measures in the EU-27 region; 2) to incorporate the temporal dynamics of this relationship into the analysis. We thus propose the following research questions:

RQ1. To what extent does green innovation contribute to the reduction of emissions, and are there lagged effects associated with this relationship?
RQ2. To what extent does green innovation enhance energy and material efficiency, and are there lagged effects associated with this relationship?

To address our two research questions, we built a dataset that covers the period from 1993 to 2017. It includes environmental patents (number of applications) from the EPO, using PATSTAT (2021 edition) as a measure of green innovation. As a proxy for emissions, we use greenhouse gas (GHG) emissions, and for efficiencies, energy and material productivities. In addition, we apply panel models with lag structures to test the main associations. Finally, we conduct this analysis in the EU-27, a group of countries with similar income levels and environmental regulations. The study of this region, the EU-27, is justified by the availability of patent data and the specific call for regional analysis issued by Song et al. (2024). Furthermore, the European Union is implementing various initiatives under the European Green Deal, in which emission reduction is the first target —climate neutrality by 2050— (Vieira et al., 2021). The effort made by the EU to achieve emission neutrality by 2050 justifies the selection of the EU-27 as the region analysed in this paper.

This article contributes to the literature from three complementary perspectives. From a theoretical perspective, the study advances existing research by integrating emissions and resource efficiency within a unified analytical framework, while explicitly incorporating lagged effects. This dynamic approach provides a more nuanced understanding of how green innovation influences environmental performance over time. From an empirical perspective, the study offers novel evidence for the EU-27, showing that the effects of green innovation are not immediate but unfold over time and differ across environmental dimensions. In particular, the results identify distinct lag structures for emissions, energy efficiency, and material efficiency. From a policy perspective, the findings highlight the importance of considering time lags when designing and evaluating environmental and innovation policies. These results provide relevant insights for policymakers within the context of the European Green Deal, suggesting that the impacts of green innovation policies may materialise with delays depending on the targeted environmental outcome.

The results show a negative association between green innovation and emissions and a positive association between green innovation and resource efficiencies. However, the link is not immediate and differs according to the type of indicator –there are lagged relationships–. While emission reductions and material efficiency gains can take up to two years to be reflected, energy efficiency increases appear when considering only the first lag of green innovations. The findings indicate that green innovation contributes to climate change mitigation by reducing emissions while simultaneously enhancing efficiencies. The results underscore the dual function of green innovation in both lowering carbon intensity and optimising resource utilization. Importantly, these effects materialise over time rather than instantaneously, highlighting the dynamic role of green innovation.

The rest of this paper is organised as follows. In the next section, we describe the literature that supports our analysis. Then, Section 3 presents the methodology applied, and Section 4 shows the main results found in this analysis. The final section covers the main conclusions of the study.

2. Green innovation effects: reduced emissions and increased resource efficiency

According to pioneering definitions, green innovations are new or improved products or processes introduced into the market that reduce environmental risk, pollution, and resource consumption (Kemp and Pearson, 2007: p. 7). Therefore, this concept refers to products or processes that are environmentally sustainable and eco-friendly.

Building on this definition, green innovation can be conceptualised as a dynamic, staged process through which environmentally sustainable technologies translate into measurable improvements in environmental performance. Several theoretical perspectives—eco-innovation theory (Rennings, 2000), Porter's hypothesis (Porter and van der Linde, 1995), and ecological economics (Costanza et al., 1991; Daly and Farley, 2011)—converge within this framework, highlighting the dual role of green innovation in reducing emissions and increasing resource efficiency. These perspectives collectively imply that the environmental benefits of green innovation emerge progressively as innovations move through different stages of development, adoption, and structural integration.

The process begins with the stage of knowledge creation, where eco-innovation theory explains that green innovations originate as new technological knowledge aimed at internalising environmental externalities (Rennings, 2000). This inventive activity is often captured by green patenting, reflecting the generation of potential solutions rather than immediate environmental outcomes. At this stage, the focus is on creating the capacity to reduce emissions and improve efficiency in the future. In this sense, the diffusion of newly created knowledge is initially limited, as green innovations tend to be adopted first by a small group of early movers. Diffusion of innovation theory suggests that adoption follows an S-shaped trajectory, meaning that technological diffusion begins slowly among early adopters, accelerates as adoption spreads across firms and sectors, and eventually stabilises once the technology becomes widely implemented (Rogers, 2003; Dedehayir et al., 2017). Early diffusion is typically constrained by uncertainty, information asymmetries, and risk aversion, which delay the broader adoption of green technologies. This gradual diffusion provides a first theoretical explanation for the delayed environmental impacts of green innovation.

Subsequently, Porter's hypothesis highlights how firms translate this knowledge into practice (Porter and van der Linde, 1995). Environmental regulation and competitive pressures incentivise firms to adopt green innovations, reorganise production processes, and optimise resource use. These adjustments enhance both environmental performance and productive efficiency, but they require time to be fully implemented, reinforcing that the benefits of green innovation are realised after the invention stage. In particular, the adoption of green technologies entails adjustment costs, organisational restructuring, and

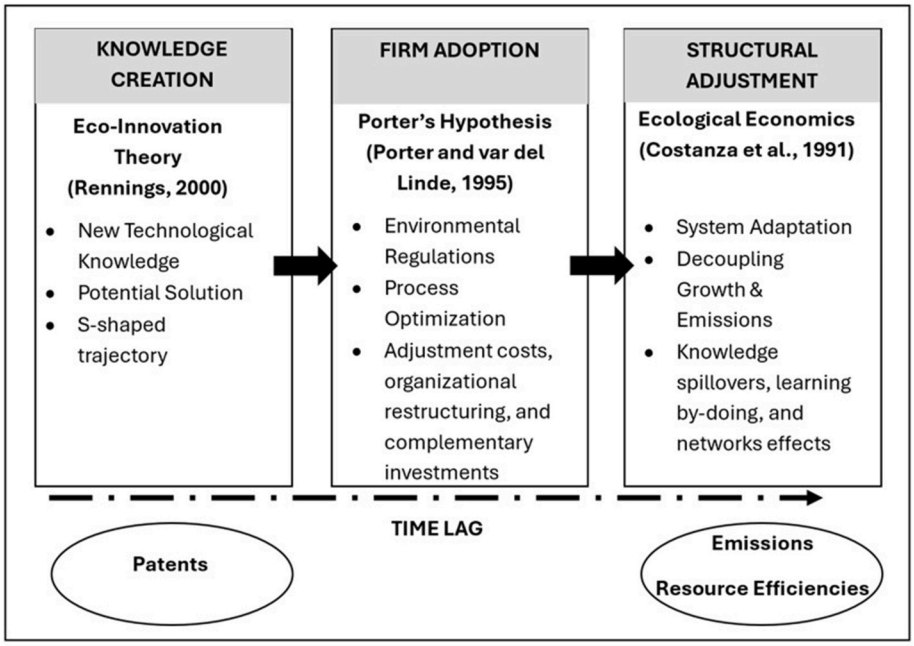


Fig. 1. Integrated staged framework.
Source: Authors' own elaboration

complementary investments in capital, skills, and managerial capabilities (Dosi, 1988; Teece, 1986). Firms need time to integrate new technologies into existing production systems, which delays the materialisation of improvements in emissions and efficiency.

Finally, ecological economics situates these firm-level changes within a broader structural context (Costanza et al., 1991; Daly and Farley, 2011), emphasising that sustainable environmental improvements depend on long-term adaptation of economic and production systems. At this stage, green innovations contribute to the gradual decoupling of economic activity from emissions and resource consumption, producing cumulative environmental benefits at the system level. This system-wide transformation is reinforced by knowledge spillovers, learning-by-doing, and network effects, which accumulate over time as technologies reach a critical mass of adoption (Jaffe et al., 2005). Consequently, the environmental benefits of green innovation emerge with a delay rather than contemporaneously.

Although none of these theories explicitly model temporal delays, integrating them into this staged framework implies that the environmental effects of green innovation do not manifest instantaneously. This time lag reflects the sequential nature of the process —from knowledge creation to firm adoption and structural adjustment— providing a coherent explanation for why patenting activity does not immediately translate into observable reductions in emissions or gains in resource efficiency. Moreover, the temporal dynamics of green innovation are also expected to differ across environmental dimensions due to the heterogeneous nature of the technological and structural changes involved. Reductions in greenhouse gas emissions often depend on the gradual replacement of carbon-intensive infrastructures and broader transitions in energy and production systems, which require longer diffusion and adjustment periods before aggregate effects become observable (Unruh, 2000; Jaffe et al., 2005). By contrast, improvements in energy efficiency are frequently associated with more incremental and directly implementable technological changes, allowing benefits to materialise more rapidly once innovations are adopted (Acemoglu et al., 2012; Aghion et al., 2016). Finally, improvements in material efficiency usually involve broader transformations in production chains, product design, and resource management practices, implying slower structural adjustment processes and more delayed environmental impacts (Cainelli et al., 2011; Li et al., 2024).

In this sense, Popp (2001, 2005, 2019) argued that the introduction of lagged effects for testing the relationship between green innovation and efficiencies could add information about the overall impacts of technological change over time. Taken together, these mechanisms offer a strong conceptual foundation for expecting lagged effects and justify the use of dynamic panel models. Fig. 1 illustrates the theories described above.

Beyond this conceptual convergence, the specific mechanisms through which green innovations contribute to emission reductions have been explored in the *literature*. Green innovation is a powerful tool for the reduction of emissions —supporting the goal of reaching net zero by 2050— around the world (International Energy Agency, 2024). Low-emission technologies, carbon capture systems, industrial efficiency, or electric mobility enable the reduction of carbon intensity in key sectors such as energy, industry or transport (Dechezleprêtre et al., 2017; International Energy Agency, 2024). Moreover, to the extent that these innovations are disseminated on a large scale, they generate positive externalities, modifying the technological structure of the economic system (Jaffe et al., 2005). However, there are numerous factors that can influence the process: the degree of penetration of clean technologies, environmental regulation, the relative price of inputs or the technological absorption capacity (Horbach et al., 2012; Rubashkina et al., 2015). Recent literature has also highlighted the role of green finance as a complementary mechanism supporting environmental transitions. In particular, green finance can stimulate technological innovation and facilitate pollution and carbon mitigation through the promotion of high-quality green patents, especially in developed economies (Chen et al., 2025; Xiong et al., 2025). Nonetheless, rebound effects can also arise. The use of cleaner technologies can increase efficiency and even reduce costs, but they can also increase economic activity, which can offset emission reductions (Sorrell, 2009).

From a *practical perspective*, the effects of green innovation on the reduction of emissions can be explained as the process of replacing polluting inputs with cleaner ones, or as a technical improvement in production processes that imply reductions in emissions (International Energy Agency, 2024).

The role of green innovation in reducing emissions has also been analysed from a more *empirical perspective* (Du et al., 2019; Chen et al., 2021; Luo et al., 2023). However, there is still limited evidence supporting this relationship, and mixed results have been reported depending on the region, and therefore, the level of income of the countries and the type of emissions analysed.

Among *individual countries*, the main country analysed is China. Authors such as Chen et al. (2021, 2023) and Fang et al. (2022) explore the relationship between green innovations and CO_2 emissions, showing the key role played by green technology in reducing emissions, both at the sectoral and urban level. On the other hand, the paper of Li et al. (2024) analyses the positive relationship between green innovation and the reduction of CO_2 emissions in China using a nonlinear autoregressive distributed lag in the short run. However, those effects become positive in the long run. Finally, Luo et al. (2023) analyse the effect of green innovation on SO_2 emissions, finding that utility patents negatively affect SO_2 emissions, while design patents positively affect China's SO_2 emissions. In addition, some types of green innovations have been also incorporated in this analysis. This is the case of Qu and Li (2023), who demonstrate the positive effect of renewable energy technology innovation on carbon emissions reduction. For their part, Xu et al. (2021) study the effects of different types of green innovation on carbon emission performance using panel data in cities in China in a period from 1996 to 2012. They show a negative relationship, although the impact varies according to the type of innovation and the Chinese region analysed.

There is also some evidence from various *countries* or *regions* provided by, among others, Ghimire et al. (2023). These authors capture a negative impact of green innovation on CO2 emissions in a sample of 64 countries. Similarly, Du et al. (2019) find that green innovation reduces CO_2 emissions in a sample of 71 economies. However, these effects depend on the level of income of the different economies, showing that positive impacts occur primarily in countries whose income levels surpass a certain threshold.

In addition, there are also some studies that focus more on countries belonging to the same economic bloc, such as the OECD or the EU-27, which are under similar environmental regulatory frameworks. In this sense, Kwon et al. (2017) analysed the effect of green technology across different technological fields: energy-related technologies linked to fossil fuels, renewable energy, and storage technologies, over a decomposition of different factors of CO_2 emissions in 12 European countries. They find that the efficiency of technologies varies between countries, with renewable energy technologies presenting the greatest impact on CO_2 emission, while fossil fuel technologies are the least efficient. Other authors, such as Töbelmann and Wendler (2020), analyse the effects of environmental innovation on carbon dioxide emissions in the EU-27 in the period 1992-2014. This study compares environmental innovation and general innovation, and it demonstrates that green innovation shows a decreasing effect on carbon dioxide emissions. Finally, Hashmi and Alam (2019) study in countries of the OECD the dynamic relationship between green innovation and CO_2 emissions using the SPIRPAT model, showing that when environmental patents increase by 1%, CO_2 emissions decrease by 0.017%.

However, this body of literature has emphasised that the relationship between green innovation and emissions is often non-linear. For example, Du et al. (2019), Chen et al. (2023), Fang et al. (2022), and Qu and Li (2023) suggest that the effect of innovation may vary across different levels of development or technological maturity. Recent evidence also shows that this relationship is both heterogeneous and non-linear across countries, with the environmental impact of patenting activity depending on the economic context and the technological orientation of innovation (Alexiou and Petreski, 2025). Moreover, it does not occur instantaneously, as innovations take time to be integrated into production processes – reflecting lagged effects. This delay is also supported by recent findings showing that the environmental effectiveness of green patents depends on their quality and is shaped by time lags between patent registration and their widespread adoption and diffusion (Yu et al., 2026). In this sense, several authors point out the importance of including lag structures in the analysis of the impacts of green innovation (Kwon et al., 2017; Du et al., 2019).

In summary, all the previous literature shows mainly negative effects of green innovation on the level of emissions. This will allow us to assess whether the environmental and innovation policies adopted in the EU-27 are generating positive effects in the fight against climate change in recent years. According to the previous background, we propose the following hypothesis.

H1. There is a negative relationship between green innovation and emissions level in the EU-27 countries and this association exhibits lagged patterns.

Beyond emissions, the second dimension of the dual effect of green innovations lies in their contribution to resource efficiency. Green innovation can lead to higher levels of resource efficiency (Sun et al., 2023). Indeed, it is recognized as a relevant factor driving the increase in resource productivity (Cainelli et al., 2020), and especially as a key driver of energy productivity (Sun et al., 2019).

Considering two types of resource efficiency—energy and material—it should be highlighted that energy efficiency refers to the ability to generate the same economic output using less energy (Simsek, 2014), and material efficiency means the ability to generate economic value using fewer material resources, either by creating more durable products or reducing waste (Korhonen et al., 2018).

Energy efficiency, therefore, is related from a practical perspective to the decoupling of the output and energy consumption, indicating that an economy can grow without necessarily increasing energy use proportionally (Tapio, 2005; Wang et al., 2023; Gbadeyan et al., 2024). However, it can also be the case that improving energy efficiency could reduce production costs, which can lead to an increase in economic activity and, in some cases, an increase in energy consumption (Vance et al., 2015; Kortelainen, 2008). The literature has highlighted that the relationship between green innovation and energy efficiency is still ambiguous and there are some unresolved questions considering different regions and time (Song et al., 2024). In this sense, recent studies suggest that the relationship between green innovation and energy efficiency is highly heterogeneous and depends on institutional conditions, regional contexts, firm characteristics, and the type of green technology (Sun et al., 2019; Gao and Ren, 2023; Zheng et al., 2025).

Considering these heterogeneous dimensions, empirical evidence has primarily focused *on the effects of green innovation on energy efficiency*. For example, Sun et al. (2019), in a study for 71 economies, show that green innovation can positively influence energy efficiency, but its impact depends on other factors such as the regulatory framework or institutional quality. Similarly, Song et al. (2024) in a study for the top ten green innovator economies find that green innovations improve energy efficiency. Complementing this macro-level evidence, Magdalena et al. (2025) show, using a sample of 34 countries, that both AI-related technologies and green patenting activities significantly enhance energy efficiency in renewable and nuclear power sectors, further reinforcing the positive role of technological innovation in improving energy performance across different energy systems. Recent studies also confirm this positive relationship while emphasising the importance of technological heterogeneity and contextual factors. Gao and Ren (2023), using firm-level evidence for China, show that higher-quality patents generate stronger improvements in energy efficiency, although these effects differ across ownership structures and regions. Similarly, Zheng et al. (2025) find that green technological innovation significantly improves total-factor energy efficiency, with green utility patents

displaying stronger effects than green invention patents. These findings suggest that not all forms of green innovation contribute equally to energy efficiency improvements. In addition, other studies for China show that the positive impact of green innovation on energy efficiency appears above a certain minimum threshold level of innovation (Liu et al., 2024; Zhai and Shi, 2022).

Material efficiency, on the other hand, can be understood from a practical perspective as efforts to reduce environmental impacts by reducing the amount of material used in the production process, without affecting the functioning of the economy (Rennings, 2000). Moreover, when resources are scarce or costly, green innovations can offer competitive advantages such as acquiring alternative or cheaper resources, which drives their adoption by firms (Porter and van der Linde, 1995). However, material efficiency is often incremental and largely dependent on the sector in which it is applied (Cainelli et al., 2011; Li et al., 2024).

Empirical studies on the relationship between *green innovation and material efficiency* are scarce. In fact, to our knowledge, there are none that directly address this link. Existing evidence is mostly indirect and focuses on related concepts such as material usage and natural resource utilization. For example, Wendler (2019) examines the effects of environmental innovation on material usage in European countries and finds that the relationship is not consistently significant, suggesting that improvements in material use are highly context-dependent. Similarly, Wang and Yang (2024) and Li et al. (2024) examine the relationship between green innovation and natural resources utilization, highlighting the importance of green innovation for resource conservation and climate change mitigation. Overall, these studies suggest that the relationship between green innovation and resource use is complex and heterogeneous, while direct evidence on material efficiency remains limited.

Against this backdrop, other contributions shed light on how green innovation may nonetheless influence material efficiency through specific mechanisms. For instance, Hojnik and Ruzzier (2016) and Hojnik et al. (2017) show that environmental process innovations help to reduce material costs. Furthermore, De Jesus and Mendonça (2018) explore the drivers and barriers of eco-innovation in the framework of the circular economy. The authors highlight that eco-innovation tends to promote resource reuse, waste minimisation, and the redesign of products to extend their useful life, which indirectly implies improvements in material-use efficiency. Li et al. (2024) find that green innovation could improve production methods, reduce production cost, and enhance natural resources utilization. For example, in terms of water resources, green innovation could lead to both water savings and improvements in water quality; and in terms of land resources, green innovations can support precision agriculture, increasing farmland productivity, alleviating pressure on land resources. In this sense, the improvement in resource efficiencies through green innovations will decrease dependence on some resources over time (Li et al., 2024).

Finally, a lagged structure is also expected in the analysis of green innovation and resource efficiencies (energy and material), as argued by Sun et al. (2023) using a dynamic model structure.

Therefore, despite its theoretical relevance, empirical knowledge about the effects of green innovation on different types of resource efficiency —and whether these effects behave similarly— remains limited. This is the specific focus of our second hypothesis.

H2. There is a positive relationship between green innovation and resource efficiencies (energy and material efficiency) in the EU-27 countries, and these associations exhibit lagged patterns.

Fig. 2 illustrates these hypotheses' development.

This figure and the analysis of the hypotheses address the gaps identified in the previous section of this article regarding the contribution of green patents to reducing emissions and improving resource efficiency, as well as the time-delayed effects in the EU context.

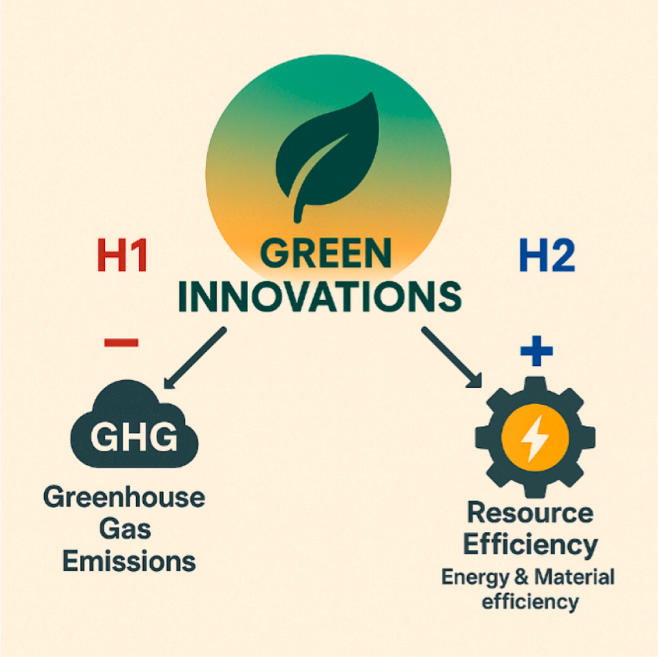


Fig. 2. Conceptual framework.
Source: Authors' own elaboration

3. Data and methodology

To test the proposed hypotheses, the empirical analysis is conducted in four sequential steps. Firstly, we collected data from PATSTAT, the OECD, UNCTAD, and the World Bank. We then harmonised and merged these data into a country-level panel dataset covering the EU-27 over the period 1993–2017. Secondly, we computed descriptive statistics and conducted graphical analyses of the main variables to identify cross-country patterns. Thirdly, we estimated panel data models (OLS, fixed effects, and random effects) to analyse the relationship between lagged green innovation and environmental performance (GHG emissions, energy efficiency, and material efficiency), including control variables, country fixed effects, and year fixed effects. Finally, to assess the stability of our results, we conducted several robustness checks and a heterogeneity analysis.

We begin by describing the data sources used in the empirical analysis. First, the green innovation variable is constructed using patent applications filed with the European Patent Office (EPO) between 1993 and 2017.[1] We define "green patents" based on the 3-digit CPC classification code Y02, which covers patents related to climate change mitigation and technologies associated with wastewater treatment or waste management, following the extant literature (Barbieri, 2015). In this sense, Angelucci et al. (2018) argue that all the green patents included in the Y02 classification represent technologies that decrease or remove emissions from the atmosphere, use renewable energy, or increase the efficiency in the use of power or resources. These Y02 classifications also include subclasses, which are described in Table A1 in the appendix.

[1] It is worth noting that patent applications are only published 18 months after their filing date, which means that the version of PATSTAT that we use, of October 2021, only includes patent applications published at the time of extraction of the data, that is, early 2020. We consider the period 1993-2017 in our analysis but acknowledge that due to this delay in publication (a consequence of the rules of the patent system) data on the most recent years may be incomplete. Nonetheless, our interest lies in the breakdown by country and sector for the whole period, rather than in their temporal evolution.

Although patents are a widely used proxy for innovation (see Griliches, 1990), they present several limitations. One important concern is truncation bias (Lerner and Seru, 2022). To mitigate this issue, we use patent applications rather than granted patents, conclude our sample in 2017 (three years prior to the last year available in PATSTAT), and focus exclusively on a single patent office (the EPO), which helps address differences in legal frameworks across jurisdictions. However, some limitations remain. Patent data tend to capture internationally valuable inventions rather than the full spectrum of innovative activity; moreover, not all innovations are patented. For instance, Taalbi (2025) reports that most innovations are not patented, and among those that are (representing 43.9% of all innovations), only a small fraction can be identified using patent-quality data. In addition, cross-country differences may reflect variation in patenting propensity and sectoral composition rather than pure differences in innovation performance. Despite these limitations, patents are a good indicator for specifically identifying "environmental" innovation, for instance through the use of technology classifications (such as the Cooperative Patent Classification, CPC), and are preferable to other innovation indicators, such as R&D expenditures, scientific publications, and innovation surveys (for more detail, see Haščič and Migotto, 2015).

For the analysis of emissions and efficiencies, we use variables sourced from official international databases, including Eurostat and OECD. These data sources provide harmonised definitions that enhance cross-country comparability and are widely used in the environmental economics literature. Some measurement limitations should be acknowledged: efficiency indicators are ratio-based and may partly reflect structural changes or trade patterns rather than pure efficiency gains, while aggregate GHG emissions are production-based and may not fully capture consumption-based impacts. Our final sample is an unbalanced panel covering the period from 1993 to 2017. Table 1 shows the description and sources of the variables used in the analysis, while Table 2 includes the main descriptive statistics.

Regarding the *descriptive results* of our main variables, Figs. 3a, 3b, 3c, and 3da–d displays the average values across countries for the period analysed, highlighting several notable patterns. The six countries with the highest GHG emissions are Luxembourg, Ireland, Denmark, the Netherlands, Czechia and Belgium. In terms of efficiencies, there are differences in the ranking when distinguishing between energy and materials. While countries such as Ireland, Italy, Denmark, Portugal, Austria, and Spain exhibit the best performance in energy efficiency, Sweden, Luxembourg, France, Austria, Belgium, Ireland, and Italy are in the top seven for material efficiency. Finally, countries such as Denmark, Latvia, Bulgaria, Lithuania, Slovakia and Cyprus stand out in terms of green patents. This comparison shows that there is no single group of countries consistently leading across all four variables; rather, the composition of the top performers varies, suggesting that strengths in emissions reduction, efficiency, and innovation are distributed differently across Europe.

Table 1
Description of the variables.

Variables	Definition	Source
Log of GHG Emissions	Natural logarithm of greenhouse gas emissions. (Kilograms per capita, Thousands)	OECD
Log of Energy Efficiency	Natural logarithm of amount of economic output that is produced per unit of gross available energy (purchasing power standard per kilogram of oil equivalent).	Eurostat
Log of Material Efficiency	Natural logarithm of gross domestic product -GDP- divided by domestic material consumption -DMC- (€/kg in 2015 constant prices)	Eurostat
Green Patents	Green Patent = Y02 IPC classification Share of green patent applications in total patent applications	PATSTAT
Log of GDP Per capita	Natural logarithm of GDP divided by population (€/person in 2015 constant prices)	World Bank
Log of Population Density	Natural logarithm of population density. Number of inhabitants per km^2	Eurostat
Log of Urban Population	Natural logarithm of total urban population	World Bank
Openness	Trade-to-GDP ratio (%). Exports and imports from UNCTAD in constant 2015 USD (adjusted using the World Bank deflator). GDP in millions of constant 2015 USD.	UNCTAD & World Bank
Industrialization level	Industrial structure. Share of industry gross value added (GVA) in GDP (%).	Eurostat
Energy Tax	Tax revenue from energy tax bases (% of total tax revenues)	Eurostat

Source: Authors' own elaboration

Table 2
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Log of GHG Emissions	643	2.098	0.618	−3.352	3.463
Log of Energy Efficiency	598	1.699	0.395	0.310	2.846
Log of Material Efficiency	545	1.969	0.631	0.564	3.395
Green Patent ratio	647	0.087	0.064	0.000	0.500
Log of GDP per capita	650	10.506	0.491	9.235	11.834
Log of Population Density	643	4.535	0.748	2.809	6.221
Log of Urban Population	650	15.534	1.291	12.693	17.972
Openness (%)	608	86.121	45.899	17.683	233.223
Industrialization level (%)	608	19.098	5.072	5.700	36.500
Energy Tax (%)	615	5.970	2.246	0.000	16.459

Source: Authors' own elaboration

As an *empirical strategy,* we apply panel data models using the dataset described above. Specifically, we estimate fixed-effects models, along with pooled OLS and random-effects specifications,[2] based on the following specifications (Wooldridge, 2010):

$$GHG\ emissions_{it} = \alpha_0 + \beta_1 Green\ patents_{it-1} + \beta_2 Green\ patents_{it-2} + \sum_{k=1}^{6} \gamma_k X_{ik} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

$$Efficiencies_{it} = \alpha_0 + \beta_1 Green\ patents_{it-1} + \beta_2 Green\ patents_{it-2} + \sum_{k=1}^{6} \gamma_k X_{ik} + \mu_i + \eta_t + \varepsilon_{it} \quad (2)$$

Where i = 1, …, N countries and t = 1, …, T years; and where $GHG\ emissions_{it}$ measured in kilograms per capita and $Efficiencies_{it}$ representing energy or material productivity, are the dependent variables (all transformed with logarithms). In addition, the main independent variables are $Green\ patents_{it-1}$ and $Green\ patents_{it-2}$ calculated as the ratio between green patents and total patents. Du et al. (2019) apply a similar ratio in their model. In our case, the green patent variable is introduced in lags because the effect of patents on GHG emissions and energy and material efficiencies takes time to manifest itself. This has been justified, among others, by Kwon et al. (2017) and Du et al. (2019). In this vein, Popp (2001) argues that the time required for reductions in emissions may exceed one year. This specification also helps mitigate potential reverse causality by using lagged values of green patent applications (t–1 and t–2) instead of contemporaneous values, thereby reducing potential simultaneity between environmental outcomes and green innovation. As noted by Bellemare et al. (2017), lagging independent variables can partially address endogeneity related to

[2] We prefer the fixed-effects model to OLS and random-effects models because it accounts for the potential correlation between unobserved individual effects and the control variables, and it controls for time-invariant, unobserved country-specific characteristics.

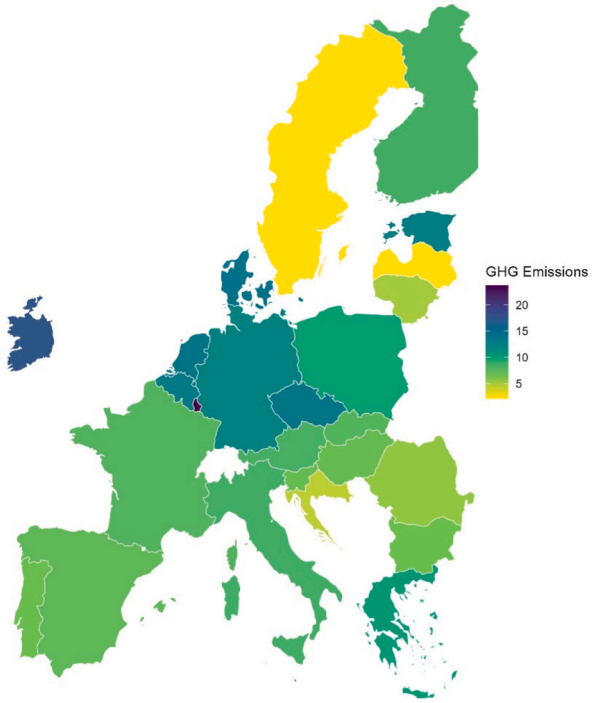


Fig. 3a. Intensity of emissions in the EU-27.

Note: Values correspond to country averages over the sample period
Source: Authors' own elaboration

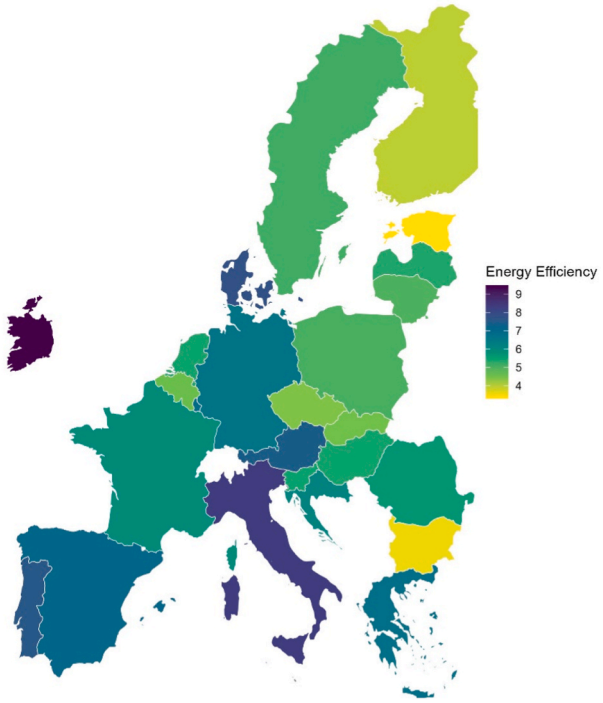


Fig. 3b. Intensity of energy efficiency in the EU-27.

Note: Values correspond to country averages over the sample period
Source: Authors' own elaboration

observable characteristics, although this strategy does not fully eliminate endogeneity arising from unobserved confounding factors.

To determine the optimal lag structure, we examine the correlation pattern across alternative lags. The high persistence observed in patent applications implies substantial collinearity across adjacent lags, raising concerns about over-parameterization when multiple lags are included simultaneously. Estimations incorporating alternative lag lengths indicate that higher-order lags do not display stable statistical significance and including them jointly does not materially affect the baseline estimates. Taken together, these results support a parsimonious specification including up to the second lag.[3]

In addition, we included a set of control variables (X_{ik}) following the specialised literature. Gross Domestic Product per capita (GDP_{it}) is included along with its squared term (GDP_{it}^2), both expressed in logarithms (Du et al., 2019; Chen et al., 2023; Fang et al., 2022). These variables are included with the aim of capturing the effects that income levels may have on the dependent variables through different economic channels, such as structural transformation towards less resource-intensive sectors, the adoption of more efficient technologies, and the strengthening of regulatory frameworks. In addition, the quadratic term of GDP per capita is also included to flexibly capture possible non-linear effects of income. This allows the marginal effect of income to vary according to the level of development, reflecting that scale, composition and technical effects may operate differently at different income levels. The same specification is maintained in all estimated models to ensure methodological consistency and comparability between equations. We also control for population density ($PopulationDensity_{it}$) in logs, as well as economic openness ($Openness_{it}$), urban population ($Urbanpopulation_{it}$) in logs, the level of industrialization ($Industrialisation_{it}$) and energy tax ($Energy\ tax_{it}$). These control variables have been widely used in previous studies (Li et al., 2024; Xia et al., 2024; Kwon et al., 2017).

Finally, μ_i *and* η_t capture country and time fixed effects, respectively, and ε_{it} denotes the error term. Therefore, the main advantage of this methodology is that it allows us to capture the evolution of the variables over time and to control for unobserved country-specific heterogeneity. We fully acknowledge that our empirical strategy cannot completely eliminate endogeneity concerns. Given that this problem cannot be fully addressed, we rely on fixed-effects estimators, as they provide evidence of association rather than causality.[4]

To assess the robustness of our baseline specification, we implement several additional tests. First, we re-estimate the models excluding the crisis period (2008–2010), in order to verify that our results are not driven by extraordinary macroeconomic conditions associated with the global financial crisis. Second, we replace total GHG emissions with CO_2 emissions as an alternative dependent variable, given that CO_2 constitutes the largest component of greenhouse gas emissions. This allows us to examine whether the estimated associations between green patenting and environmental outcomes remain consistent when focusing on a more specific emission indicator. Finally, we assess heterogeneity through interaction terms that capture differential effects across leader and laggard groups.

[3] The correlation matrix of the lagged variables and the regressions used to determine the optimal lag structure are available upon request.

[4] The size of our sample does not allow us to adopt, for instance, a system GMM estimator for addressing the endogeneity. Another potential approach would be the use of instrumental variables. However, this would require a valid exogenous instrument (e.g., a new policy or regulatory change) that is closely related to the underlying theoretical mechanism. Such an instrument would need to satisfy both the exclusion and relevance restrictions and would likely alter the theoretical framework of the paper.

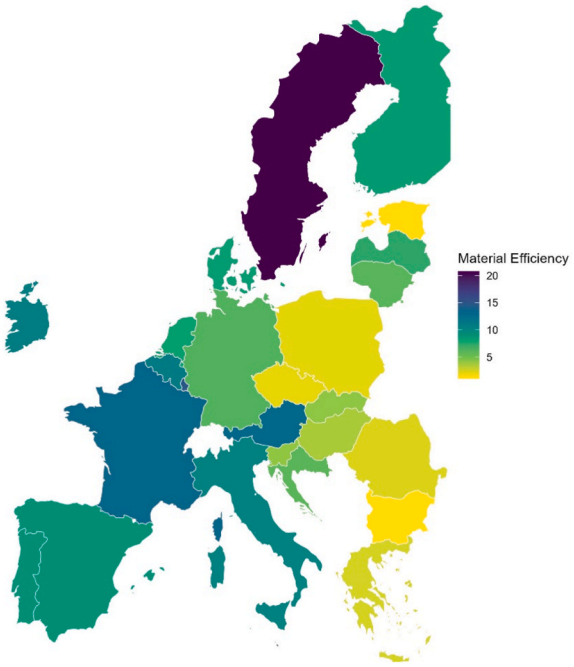


Fig. 3c. Intensity of material efficiency in the EU-27.

Note: Values correspond to country averages over the sample period
Source: Authors' own elaboration

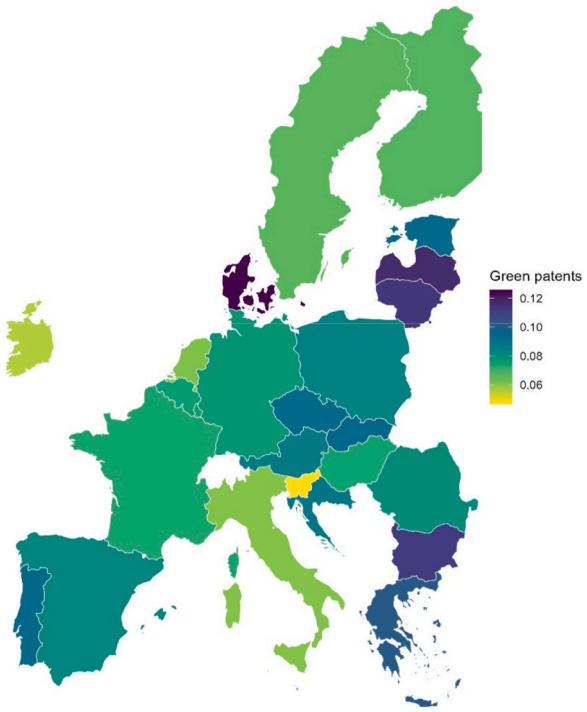


Fig. 3d. Intensity of green patents in the EU-27. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Note: Values correspond to country averages over the sample period
Source: Authors' own elaboration

Lastly, the correlation matrix of the variables used in the analysis can be found in Table A2 of the Appendix.

4. Results and discussion

In this section, we discuss our results considering three models (one for each dependent variable) presented in Table 3.

Our main findings highlight the existence of a relationship between green innovations and emissions, as well as resource efficiencies, in line with Sustainable Development Goal (SDG) 13. This means that green innovation has a negative association with GHG emissions and a positive association with resource efficiencies, confirming the dual role of green innovation (Rennings, 2000; Costanza et al., 1991; Du et al., 2019). Regarding the models, it should be noted that the coefficients are very robust and remain very similar across the different specifications (OLS, FE and RE), indicating a good fit for the models. Finally, we should mention that some of the control variables are significant when we estimate the models without time and country dummies.

However, the timing of these associations varies across the three variables. It should be noted that the effects of green innovations can manifest themselves with varying intensity and speed depending on the nature of the process affected (see Fig. 4). While some innovations act directly on specific technologies or processes, others require broader transformations in infrastructure, supply chains or usage patterns (Geels, 2011). From a macro-level perspective, this distinction resonates with the literature on directed technical change and environmental innovation, which emphasises path dependency, capital vintage effects and the gradual nature of structural adjustment (Acemoglu et al., 2012; Aghion et al., 2016; Popp, 2019). These structural differences shape the speed with which the effects materialise and explain the presence of heterogeneous time lags between the variables analysed.

Therefore, given that the results differ when the three variables are considered separately and time lags are incorporated, the following subsections examine in detail the association of green innovation with GHG emissions, energy efficiency, and material efficiency, in order to provide a clearer interpretation of these heterogeneous patterns.

These results are consistent with the findings of previous studies, which show a negative relationship between green innovation and greenhouse gas emissions, and a positive relationship between green innovation and resource efficiency, confirming the dual role of green innovation (Rennings, 2000; Costanza et al., 1991; Du et al., 2019; Sun et al., 2019, 2023; Jebali et al., 2017; Cainelli et al., 2020). However, our study extends the existing literature in three main ways. Firstly, we jointly analyse GHG emissions, energy efficiency, and material efficiency within a unified framework. Secondly, our empirical analysis incorporates the temporal dimension of green innovation by including lagged effects, showing that the relationship varies across different environmental outcomes. Finally, our results suggest that energy efficiency responds more rapidly to green innovation than GHG emissions and material efficiency, highlighting the different adjustment processes that have received limited attention in previous empirical research. The following subsections discuss these three findings in greater detail.

4.1. The dual role of green innovation in climate mitigation

Regarding GHG emissions, we find that green patents have a negative association with GHG emissions at the 10% significance level in the second lag. This implies that green patents contribute to reducing these emissions as pointed out in previous literature (Du et al., 2019; Ghimire et al., 2023; Töbelmann and Wendler, 2020). However, this association is not immediate; rather, it is delayed over time.

Table 3
Main results.

	Log of GHG Emissions			Log of Energy Efficiency			Log of Material Efficiency		
	OLS	FE	RE	OLS	FE	RE	OLS	FE	RE
Green Patents $_{t-1}$	−1.009	−1.009	−1.009	0.170**	0.170**	0.170**	−0.024	−0.024	−0.024
	(0.893)	(0.873)	(0.893)	(0.078)	(0.076)	(0.078)	(0.078)	(0.076)	(0.078)
Green Patents $_{t-2}$	−0.259*	−0.259*	−0.259*	0.087	0.087	0.087	0.145*	0.145*	0.145*
	(0.140)	(0.137)	(0.140)	(0.062)	(0.060)	(0.062)	(0.075)	(0.073)	(0.075)
Patent applications $_{t-1}$	−0.000	−0.000	−0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patent applications $_{t-2}$	0.000	0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of GDP per capita	−2.623	−2.623	−2.623	3.548***	3.548***	3.548***	−0.166	−0.166	−0.166
	(3.717)	(3.632)	(3.717)	(1.227)	(1.199)	(1.227)	(2.450)	(2.388)	(2.450)
Log of GDP per capita^2	0.146	0.146	0.146	−0.134**	−0.134**	−0.134**	0.031	0.031	0.031
	(0.185)	(0.180)	(0.185)	(0.057)	(0.056)	(0.057)	(0.120)	(0.117)	(0.120)
Log of Population density	0.570	0.570	0.570	0.059	0.059	0.059	−0.229	−0.229	−0.229
	(0.860)	(0.840)	(0.860)	(0.361)	(0.352)	(0.361)	(0.481)	(0.469)	(0.481)
Log of Urban population	0.000	0.000	0.000	−0.000	−0.000	−0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Openness	−0.003	−0.003	−0.003	0.006	0.006	0.006	−0.008	−0.008	−0.008
	(0.016)	(0.016)	(0.016)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
Industrialization	−1.674	−1.674	−1.674	0.294	0.294	0.294	0.751	0.751	0.751
	(1.311)	(1.281)	(1.311)	(0.349)	(0.341)	(0.349)	(0.552)	(0.538)	(0.552)
Energy Tax	0.017	0.017	0.017	−0.000	−0.000	−0.000	0.008	0.008	0.008
	(0.016)	(0.016)	(0.016)	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)
Constant	12.601	12.513	12.601	−23.438**	−23.403**	−23.438**	0.742	0.295	0.742
	(28.721)	(28.160)	(28.721)	(9.564)	(9.375)	(9.564)	(14.889)	(14.571)	(14.889)
Observations	584	584	584	588	588	588	539	539	539
R-squared	0.847	0.224	0.847	0.972	0.949	0.972	0.985	0.798	0.985
Number of countries	26	26	26	26	26	26	26	26	26
Country dummies	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: We include the total number of patent applications (Patent applications t–1 and Patent applications t–2) as control variables to preserve the interpretation of the green patent variable. Clustered standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

In fact, considering the lag structures, this relationship emerges only at the second lag, yielding results broadly consistent with Du et al. (2019). However, unlike their findings, where a negative association appears at the first lag only when the green patent variable is interacted with a dummy indicating whether an economy belongs to the high-income group, and remains non-significant without this interaction, our results do not replicate this pattern.

This evidence indicates that green innovations do not generate immediate reductions in GHG emissions, but rather their impact emerges gradually, in line with evidence highlighting the gradual diffusion of technological advances (Jaffe et al., 2005; Kwon et al., 2017). From a macro-level perspective, this delayed relationship reflects the structural nature of decarbonisation processes, which are characterised by path dependency, capital vintage effects, and technological lock-in, as highlighted in the literature on directed technical change and environmental transitions (Acemoglu et al., 2012; Aghion et al., 2016). GHG emissions are closely linked to carbon-intensive production and energy infrastructures, characterised by high levels of technological lock-in that hinder the rapid replacement of existing technologies (Unruh, 2000; Jaffe et al., 2005). Consequently, green innovations only generate appreciable reductions when their adoption reaches a sufficient scale and progressive adjustments are made to supply chains and the energy mix (Popp, 2010; Geels, 2011). These mechanisms explain why the estimated associations on aggregate emissions emerge with a two-year lag, even when innovative activity is already underway.

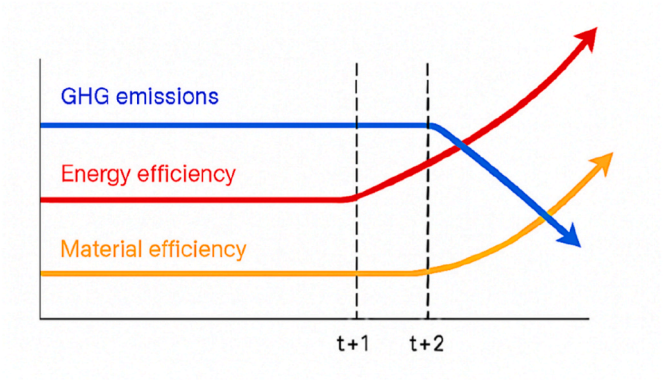


Fig. 4. Dynamics between green innovations and GHG emission, energy and material efficiencies. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
Source: Authors' own elaboration

Concerning the control variables, it is noteworthy that GDP per capita is not significant, which could be explained by the fact that high-income economies may have already reached a stage where emission reductions are no longer dependent on income levels, given their relative similarity. This idea has been argued by Du et al. (2019), and a lack of significance has been found in Fang et al. (2022). We have not found any additional significant variables in this model. Therefore, these results confirm the first hypothesis of our paper and answer our RQ1, although the relationship between green innovation and GHG emissions takes time.

Related to energy efficiency, we observe a positive association between green innovation and energy efficiency at the 5% significance level in the first lag. This positive relationship is consistent with the findings of Sun et al. (2019). However, in their study, the impact of green technologies on energy intensity is estimated contemporaneously, without incorporating any lag structure.

Compared with GHG emissions, the association of green innovation with energy efficiency appears earlier. We have found that this link emerges when we consider the first lag in our model, and is not significant when considering subsequent lags. This suggests that improvements in energy efficiency tend to appear relatively quickly, given that many green innovations act directly on the energy consumption of processes, equipment and technologies, generating savings and

optimising energy use from the moment they are adopted (Sun et al., 2019). This pattern is also consistent with macro-level studies on directed technical change, which show that energy-efficiency improvements embodied in capital goods tend to generate rapid gains once adopted, without requiring extensive structural adjustment (Acemoglu et al., 2012; Aghion et al., 2016). Unlike other environmental dimensions, these improvements do not require complex systemic transformations or the reconfiguration of supply chains, which makes it easier for the benefits to be reflected early on in the aggregate data. The absence of significant associations in subsequent lags could be explained by the fact that, as these are direct and concentrated impacts, most of the benefit materialises in the first period, leaving little room for additional effects in subsequent periods (Popp, 2010).

In this model, we also find a positive relationship between GDP per capita and energy efficiency, as well as a negative association between squared GDP per capita and energy efficiency, indicating a nonlinear relationship between income and energy efficiency. Specifically, increases in income are initially associated with improvements in energy efficiency, but the positive relationship diminishes at higher income levels. This pattern suggests that structural and technological improvements dominate at lower income levels, while scale effects become more relevant as income rises. This result has been postulated by other authors such as Sun et al. (2019) and Jebali et al. (2017) and is consistent with the decoupling approach between growth and energy consumption (Tapio, 2005). The remaining control variables are not significant in this model, which reinforces the central role of green innovation and income level as the main determinants of energy efficiency in our analysis. In this respect, the positive relationship observed confirms the second hypothesis of our paper for energy efficiency, with associations appearing in the first lag in the analysis and partially answering our RQ2.

Finally, considering material efficiency, the results suggest a positive relationship between green innovation and material efficiency at the 10% significance level in the second lag (Cainelli et al., 2020; Sun et al., 2023).

In contrast to energy efficiency, the association of green patents with increases in material efficiency appears to take longer to manifest and is not immediate. The model shows that this positive link between green patents and material efficiency emerges at the second lag. This pattern is in line with Li et al. (2024), who point out that the improvement in natural resource efficiency through green innovation occurs mainly through industrial structural transformation and reduction of resource dependence. These dynamics reflect structural adjustment processes in which material efficiency improvements depend on changes in production structures and supply chains, implying slower diffusion and delayed aggregate effects (Aghion et al., 2016). Such processes often involve gradual adjustments to production methods and, in many cases, changes in product design and supply chain organisation, which explains why their relationship takes longer to manifest itself. However, this positive association contrasts with the findings of Wendler (2019), who reports a non-significant impact of environmental innovation on material usage. A key difference between his results and ours is that he does not account for the dynamic nature of innovation, instead modelling environmental innovation contemporaneously. Moreover, he disaggregates innovation into different categories, obtaining results that are partly consistent with ours, particularly in areas related to energy efficiency, as well as recycling and reuse.

The remaining variables are not significant in this model. The lack of significance of the industrialization variable suggests a certain level of independence from resources, as argued by Li et al. (2024), since we are considering high-income economies. However, some literature has considered it as a factor affecting that relationship (Cainelli et al., 2011; Li et al., 2024). This result can be interpreted as a sign that, in high-income economies, pressure on material resources is more contained, reducing the sensitivity of material efficiency to industrial intensity. Moreover, as pointed out by Cainelli et al. (2011), the impact of green innovations on material efficiency is highly dependent on the type of industry and the regional context, which could explain the lack of significance in aggregate models. Therefore, we also confirm the second hypothesis for material efficiency, with this relationship not appearing immediately, and answering the second part of our RQ2.

Table 4
Summary of hypothesis testing.

Hypotheses	Relationship	Time
H1. Green patents and emissions	-	Long-term association
H2a. Green patents and energy efficiency	+	Short-term association
H2b. Green patents and material efficiency	+	Long-term association

Source: Authors' own elaboration

In summary, considering the three analyses together, the results show that green innovation helps to combat climate change by reducing emissions and increasing resource efficiency. These findings highlight the dual role of green innovation in mitigating emissions and optimising resource use. Overall, these findings complement previous studies analysing the relationship between green innovation and GHG emissions (Du et al., 2019; Ghimire et al., 2023; Töbelmann and Wendler, 2020), as well as the relationship between green innovation and resource efficiency (Sun et al., 2019, 2023; Jebali et al., 2017; Cainelli et al., 2020). Unlike the existing literature, which generally explores these relationships independently and without considering their temporal dynamics, our findings highlight that the relationship between green innovation and environmental outcomes can be analysed within a unified analytical framework. The results also show that the relationship between green innovation and environmental outcomes varies over time and is not immediate, reinforcing the dynamic nature of this relationship.

Table 4 summarises the results of the hypotheses tested in this analysis. Nevertheless, these findings should be interpreted with caution, as they do not imply causality and omitted variables may introduce bias into our estimations. However, our empirical approach provides evidence of statistically significant associations.

4.2. Robustness check and heterogeneity in innovation impacts

The heterogeneous lag structures reflect different degrees of systemic change**.** For instance, energy efficiency gains are associated with more readily adoptable technologies, whereas improvements in material efficiency and reductions in GHG emissions are linked to broader structural transformations that take longer to materialise. This dynamic perspective is consistent with the lag structures discussed by Jaffe et al. (2005) and Du et al. (2019), and highlights the importance of long-term policy commitment to support environmental transitions. To strengthen the credibility of our results, we present robustness checks and a heterogeneity analysis in this section.

In the first robustness check, we exclude the crisis years (2008–2010) from the sample and obtain results consistent with the baseline specification reported in Table 3 (see Table A3 in the appendix). A negative association between green patents and GHG emissions is still observed at the second lag, along with positive associations between green patents and efficiencies (at the first and second lags for energy efficiency, and at the second lag for material efficiency).

To further strengthen our findings, we replace total GHG emissions with CO_2 emissions as a second robustness check, a major component of total greenhouse gas emissions. The results indicate a negative association between green patents (t–1 and t–2) and CO_2 emissions, thereby supporting the baseline findings (see Table A4 in the Appendix). Finally, we examine heterogeneity between innovation leaders and laggards using interaction terms. The results provide limited evidence of systematic differences between the two groups (see Table A5 in the Appendix).

5. Conclusions

Green innovations are a catalyst for green development, facilitating economic growth, and at the same time mitigating environmental harm by reducing emissions and increasing efficiencies. This paper provides new empirical evidence on the dynamic and heterogeneous relationships of green innovations with GHG emissions, energy efficiency and material efficiency. It jointly analyses these dimensions, which, to the best of our knowledge, have not been examined together within a dynamic framework in the context of climate change mitigation.

The main finding of this study is that the environmental associations of green innovation are not homogeneous over time. This is particularly evident in the cases of emissions and material efficiency, where we observe that this relationship emerges at the second lag. This means that green innovation will decrease GHG emissions and increase material efficiency over time. However, the effect of green innovation on energy efficiency is more immediate, showing a positive association at the first lag. Therefore, the relationship between green innovations and energy efficiency occurs earlier. This temporal asymmetry highlights that green innovation fulfils a dual role in combating climate change, but through differentiated mechanisms and speeds.

The faster association between green innovation and energy efficiency versus emissions or material efficiency suggests structural differences in the mechanisms of technological adoption. While many green innovations have a direct impact on energy processes and equipment, generating relatively immediate improvements, others require broader transformations in infrastructure, supply chains and production systems. In these cases, the relationship tends to materialise more gradually.

This paper makes three main contributions to the literature. First, it provides novel empirical evidence showing that the relationships between green innovation and environmental performance are dynamic and heterogeneous over time, differing across greenhouse gas emissions, energy efficiency and material efficiency. By accounting for lagged associations and exploiting detailed patent data from PATSTAT, the analysis highlights the importance of a dynamic perspective when assessing the relationship between innovation and environmental outcomes. Second, the paper contributes by jointly analysing these environmental dimensions within a single analytical framework, allowing for an integrated assessment of climate mitigation and resource efficiency objectives. Third, the study offers new evidence for the EU-27 as an underexplored regional context, with direct relevance for European environmental and innovation policies, particularly in the framework of the European Green Deal. Overall, the findings contribute to the empirical assessment of progress towards SDG 13 (Climate Action) by clarifying the timing and channels through which green innovation affects environmental outcomes.

Beyond the theoretical contributions discussed above, these findings have important policy and managerial implications. From a policy perspective, first, our findings highlight the urgency of developing green innovation capabilities to combat climate change through the reduction of emissions and the improvement of energy and material efficiency. In this regard, policies promoting green technologies, R&D investment, and environmental innovation ecosystems are crucial in the EU-27, where advanced economies possess greater capacity to develop and diffuse sustainable technologies. Second, given that the associations of green innovation are not immediate and differ across environmental dimensions, policy frameworks should explicitly incorporate differentiated temporal expectations into both policy design and evaluation. Our results show that energy efficiency responds relatively quickly to innovation efforts, whereas reductions in greenhouse gas emissions and improvements in material efficiency materialise only after longer adjustment periods. This implies that policymakers should set short- and long-term targets aligned with the expected timing of impacts, avoid evaluating policy effectiveness solely on the basis of short-term indicators—which may underestimate long-run environmental benefits—and design evaluation criteria that explicitly recognise that some benefits of green innovation only emerge over longer time horizons. Third, these findings underscore the importance of policy stability and continuity. Firms require time to adopt, integrate, and scale green technologies; therefore, long-term regulatory commitments, predictable environmental standards, and multi-year funding schemes are essential to reduce uncertainty and encourage sustained investment. In this context, coordinated policy mixes that combine innovation incentives (e.g. R&D subsidies, green tax credits, or programs such as Horizon Europe), robust environmental regulation (e.g. emissions standards, carbon pricing mechanisms such as the EU Emissions Trading System), and support for technology diffusion (e.g. demonstration projects, public procurement, or initiatives linked to the European Green Deal) can facilitate the gradual structural transformation needed to achieve climate neutrality objectives in the EU-27. Furthermore, policymakers should explicitly integrate the lagged nature of green innovation into monitoring and evaluation systems. This includes designing evaluation frameworks that distinguish between immediate efficiency gains and longer-term systemic effects and adopting adaptive policy mechanisms capable of adjusting support intensity as technologies evolve from invention to diffusion and large-scale deployment.

From a managerial perspective, the results suggest that green innovation strategies should be aligned with realistic time horizons that are differentiated according to the type of environmental outcome pursued. While investments in energy-efficient technologies can generate relatively quick returns, innovations aimed at reducing emissions or increasing material efficiency typically require longer-term planning and greater coordination within organisations and across the supply chain. In this context, managers should integrate green innovation into strategic decision-making, allocating resources gradually and consistently with the expected environmental and economic return timescales. Additionally, managing expectations is key to avoiding premature assessments of the performance of green initiatives, especially those aimed at structural changes. Furthermore, highlighting the social and environmental benefits associated with green innovation strategies (both within the organisation and to investors and other stakeholders) can help reduce the perception of risk, encourage private sector engagement, and strengthen the role of companies in the green transition.

Despite these important contributions and implications, this study is subject to several limitations that should be acknowledged. These limitations also provide valuable opportunities for future research. As a first limitation of our paper, it should be mentioned that patents are a commonly used indicator of the output of research and development activities and technological capabilities (Griliches, 1979; OECD, 2009), even though it is commonly acknowledged that not all inventions are patentable or intended to be patented (Dosi et al., 1990). We use patent applications in our analysis, given the lack of better indicators of innovative capabilities at the product level across countries and over time, while being aware that this choice may underestimate certain forms of innovation, especially those of an organisational or incremental nature. We also recognise that some countries may have stronger intellectual property cultures than others, and some sectors may be more prone to patenting than others, which could influence the measurement of innovative activity. In addition, the second limitation of our analysis is related to our country sample. In this sense, we analyse patent data in the European Union countries. We were not able to divide our sample by regions. Moreover, in this analysis we could not study this relationship across industrial sectors, which prevents us from capturing possible heterogeneities in the relationship between green innovation, emissions and resource efficiency. Finally, we acknowledge the potential endogeneity concerns that are not fully addressed in our current empirical framework, due to omitted unobservable variables (confounders) and the dynamic nature of the dependent variable. In particular, the presence of omitted time-varying factors may influence the estimated coefficients, meaning that the results should be interpreted as dynamic associations rather than strict causal effects. Additionally, although the

use of lagged variables allows us to capture delayed relationships, it does not fully disentangle the underlying mechanisms driving these temporal patterns. Taken together, these limitations suggest that the estimated relationships should be interpreted with caution, as not all relevant factors may be fully captured in the model. Despite these limitations, we believe that our results are robust and provide consistent evidence of the relationship between green innovation, emissions, and efficiency.

Building on these limitations, several opportunities for future research can be identified. Future studies could complement the use of patents with alternative indicators of green innovation that capture forms of innovation that are not patentable. In addition, extending the analysis to other geographical contexts and adopting sectoral or regional approaches would allow for a deeper understanding of possible heterogeneities in the relationship of green innovation with environmental outcomes. Further research could also explore alternative identification strategies to better address remaining endogeneity concerns. Finally, future research could investigate the mechanisms through which green innovation translates into environmental improvements over time. In particular, distinguishing between invention, technology diffusion, firm adoption and large-scale deployment would help explain the heterogeneous temporal patterns identified in this study and provide further insights into the pathways linking green innovation to climate change mitigation.

CRediT authorship contribution statement

Guillermo Arenas Díaz: Data curation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Celia Torrecillas:** Conceptualization, Data curation, Supervision, Writing – original draft, Writing – review & editing. **Sara Fernández:** Conceptualization, Data curation, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Y02 Technologies or Applications for Mitigation or adaptation against climate change

Y02B	Indexing scheme relation to climate change mitigation technologies related to buildings, e.g. Including housing and appliances or related end-user applications
Y02C	Capture, storage, sequestration or disposal of Greenhouse Gases (GHG)
Y02E	Reduction of greenhouse gases (GHG) emissions, related to energy generation, transmission or distribution
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management

Note: We have not considered Y04S because 2/3 of its codes are connected to Y02.
Source: own elaboration based on Angelucci et al. (2018).

Table A2
Correlation Matrix

	Green Patent ratio	Log of GDP per capita	Log of Population density	Log of Urban Population	Openness	Industrialization level	Energy tax
Green Patent ratio	1						
Log of GDP per capita	−0.1059	1					
Log of Population density	−0.0413	0.2891	1				
Log of Urban Population	−0.0573	0.0151	0.3514	1			
Openness	−0.0021	0.0397	0.1704	−0.2538	1		
Industrialization level	−0.1277	−0.3484	−0.1409	0.1897	0.2439	1	
Energy tax	0.0433	−0.3023	−0.0607	−0.2223	−0.0112	0.0854	1

Table A3
The Relationship between GHG emissions, efficiencies, and Green Patents (excluding the crisis period)

	Log of GHG Emissions	Log of Energy Efficiency	Log of Material Efficiency
	FE	FE	FE
Green Patents $_{t-1}$	−1.032	0.181**	0.033
	(0.873)	(0.078)	(0.101)
Green Patents $_{t-2}$	−0.272**	0.114*	0.158**
	(0.128)	(0.058)	(0.070)

(*continued on next page*)

Table A3 (*continued*)

	Log of GHG Emissions	Log of Energy Efficiency	Log of Material Efficiency
	FE	FE	FE
Patent applications $_{t-1}$	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Patent applications $_{t-2}$	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Log of GDP per capita	−2.819	3.272**	−0.303
	(3.749)	(1.257)	(2.559)
Log of GDP per capita^2	0.155	−0.119*	0.039
	(0.187)	(0.058)	(0.125)
Log of Population density	−1.908	0.268	0.814
	(1.378)	(0.370)	(0.528)
Log of Urban population	0.680	0.100	−0.253
	(0.905)	(0.347)	(0.463)
Openness	0.000	−0.000	0.000
	(0.001)	(0.000)	(0.001)
Industrialization	−0.004	0.005	−0.009
	(0.018)	(0.004)	(0.007)
Energy Tax	0.017	0.001	0.006
	(0.015)	(0.004)	(0.006)
Constant	12.920	−22.573**	0.992
	(28.836)	(10.151)	(15.593)
Observations	506	510	461
R-squared	0.228	0.953	0.814
Control variables	Yes	Yes	Yes
Country dummies	No	No	No
Time dummies	Yes	Yes	Yes
Number of countries	26	26	26

Note: We include the total number of patent applications (Patent applications t–1 and Patent applications t–2) as control variables to preserve the interpretation of green patents. Clustered standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Table A4
Alternative definition of GHG emissions (CO2 emissions).

	Log of GHG Emissions	Log of CO2 emissions
	FE	FE
Green Patents $_{t-1}$	−1.009	−0.148*
	(0.873)	(0.075)
Green Patents $_{t-2}$	−0.259*	−0.159**
	(0.137)	(0.074)
Patent applications $_{t-1}$	−0.000	−0.000
	(0.000)	(0.000)
Patent applications $_{t-2}$	0.000	0.000
	(0.000)	(0.000)
Log of GDP per capita	−2.623	−3.014*
	(3.632)	(1.744)
Log of GDP per capita^2	0.146	0.168*
	(0.180)	(0.084)
Log of Population density	−1.674	−0.016
	(1.281)	(0.427)
Log of Urban population	0.570	0.424
	(0.840)	(0.441)
Openness	0.000	0.000
	(0.001)	(0.001)
Industrialization	−0.003	−0.003
	(0.016)	(0.005)
Energy Tax	0.017	0.001
	(0.016)	(0.007)
Constant	12.513	10.994
	(28.160)	(13.663)
Observations	584	588
R-squared	0.224	0.568
Control variables	Yes	Yes
Country dummies	No	No
Time dummies	Yes	Yes
Number of countries	26	26

Note: We include the total number of patent applications (Patent applications t–1 and Patent applications t–2) as control variables to preserve the interpretation of green patents. Log of CO2 emissions is the natural logarithm of total carbon dioxide (CO2) emissions, excluding LULUCF (measured in Mt CO2e), obtained from the World Bank. Clustered standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Table A5
Heterogeneity: Leader vs laggard countries

	Log of GHG Emissions			Log of Energy Efficiency			Log of Material Efficiency		
	FE	OLS	OLS	FE	OLS	OLS	FE	OLS	OLS
Green Patents $_{t-1}$	−1.009	−1.009	−0.973	0.170**	0.170**	0.117	−0.024	−0.024	−0.055
	(0.873)	(0.893)	(0.947)	(0.076)	(0.078)	(0.069)	(0.076)	(0.078)	(0.074)
Green Patents $_{t-2}$	−0.259*	−0.259*	−0.227	0.087	0.087	0.070	0.145*	0.145*	0.136*
	(0.137)	(0.140)	(0.142)	(0.060)	(0.062)	(0.044)	(0.073)	(0.075)	(0.078)
Patent applications $_{t-1}$	−0.000	−0.000	−0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patent applications $_{t-2}$	0.000	0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leader	–	–	1.329	–	–	−0.081	–	–	−0.340
	–	–	(1.729)	–	–	(0.673)	–	–	(0.997)
Leader* Green Patents $_{t-1}$	–	–	−0.237	–	–	0.517**	–	–	0.277
	–	–	(0.618)	–	–	(0.239)	–	–	(0.278)
Leader * Green Patents $_{t-2}$	–	–	−0.127	–	–	−0.054	–	–	−0.046
	–	–	(0.264)	–	–	(0.213)	–	–	(0.214)
Log of GDP per capita	−2.623	−2.623	−2.848	3.548***	3.548***	3.817***	−0.166	−0.166	0.037
	(3.632)	(3.717)	(3.504)	(1.199)	(1.227)	(1.134)	(2.388)	(2.450)	(2.285)
Log of GDP per capita^2	0.146	0.146	0.157	−0.134**	−0.134**	−0.147**	0.031	0.031	0.021
	(0.180)	(0.185)	(0.174)	(0.056)	(0.057)	(0.053)	(0.117)	(0.120)	(0.112)
Log of Population density	−1.674	−1.674	−1.673	0.294	0.294	0.293	0.751	0.751	0.755
	(1.281)	(1.311)	(1.305)	(0.341)	(0.349)	(0.335)	(0.538)	(0.552)	(0.554)
Log of Urban population	0.570	0.570	0.545	0.059	0.059	0.094	−0.229	−0.229	−0.215
	(0.840)	(0.860)	(0.839)	(0.352)	(0.361)	(0.339)	(0.469)	(0.481)	(0.492)
Openness	0.000	0.000	−0.000	−0.000	−0.000	−0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Industrialization	−0.003	−0.003	−0.004	0.006	0.006	0.006*	−0.008	−0.008	−0.008
	(0.016)	(0.016)	(0.016)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
Energy Tax	0.017	0.017	0.017	−0.000	−0.000	−0.000	0.008	0.008	0.008
	(0.016)	(0.016)	(0.016)	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)
Constant	12.513	12.601	12.836	−23.403**	−23.331**	−25.329**	0.295	1.089	−0.225
	(28.160)	(28.721)	(28.499)	(9.375)	(10.120)	(9.136)	(14.571)	(15.402)	(14.699)
Observations	584	584	584	588	588	588	539	539	539
R-squared	0.224	0.847	0.847	0.949	0.972	0.973	0.798	0.985	0.985
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	No	No	No	No	No	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	26			26			26		

Note: Leader is a dummy variable equal to one if a country belongs to the group of leader countries and zero otherwise. Leader countries include Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Ireland, Luxembourg, the Netherlands, and Sweden, whereas laggard countries include Bulgaria, Croatia, Cyprus, Czechia, Greece, Hungary, Italy, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. Clustered standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.10.

Data availability

The authors do not have permission to share data.

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