

Cap-and-trade policies and regional environmental innovation: evidence from the EU Emissions Trading System

Tim Becker^{1,*}, Sandro Montresor², Sebastian Losacker^{1,3}

¹Department of Geography, Justus Liebig University Giessen, Senckenbergstraße 1, 35390 Giessen, Germany

²Department of Economics and Management, University of Trento, Via Vigilio Inama, 5, 38122 Trento TN, Italy

³CIRCLE—Center for Innovation Research, Lund University, Sölvegatan 16, 223 62 Lund, Sweden

*Corresponding author: Department of Geography, Justus Liebig University Giessen, Senckenbergstraße 1, 35390 Giessen, Germany.
E-mail: tim.becker@geogr.uni-giessen.de

Abstract

We investigate whether more regionally stringent cap-and-trade (C&T) policies induce regional innovation in environmental technologies and whether this effect spills over to proximate regions. Compiling a novel regional dataset, we test this argument for the EU Emissions Trading System (EU ETS) over the period 2005–2020. We find evidence of an intra-regional spillover effect, which is weaker in regions specialized in environmental technologies. We also identify inter-regional spillovers through spatial proximity and trade relationships, but not via knowledge networks. Instrumenting C&T exposure with a Bartik IV supports a causal interpretation of our estimates.

Keywords: cap-and-trade policy; environmental innovation; spillovers; EU ETS.

JEL classifications: Q55; Q58; R11; R12.

1. Introduction

Reducing CO₂ emissions is the most important lever to mitigate climate change and reach a net-zero transition (IPCC 2022). In turn, such a reduction is crucially linked to the adoption of low-emission technologies, an important part of which is still embryonic and needs to be developed through innovations (IEA 2021). As the academic literature has widely ascertained, innovations leading to new clean technologies—hereafter, *environmental innovations* (EI)—suffer from a double externality problem (innovation and environmental, for which see Jaffe et al. 2003), and a policy intervention is thus required for a socially desirable level of EI. Among the different kinds of interventions, market-based policies (like carbon taxation) have found wide applications across different OECD countries (Kruse et al. 2022). This is particularly the case for cap-and-trade (C&T) policies, on which the European Union has established the EU

Received: 13 May 2024. **Accepted:** 31 December 2025

© The Author (2026). Published by Oxford University Press.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted reuse, distribution, and reproduction in any medium, provided the original work is properly cited.

Emissions Trading System (EU ETS) in 2005 (European Commission 2005). In a nutshell, a C&T policy sets a declining cap over time on the overall emissions of regulated installations and allocates or auctions tradable emission allowances among them within this cap. In doing so, a C&T policy first creates financial incentives to reduce emissions. Furthermore, it reduces the marginal cost of EI and increases its marginal benefits (Calel 2020), thus “inducing” regulated installations to develop and use new environmental technologies. On this basis, C&T-regulated firms are expected to develop more EI, and the same holds true for the industries and countries in which the C&T regulation is more stringent (Kruse et al. 2022).

This theoretical argument has spurred extensive empirical research on the extent to which C&T programs spur EI at the firm, industry, and country levels, with mixed results [see Calel (2020) and Teixidó et al. (2019) for reviews on the USA and the EU]. Unfortunately, the relationship at stake has not yet been addressed at the regional level, thereby disregarding important spatial mechanisms that could affect its unfolding. Indeed, the regional and economic geography literature on C&T (and climate change) policies is not yet very extensive, and has mainly addressed the spatial distribution of carbon trading (Knox-Hayes 2009; Knight 2011; Flori and Spelta 2025), the local impact of these policies on the reduction of greenhouse gas emissions (Baldwin and Wing 2013; Naqvi 2021; Mascia and Onali 2024), and the unequal exposure of regions depending on their development level (Mangiante 2024).

This gap appears unfortunate for two reasons. First, from an empirical perspective, regional evidence on C&T programs reveals some important spatial patterns, which deserve careful consideration. To begin with, the distribution of regulated installations is uneven, not only across countries but also within them. This is evident with respect to the EU ETS. Figure 1, which maps all individual ever-regulated installations of our empirical analysis at the NUTS2 level (see Section 3), shows that, for nearly all EU countries, their density peaks in some hotspots located in different regions and is otherwise sparser. This uneven distribution also emerges elsewhere and at a finer level of analysis (see Mascia and Onali 2024). Furthermore, the data show substantial evidence of regulated installations owned by firms (approximated by their “account holders”) operating across multiple administrative regions: for example, in our dataset of regions covered by the EU ETS, about 4,800 installations out of 16,205 (around 30 per cent) belong to such inter-regional firms at the NUTS2 level.

Second, from a theoretical perspective, these spatial characteristics of the C&T policy introduce additional mechanisms in its relationship with EI, which may interact with—and potentially offset—its well-known inducement effect, thus making its regional analysis a novel and salient field of study. These mechanisms have so far been investigated mainly with respect to the C&T impact on local greenhouse gas emissions, and are mostly identified as “carbon leakage” and “regulatory arbitrage” effects (Weller 2012; Cui et al. 2017). However, spatial effects can also be envisaged when looking at the impact of C&T policies on EI, in two respects. On the one hand, as we elaborate further in Section 2, increased local stringency of the C&T policy elevates the compliance costs for regional firms with respect to their local installations. According to Hicksian innovation-inducement mechanisms and the indirect effects outlined in the Porter hypothesis (Porter and van der Linde 1995; Ambec et al. 2013), this increased regulatory pressure should, in theory, stimulate regional EI. However, firms that operate installations across multiple regions may mitigate the local impact of heightened regulatory stringency by adjusting production and allowance allocations across installations in different regions, thereby avoiding the need for costly local innovation. Furthermore, the green knowledge base of the regions where firms (or installations) are based may attenuate (rather than reinforce) the need and/or the capacity to react to a more stringent C&T policy by developing new environmental technologies: for example, in regions specialized in environmental technologies, the policy stringency could be met with pre-existing technologies. These mechanisms suggest that the expected theoretical impact of the policy on regional EI is not straightforward and requires empirical investigation.

On the other hand, as also discussed in Section 2, heightened C&T stringency in a given region may also spur EI in neighboring regions. Indeed, the C&T policy’s effects could potentially spill over to other regions through various proximity-based relationships, including tangible exchanges of intermediate

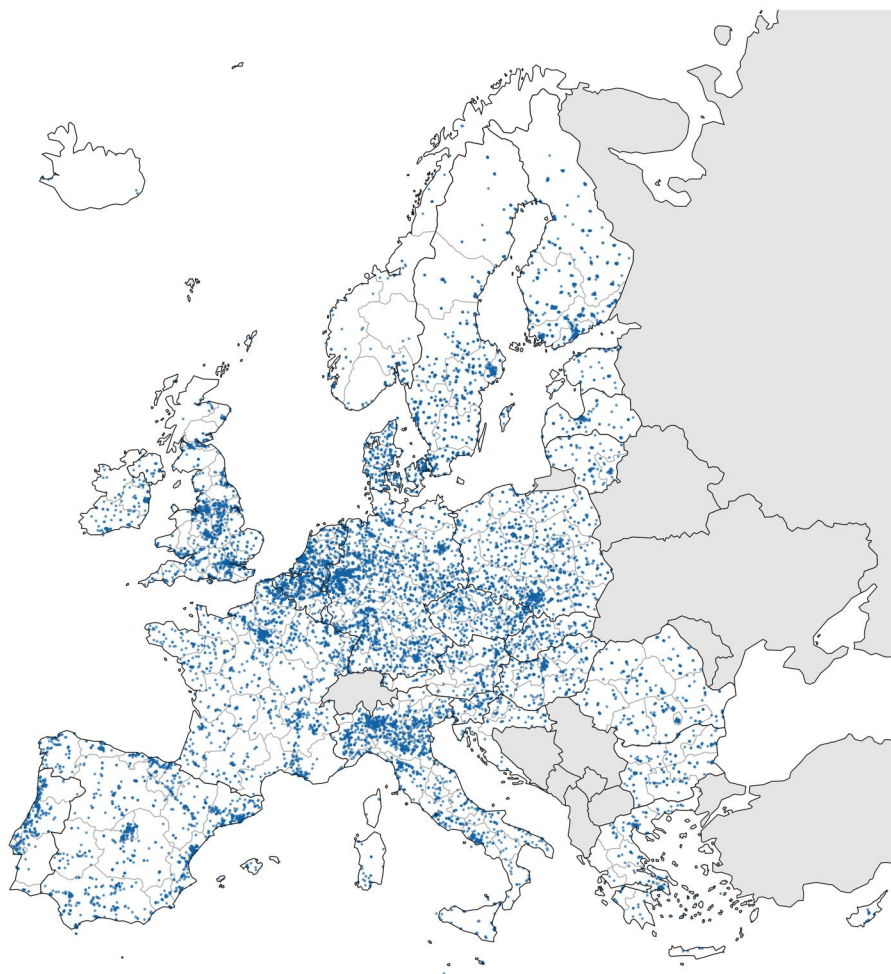


Figure 1 All installations ever regulated under the EU ETS in the period 2005–2020, by NUTS2 regions.
 Source: Authors' illustration; data from [Abrell \(2021\)](#).

goods and intangible flows of knowledge. As a result, the EI impact of a more locally stringent C&T policy may not be confined to the regulated region but rather extend beyond its boundaries.

We test these arguments empirically with respect to the EU ETS for 2005–2020. Drawing on and georeferencing information on 16,205 regulated installations from the European Union Transaction Log (EUTL), we propose a new regional indicator of ETS stringency across 292 NUTS2 regions, covering the EU, the UK, Liechtenstein, Norway and Iceland. We then investigate whether greater stringency raises local EI—measured by regional patenting—and whether this effect spills over to other regions.

Using spatial panel models with dynamic specification and two-way fixed effects (region and time), we find that more stringent regional ETS regulation is positively associated with higher levels of regional EI. The effect strengthens over time and remains robust when controlling for ownership structures and regional specialization in environmental technologies. We further find evidence of inter-regional spillovers, as stringent ETS regulation in one region stimulates EI in geographically proximate and trade-connected regions, but not in those connected through knowledge networks. The results are robust to

various alternative specifications, including a Bartik instrumental variable strategy for ETS stringency, which lends causal support to the observed relationships.

The remainder of this article is structured as follows. Section 2 presents the theoretical background and our research hypotheses. Section 3 describes the dataset and the econometric models used in our empirical application. Section 4 presents and discusses the results, and Section 5 concludes.

2. Theoretical background and research hypotheses

2.1 Environmental regulation and environmental innovation

As is well known, C&T policies constitute a specific type of market-based environmental regulation, akin to carbon taxes. Alongside non-market-based instruments—which impose emission limits and performance standards—and technology support measures—such as public funding for research and development of environmental technologies—they form a broad and multifaceted set of policy tools, whose stringency is regularly monitored across countries (Kruse et al. 2022). The effects of these instruments on EI have been widely examined and substantiated in both the theoretical and empirical literature (Lanjouw and Mody 1996; Valentini and Vitale 2019; Jaffe et al. 2002, 2005; Stavins 2003; Requate 2005; Newell 2010; Schmalensee and Stavins 2017; D'Amato et al. 2021). In what has been termed the “regulatory push-pull/technology push/demand pull” approach to EI (Horbach et al. 2012), environmental regulations play a pivotal role in addressing their “double externality” (innovation and environmental) and “induce” their development along with other drivers related to advancements, market-demand dynamics, and specific capabilities, internal and external to firms.¹

In a nutshell, a regulatory effect on EI is expected by extending John Hicks's (1932) induced-innovation hypothesis to the environment: putting a price on CO₂ renders the use of the environmental “factor” relatively more costly and spurs innovation aimed at economizing on its use, that is, EI.² While this is the basic argument, recent studies have shown that environmental regulations affect EI through a more articulated set of mechanisms. For example, Ghisetti and Quatraro (2013) argue that the inducement effect of regulations can be “endogenous”, especially in weak (exogenous) regulatory contexts, where factors like environmental performance and brand reputation can, in turn, induce EI. According to Fusillo et al. (2022), the regulatory framework does not exert a direct effect on EI, but rather stimulates the formation of alliances among firms to generate new green technological knowledge. Interestingly, while green advancements often rely on complementary developments in conventional technologies, environmental policies do not negatively impact the generation of non-environmental interdependent technologies (Barbieri et al. 2023). This eliminates the risk of a policy paradox in which such policies would hinder the development of the knowledge base necessary for EIs.

As far as the specific case of a C&T program is concerned, the incentives for a regulated firm to invest in EI arise from the surplus it can expect from this investment, for three reasons (Calel 2020). First, by employing the prospective new environmental technology internally, the innovative firm can decrease its emissions and the emission allowances to be purchased on the market, thereby lowering its abatement costs. Secondly, through the same internal use, the firm could reduce its emissions to such an extent that it gains emission allowances to be sold on the market. Thirdly, if the developed technology is adopted by other firms, which can thus reduce their demand for emission allowances, the focal firm can also benefit from a lower general allowance price (Calel 2020).

1. Indeed, environmental technologies generally rely on novel and more complex knowledge inputs than non-environmental ones (Barbieri et al., 2020). Accordingly, they require a higher degree of R&D cooperation and external knowledge, and demand higher levels of technical expertise and cognitive skills (De Marchi 2012; Ghisetti et al. 2015; Consoli et al. 2016; Quatraro and Scandura 2019; Orsatti et al., 2020).

2. As is well-known, this mechanism has led to the development of the so-called Porter hypothesis (see Porter and van der Linde 1995; Jaffe and Palmer 1997).

This theoretical argument has been tested empirically by an extensive body of studies and has yielded mixed results. As the literature review by [Teixidó et al. \(2019\)](#) reveals with respect to the EU ETS, early analyses are mainly non-econometric and do not find a clear impact on EI (see, e.g. [Hoffmann 2007](#); [Rogge and Hoffmann 2010](#); [Rogge et al. 2011](#)). Recent econometric studies are instead more supportive when considering the EI impact of the EU ETS at the industry and firm levels. At the industry level, the evidence is confirmatory but nuanced, pointing to some conditional aspects that require consideration also at the regional level. [Borghesi et al. \(2015a\)](#), for example, find that ETS-regulated sectors in Italian manufacturing introduced EI more often than non-regulated ones in 2006–2008. However, when the stringency of the policy is measured at the sectoral level, it correlates negatively with EI introduction. This may reflect anticipatory behavior by regulated firms and highlights the importance of time in the unfolding of the C&T impact. [Borghesi et al. \(2015b\)](#) find a positive effect on EI for four different sectors regulated by the EU ETS, although the effect is moderate and concentrated in the energy sector, where it is mainly driven by carbon capture and storage projects. [Scotti et al. \(2024\)](#) also highlight sectoral heterogeneity: the EU ETS raises EI in light manufacturing, whereas in the energy sector it does so only when coupled with financial support.

Recent studies at the firm level are more confirmatory and point to additional mechanisms on which we also base our theoretical hypotheses. [Calel and Dechezleprêtre \(2016\)](#), for example, compare regulated and structurally similar “would-be-regulated” firms across 23 EU countries before and after the launch of the EU ETS in 2005. They find that the introduction of the policy led low-carbon patenting (as a proxy for firms’ EI) to increase more for regulated than non-regulated firms. In an aligned paper, [Calel \(2020\)](#) compares regulated firms with counterfactual unregulated ones in Britain between 2000 and 2012 to estimate the impact of the EU ETS launch on their CO₂-intensity, low-carbon patenting, and low-carbon R&D expenditures. Interestingly, the EU ETS is found to encourage low-carbon patenting and R&D spending by treated firms more than by non-treated ones. However, the same effect is not found on CO₂-intensity, arguably entailed by the adoption of available low-carbon technologies. This result contradicts the evidence of an adoption rather than an innovation effect found by earlier C&T programs in the USA ([Schmalensee et al. 1998](#); [Kerr and Newell 2003](#); [Fowlie et al. 2012](#)). [Calel \(2020\)](#) attributes this to evolving carbon markets and novel pollution-control technologies, which make innovation more attractive than adoption.

Although these recent studies focus on the impact of the C&T policy on regulated firms, they allude to the possibility that the same policy could have a third-party-induced innovation effect, also affecting non-regulated firms ([Calel 2020](#)). [Calel \(2020: 195–6\)](#), for example, provides arguments and first indications that there may be such an effect across firms, in line with [Miller \(2014\)](#), but not found by [Calel and Dechezleprêtre \(2016\)](#). This argument is pivotal in a regional analysis of C&T policy like ours and, as we will argue, can be made more salient by referring to the notion of innovation spillovers in broad terms, within and across regions where C&T-regulated firms are located.³

2.2 Regional (stringency of) C&T policies and regional environmental innovation

The tendency of firms’ newly generated knowledge to spill over to proximate firms, thereby enhancing those firms’ innovation performance, is a central principle in the geography of innovation literature ([Audretsch and Feldman 2004](#); [Carlino and Kerr 2015](#)). Similar spatial spillovers are likely to operate in the case of EIs induced by policies such as C&T systems. However, the operation of these policy-induced spillovers is influenced by additional spatial mechanisms, which may interact with—or even counteract—the standard, aspatial inducement effects of C&T schemes. To the best of our knowledge, these

3. Although we refer to the relevance of these spillovers for the local EI impact of regional C&T stringency, our article does not aim to measure them empirically. This is certainly a relevant issue, which would, however, require different data and a different empirical strategy from the one we propose in this article, which aims to detect their potential relevance.

spatial mechanisms have not yet been explicitly explored in the existing literature, and their analysis constitutes the main contribution of this article.

(i) *Intra-regional spillovers.* Starting with intra-regional spillovers from the C&T policy, their emergence can be theorized from both a technology-push and a demand-pull perspective. On the one hand, following a standard argument in the literature on innovation agglomeration (Carlino and Kerr 2015), it can be argued that some of the new knowledge underpinning the EIs introduced by regulated firms—and that these firms are unable to fully appropriate—spills over to other actors in their spatial proximity: a typical local knowledge spillover effect. In brief, not only do regional firms regulated by a C&T policy have stronger incentives to EI (see above), but they also create spillovers from which other local non-regulated firms (and, to be sure, other local regulated firms too) can benefit to innovate in environmental technologies. On the other hand, a spillover effect can also be envisaged from the demand side. C&T-regulated firms are generally specialized in production activities and not in R&D in environmental technologies. Accordingly, firms located in geographical proximity (initially, within the same region) to regulated firms, and which are instead active in R&D, can be more easily exposed to their demand signals and innovate, thereby contributing to regional EI. This kind of C&T innovation effect on non-regulated entities has already been found by studies of the EU ETS at the country level (Bel and Joseph 2018), which, however, do not account for the regional distribution of regulated installations. More recent studies have started investigating the same effect at the regional level, but in a narrower context than the ETS, such as a pilot C&T policy in China (Wang et al. 2019; Du et al. 2021; Liu and Sun 2021; Zhang et al. 2021).

When considering a broader C&T framework, such as the EU ETS, the two types of spillovers discussed above would seem to support the expectation—also at the regional level—of a positive correlation between the stringency of environmental regulation and EI, as outlined in the previous subsection. However, upon closer examination, this relationship is not guaranteed at the regional level, due to different intervening factors that may complicate or offset the expected inducement effect.

First, intra-regional EI spillovers from the C&T policy could be undermined by the opportunity of transferring regulatory pressure (i.e. emissions) outside the region, offered by the ownership structure of regulated installations. As we have seen in our sample (Section 1), a significant number of local C&T-regulated installations belong to firms that also have installations in other regions. These “inter-regional” firms can therefore respond to the costs of a higher C&T stringency by shifting operations and emissions to their own installations facing lower stringency in other regions. In addition, they have greater flexibility to reallocate emission allowances internally across installations to meet compliance needs. In so doing, they might refrain from developing local EI to reduce the compliance costs of the policy. This would be consistent with evidence from Bartram, Hou, and Kim (2022), who find that the California C&T program, aimed at mitigating climate risk at the local level, was neutralized by firms’ regulatory arbitrage, which shifted emissions and output from California to other states. This is particularly so for financially constrained firms, as the proportion of verified emissions covered by emission permits conditions the relationship between carbon prices and the stock prices of regulated firms (Bolton et al. 2025).

Secondly, in multi-regional firms, production activities and innovation-oriented units or R&D facilities may be located in different regions, weakening the spatial link between regulatory stringency and innovation outcomes. Firms operating only a single installation in a region may also exhibit lower regional embeddedness, reducing spillovers to other regional actors. Additionally, it can be questioned whether investment decisions are made at the firm or installation level, which may attenuate the strength of the relationship between regional C&T stringency and regional EI.

For these reasons, the expected intra-regional EI spillover effects of the C&T policy may be weaker in regions with a high concentration of installations owned by non-regional firms, whose contribution to local EI could even be negative. More importantly, it remains uncertain whether the regional spillover effects we propose persist once the ownership structure of regulated installations is taken into account.

Another spatial mechanism that may shape the relationship between regional C&T stringency and regional EI is the existing green knowledge base of the regions in which regulated firms (or their installations) are located. For example, the EI effect of the policy may vary with the degree of regional

specialization in environmental technologies. On the one hand, specialized regions have the infrastructure, knowledge networks, and human capital necessary for EI and can build on existing regional (related) capabilities. Policymakers in these regions are likely more attuned to EI and may introduce complementary policies. However, already specialized regions may experience weaker impacts of the C&T on their overall green technological trajectory, as its stringency could be met with pre-existing technologies in the region, reducing the need for further technological advancements. On the other hand, non-specialized regions could rely more on regulatory stringency to drive environmental technology innovation in the first place. Without a broad portfolio of existing technologies of this kind, they are forced to build the infrastructure, knowledge networks, and human capital required for EI as policy stringency increases. Policymakers in these regions may also see a greater need to introduce complementary policies, while regulated installations may be pushed to establish new networks and collaborations.

As a result, when considering the conditioning role of the regional knowledge base in environmental technologies, the effect of C&T stringency on regional EI remains uncertain. Alongside the previously discussed mechanism related to the ownership structure of regulated firms, this additional spatial factor further complicates the theoretically expected positive relationship between regional policy stringency and regional EI. This underscores the importance of empirically testing whether the following hypothesis holds:

.....
H1: *Regional innovation in environmental technologies increases with the regional stringency of a C&T policy.*
.....

(ii) *Inter-regional spillovers.* The second hypothesis that we put forward follows from the spillover argument of the first one. Although these spillovers normally occur to a greater extent at the local level, regional boundaries are not impermeable to their unfolding. Conversely, although possibly to a lesser extent, spillovers may also unfold across regions, shaped by proximity between the region under more stringent C&T regulation and its neighboring ones (Greunz 2003; Crescenzi et al. 2007; Rodríguez-Pose and Crescenzi 2008). At the outset, one could argue that, as in the case of H1, greater geographical proximity among regions may serve as a conduit for the spillover effects of the C&T policy. Indeed, this is coherent with previous studies that have documented external spillover effects of environmental regulation at the country level, that is, across different countries (Lanjouw and Mody 1996; Peters et al. 2012; Dechezleprêtre et al. 2015; Costantini et al. 2017). This effect is also conceivable at the regional level, since demand-pull policies, such as the EU ETS, increase the potential market for environmental technologies across the board. Furthermore, the increased regional demand for new environmental technologies, along with the knowledge spillovers we have noted above, could be more strongly perceived and more easily absorbed by firms located in geographically closer regions.

However, geographical proximity is not the only channel through which spillovers may occur, as inter-regional proximity can also manifest itself along other dimensions, both tangible and intangible (Boschma 2005). As for the former, regulated installations within a region may transmit both knowledge and demand signals induced by the C&T policy to installations in other regions through trade flows of intermediate and final goods. This could occur along global value chains that span across different countries (Bolea et al. 2022), with regulated regions located both upstream and downstream within them. On the one hand, firms located in more stringently regulated regions may demand cleaner or more technologically advanced intermediate products, thereby creating EI incentives upstream for their suppliers in other regions. On the other hand, when more stringently regulated regions specialize in upstream activities within the value chain—such as the production of key components or raw materials—they may impose environmental standards or specifications that compel downstream firms, even in less regulated areas, to adjust their processes or inputs accordingly. This, in turn, can drive EI downstream, as these firms are pushed to meet the higher environmental requirements embedded in the upstream supply.

While trade flows are sensitive to geographical distance, following the logic of standard gravity models (De Benedicts and Taglioni, 2011), the proximity of regions in the exchange of commodities does not necessarily coincide with their geographical proximity, as global value chains are increasingly dispersed over long distances (WIPO 2019). Accordingly, the extent to which trade-based proximity facilitates the EI spillovers of the C&T policy needs to be tested separately, by looking at the strength of inter-regional trade flows.

The local stringency of a C&T policy can also have EI spillovers on other regions through inter-regional relationships of an intangible nature, such as those through which new technological knowledge is developed. As is well known, regional actors develop and renew their local knowledge base in an open manner, notably through participation in knowledge networks that often have a global reach (Fusillo et al. 2024). Such networks may involve inter-regional R&D collaborations, innovation partnerships, and co-patenting activities, fostering a form of proximity that emerges from the intensity of intangible interactions rather than mere geographical closeness.⁴ These intangible inter-regional relationships can act as transmission channels for C&T-induced EI in different ways. The first mechanism is, of course, represented by the EI knowledge spillovers that innovation collaborations can foster (Zhao and Islam 2017). Furthermore, when regulated actors occupy central positions within innovation networks, they may push non- or less-regulated actors to internalize their regulation-driven EI priorities, aligning their research agendas and adapting their technological trajectories accordingly. Although geographical proximity may still facilitate these collaborations, the codified and transferable nature of the exchanged knowledge may reduce the constraints of physical distance, allowing spillover effects to occur even across long-distance inter-regional ties (WIPO 2019). On this basis, the proximity among partners arising from these intangible relationships may mediate the spillover effects of a C&T policy across regions in ways that differ from those associated with geographical or trade-based ties. Given that these different forms of proximity are likely to be only weakly correlated, it is particularly relevant to empirically test the following general hypothesis:

H2: *Regional innovation in environmental technologies increases with the stringency of a C&T policy in other regions that are proximate in geographical, trade, or knowledge-based terms.*

3. Empirical application

3.1 Data

We test our two research hypotheses on the relationship between regional EI—our dependent variable—and the regional stringency of the C&T policy—our main explanatory variable—by focusing on the EU ETS: the most developed and longest-running C&T policy in the world, and the primary focus of the literature to date.⁵ Operational since 2005, the EU ETS regulates around 40 per cent of EU greenhouse gas emissions from electricity and heat generation, energy-intensive industries (e.g. steel, cement, and paper), and

4. This form of proximity is conceptually related to what Boschma (2005) defines as “cognitive proximity,” although it differs in that it stems from the intensity of interactions involving cognitive capabilities, regardless of the similarity in the knowledge bases shared by the partners. By contrast, the other form of proximity we referred to—based on trade relationships—is more akin to Boschma’s notion of “organizational proximity,” but with an exclusive focus on a specific type of market-based organizational relationship that unfolds through trade exchanges.

5. Since 2021, the Chinese ETS regulates around 5 billion tonnes of CO₂, making it the largest carbon market in the world. Unlike the EU ETS, however, it operates without an absolute cap, relying instead on intensity-based benchmarks. It has long remained in pilot mode, and questions remain about the extent to which emissions trading has progressed. Although the 2025 expansion to cement, steel, and aluminium—adding about 3 billion tonnes of CO₂ and increasing coverage to around 60 per cent of national emissions—marks a step toward a more comprehensive and mature system (ICAP 2025), the EU ETS may still be considered the world’s most developed carbon market.

commercial aviation. The system covers emissions in 30 countries (EU27 plus Norway, Liechtenstein, and Iceland), with the UK previously included until December 2020. The C&T mechanism sets a total emissions limit that is gradually reduced over time, allowing regulated entities to trade allowances. Regulated installations receive or purchase European Union Allowances (EUAs), each representing the right to emit one tonne of CO₂-equivalent (CO₂e). Each year, installations must surrender enough EUAs to cover their verified emissions. Over its various phases, policy changes have been introduced to address challenges such as price volatility, control the supply of allowances, and stabilize CO₂ prices (see [Supplementary Appendix A](#) for a more detailed description of the coverage and evolution of this policy).⁶

Our analysis combines different datasets. The first and focal one is the EUETS.info dataset assembled by [Abrell \(2021\)](#): a relational version of the EUTL that represents the central reporting tool of the EU ETS at the installation level. This is a very rich dataset, which includes general information (address, name, etc.) along with annual emissions and freely allocated allowances (FAAs) for each regulated installation. By linking installation data from this dataset to installation operators' data from the Union Registry ([European Commission 2022](#)), we start from a dataset of 16,205 installations that have ever reported in the EUTL over the period 2005–2020.⁷ From this dataset, we retrieve installation information on address, coordinates, CO₂e emissions (hereafter, simply CO₂), FAAs, and NACE industry classes (on the definition of EUAs, CO₂e, and FAAs, see [Supplementary Appendix A](#)). We then assign each regulated installation to the corresponding NUTS2 region using its coordinates and postal codes. More precisely, we first perform a spatial matching with the Eurostat shapefiles of NUTS2 regions using the geographic coordinates of the installations, successfully matching approximately 15,900 installations. For the remaining ones, we match around 300 installations to a NUTS2 region using their postal codes. The matching process has been manually validated, confirming its accuracy and allowing for the additional matching of some installations by hand. In this way, we obtain a regional match for 16,200 ever-regulated installations, which appear distributed over 292 EU NUTS2 regions as illustrated in [Fig. 1](#) in the Introduction. By aggregating installation data at the NUTS2 level, we get the sum of verified CO₂ emissions from all installations in the region and the sum of all FAAs to that region, on which we build our focal explanatory variable for the regional stringency of the EU ETS (see below). This regionalized dataset is available for download in the [online supplementary material](#).

For our dependent variable, represented by regional EI as described below, we use the OECD REGPAT database. From this dataset, we draw EPO patent data at the regional level on environmental technologies with respect to the temporal (2005–2020) and geographical (292 NUTS2 regions) framework of the previous dataset. Finally, for the construction of the control variables in the analysis, we also use patent data from OECD REGPAT and other information from the Eurostat database ([Eurostat 2022](#)).⁸

3.2 Variables

Despite their well-recognized limitations (see [Nagaoka et al. 2010](#)), we follow the extant research on C&T/EU ETS and measure EIs using patent data. We consider as environmental all patents flagged with at least one Y02 or Y04 Cooperative Patent Classification (CPC) code, which is the standard approach in this field ([Newell et al. 1999](#); [Popp 2002](#); [Brunnermeier and Cohen 2003](#); [Johnstone et al. 2010](#); [Aghion et al. 2016](#); [Calel and Dechezleprêtre 2016](#); [Bel and Joseph 2018](#); [Popp 2019](#); [Calel 2020](#)).

By following the extant literature ([Acs et al. 2002](#)), we measure EIs of region r at time t —that is, our dependent variable $EI_{r,t}$ —using the fractional count of environmental patents filed in year t (EPO application date) by region r resident inventors. More precisely, to remediate scale effects, environmental

6. Note: All appendices referred to in the following are provided in the [online supplementary material](#).

7. Not all these installations are active throughout the 2005–2020 period, but we consider installations during their regulated period (installations may relocate or shut down, no longer exceed regulatory limits, or leave the EU ETS for a reason such as Brexit). Given the absence of regional-level emissions and allowance data, we have excluded aircraft operators from the dataset.

8. In some cases, such as for regional R&D, control variables from [Eurostat \(2022\)](#) are interpolated because of missing data.

patents per 100,000 inhabitants are used and to smooth their typical erratic trend over time, we take their 3-year rolling average.

Our focal regressor, $ETS_{r,t}$, is an indicator that quantifies the stringency of the EU ETS in region r in year t . Following [Borghesi et al. \(2015a\)](#), who construct a similar indicator at the industry level, we define this variable as the ratio of the sum of region r 's CO₂ emissions to the sum of EUAs freely allocated to it in year t , that is:

$$ETS_{r,t} = \frac{\sum_{k=1}^N E_{k,r,t}}{\sum_{k=1}^N FAA_{k,r,t}} \quad (1)$$

where $E_{k,r,t}$ denotes the CO₂ emissions of a given regulated installation k (out of N) located in region r at time t , and $FAA_{k,r,t}$ denotes the allowances freely allocated to the same installation.

The index implies that the more a region emits and the lower the level of its FAAs, the stricter the EU ETS regulation in that region. The underlying idea is that the purchase of allowances that are not freely allocated creates a cost pressure.⁹ If the indicator exceeds 1, there is cost pressure in the region because firms located there will have to buy additional EUAs to cover their emissions. By the same token, if emissions rise, and/or the FAAs fall, this cost pressure and the ETS indicator increase. It is important to note that the indicator does not measure ETS stringency at the firm level and then project it to the regional level; rather, it measures the overall cost pressure on the region by summing required EUAs. The number of regulated installations in a region is thus crucial to its definition. Indeed, having many installations in a region that need to buy EUAs increases overall regional stringency.

In investigating the relationship between $EI_{r,t}$ and $ETS_{r,t}$, we need, of course, to control for other EI determinants at the regional level ([Losacker et al. 2023](#)).

As discussed in Section 2, the first aspect we need to control for, is the opportunity to transfer the regulatory pressure of the ETS outside the region, which is offered by the ownership structure of regulated installations. We address this aspect by using a variable that captures the regional composition of regulated installations owned by firms located outside the region relative to those owned by firms within the region. To this end, we construct the variable “non-regional installation share”, which represents the share of installations in a region where the owning firm is based in a different NUTS2 region. In our dataset, each installation is linked to an account holder listed with name and address, which we refer to as national firm (following [Cameron and Garrone 2024](#)). We use the account holder's address to assign the national firm's location. The dataset includes 16,200 installations belonging to 9,329 different account holders, of which 935 (10 per cent) have installations in more than one NUTS2 region, resulting in 4,781 installations owned by these “inter-regional” firms—around 30 per cent of all installations.

Another spatial mechanism that could condition the actual unfolding of H1 is the features of the regional knowledge base where installations are located. We control for this by constructing a variable for the focal region's specialization in environmental technologies, measured by a revealed technological advantage (RTA) indicator greater than 1. The RTA is defined as the ratio of the regional share of environmental patents to the regional share of total patents, and is calculated over a 3-year window, using a threshold of six environmental patents to exclude regions with very low patent activity. To test whether this variable could condition the relationship between EI and ETS posited in H1, we use it as an interaction term when estimating the relationship between the two (see the next subsection).

As discussed in Section 2, EI is influenced not only by market-based instruments, such as the C&T system under investigation, but also by non-market-based policies whose effects we need to control for. To capture this, we use the OECD Environmental Policy Stringency (EPS) indicator, focusing on non-market-based policy stringency available only at the country level. We then regionalize this indicator by weighting it according to

9. Regulated installations are not necessarily dependent on the FAAs issued in the respective year, since they may still have EUAs from previous years. Nevertheless, companies perceive stricter regulation if their EUA stocks decrease or they can no longer sell large numbers of EUAs.

each region's share of national emissions. The idea is that regions with relatively high emissions within a country will also face stricter regulation from non-market-based instruments. We use emissions data from the EU ETS dataset to regionalize the following: $REPS\ non_market_{r,t} = non_market\ EPS_{i,t} \times \left(\frac{E_{r,t}}{\sum_{r \in i} E_{r,t}} \right)$ where $non_market\ EPS_{i,t}$ is the non-market-based EPS indicator for country i at time t ; $E_{r,t}$ denotes the emissions of region r within country i in year t ; and $\sum_{r \in i} E_{r,t}$ denotes the total emissions in country i at time t , calculated as the sum of emissions from all regions r within the country. This approach ensures that regions with higher emissions relative to their country's total emissions are assigned a proportionately higher non-market-based policy stringency.

As $EI_{r,t}$ represents new technological knowledge of an environmental kind produced in region r , we therefore control for the main regional input factors of such production (Griliches 1979; Audretsch and Feldman 2004): the regional innovation capabilities to research and develop new products and processes, proxied by applying the perpetual inventory method to R&D expenditures (since 1995); and the regional human capital, measured by the share of the regional population with tertiary education. Regarding knowledge production, we also control for the "knowledge complexity" of region r (Balland et al. 2019), which is crucial for environmental technologies, as these rely on more technological components and on diverse and novel knowledge combinations (Barbieri et al. 2020; Fusillo 2023). Reflecting developments in the economic complexity literature, we use the patent data presented (all patent classes, without filtering environmental ones) at the subclass level (four digits) and NUTS2 regions, and measure knowledge complexity with the Fitness-Complexity metric (see Mariani et al. 2015).

Finally, we control for standard economic features of the investigated regions, namely their GDP per capita, to capture economic size, and their population density, to control for agglomeration externalities (Cainelli et al. 2012; Carlino and Kerr 2015). Descriptive statistics for all variables can be found in Supplementary Appendix B, Table B.1.

3.3 Econometric model

The econometric model we use to test our hypotheses is a two-way fixed-effects panel model, which is parametric by nature. This choice is grounded in the theoretical framework developed in Section 2 and aligned with the data structure described in Sections 3.1 and 3.2. We acknowledge that model uncertainty, particularly regarding the functional form of covariate effects and the potential presence of non-linear relationships, may warrant the use of more flexible approaches, such as semi-parametric or non-parametric specifications (e.g. Bontemps et al. 2008; Cardot and Musolesi 2021). These methods can better accommodate unknown functional forms and heterogeneous effects across observational units. However, given that this article conveys, to our knowledge, the first regional-level analysis of the relationship between EI and the local stringency of the EU ETS, we have opted for a standard parametric formulation, which offers a clear and interpretable starting point. We consider this a solid baseline upon which more flexible modeling strategies could be built in future research.

To investigate the effect of EU ETS stringency on EI, we regress the latter on the former and the described controls using a two-way (region and time) fixed-effects spatial panel model with a dynamic specification, in the following logarithmic version:

$$\log(EI_{r,t}) = \beta_1 \log(ETS_{r,t-k}) + \gamma^j \log(Controls_{r,t}^j) + \eta_r + \tau_t + \varepsilon_{r,t} \quad (2)$$

where j indicates the j th control variable, η_r is a region fixed effect, τ_t is a time fixed effect, and $\varepsilon_{r,t}$ is a regression residual.¹⁰

10. The Hausman test is used to test whether to use a fixed- or random-effects model (Baltagi 2008; Wooldridge 2010), and for our data a fixed effects model is the most appropriate.

As is well known, panel models offer the advantage of controlling for time-invariant unobserved, cross-sectional heterogeneity and generally mitigate omitted variable bias (Wooldridge 2010). While potential endogeneity cannot be ruled out in estimating equation (2), preventing a fully causal interpretation of the EU ETS effect on EI, our results can be viewed at least supportive of such a relationship. To strengthen this interpretation, we estimate a Bartik IV model, instrumenting for regional EU ETS stringency, which could be claimed to be endogenous considering, for example, that part of the variation in stringency may itself reflect prior EI.

The class of panel models that we use in equation (2) allows estimation with alternative time lags in the focal regressor, indicated by k in equation (2). This enables us to account for the role of time, which the literature has identified as crucial in the unfolding of the ETS-induced EI impact (see Section 2). To capture this aspect, we estimate the model with up to five annual lags of the ETS variable. The test of our H1 relies on the coefficient of our focal regressor, *ETS*, when the share of “non-regional installations” is controlled for. The general validity of H1 should also consider the extent to which its holding varies with the regional specialization in environmental technologies, as more specialized regions could react less to the C&T-stringency, or even remain neutral to it (see Section 2). To test this, we estimate equation (2) including an interaction term between the ETS indicator and the RTA, lagged by 2 years; this is done to avoid mechanical correlation with the rolling average of environmental patents used to construct the dependent variable. To estimate short and long-run effects regarding H1, we complement our baseline estimates with finite distributed lag models including five lags and relying on our panel setting with regional controls and fixed effects. Finite distributed lag models allow the effects of an independent variable (ETS stringency) on the dependent variable (EI) to be captured for a limited period of time, while long-run effects are calculated by their cumulative estimates (Almon 1965; Baltagi 2011), that is: $\sum_{k=1}^5 \beta_k \log(ETS_{r,t-k})$.¹¹

To investigate H2 and assess potential spillover effects of the EU ETS on proximate regions—along the different dimensions outlined in Section 2—we estimate a set of SLX panel models.¹² In these models, ETS stringency (and selected controls) is “spatially” lagged with respect to neighboring regions, using alternative inter-regional proximity weight matrices. For spatial proximity, we construct a continuous inverse-distance, row-standardized spatial weight matrix, based on centroid distances between regions. For the proximity based on inter-regional tangible (trade) flows, we compute lagged ETS stringency using Multi-Regional Input-Output tables for 272 European NUTS2 regions for the period 2008–2018, provided by Huang and Koutroumpis (2023). More precisely, we filter for industry trade in sectors relevant to the EU ETS—specifically NACE B-E, which includes sectors such as manufacturing, electricity, gas, steam, and air conditioning supply—and aggregate these data for the entire period to construct a row-standardized continuous trade-weight matrix. For the proximity based on intangible exchanges among regions, we compute lagged ETS stringency using an inter-regional co-patenting matrix based on the OECD REGPAT database. To account for the relationships involving the exchange of non-green knowledge, which is often combined with green knowledge in EI, we include all patents (not only EI-specific ones). To mitigate potential endogeneity issues, we build the matrix by aggregating inter-regional co-invented patents during the period 2000–2005. As Table B.2 in Supplementary Appendix B shows, the three proximity measures are not collinear, confirming the opportunity of testing H2 with respect to all of them (VIF for all models suggest that we have no issues with multicollinearity).

11. Estimating distributed lag models for H2 would require including a large number of variables for all lags of multiple spillover channels, which would increase the risk of overfitting and multicollinearity. To maintain model parsimony and avoid estimation noise, we focus on long-run effects for H1 only.
12. As is well known, a SLX model contains spatially lagged explanatory variables and has the advantages (over other spatial models) of straightforward estimation and interpretation (Halleck Vega and Elhorst 2015). In particular, as Elhorst (2014) suggests, spatial panel models are useful tools to quantify direct and indirect effects (spillovers). While LeSage and Pace (2009) define direct and indirect effects in models with endogenous spatial lags of the dependent variable, in the SLX model these effects can be approximated by the coefficients on covariates and their (spatial) lags, which suits our focus on one-way policy spillovers without feedback dynamics.

4. Results

4.1 ETS stringency and regional environmental innovation

Table 1 shows the results of estimating the basic model of equation (2) with five different lags between the regional stringency of the ETS and regional EI. In all five specifications across columns (one per lag), heteroskedasticity- and serial-correlation-consistent standard errors were calculated following Arellano (1987) correction.¹³

As expected, the controls related to the inputs of the regional function of green knowledge production—namely R&D and human capital—are positive and statistically significant. Consistent with expectations, the coefficient associated with the complexity of the regional knowledge base (knowledge complexity) is also positive. Somewhat unexpectedly, population density is negatively and significantly associated with EI. However, this finding is in line with recent evidence highlighting the relative advantages of less metropolitan—or more rural—areas in fostering EI (Cattani et al. 2025).

Notably, a higher local stringency of non-market-based environmental policy instruments (REPS non-market) appears to positively influence EI in regions, and makes it interesting to investigate whether, according to H1, this holds true also for our market-based policy. The ETS stringency indicator that we have proposed appears to have a positive and significant effect on EI in all five specifications with different time lags. Importantly, this result holds even when controlling for the “non-regional installation share”, which itself is negatively and significantly associated with EI. Although a higher share of regulated installations with extra-regional ownership structure appears to create incentives to delocalize policy pressure—and possibly to stimulate EI outside the region—thereby reducing regional EI, the effect of ETS stringency remains positive overall, allowing us to broadly support H1.

Before considering the extent to which the ETS effect proposed by H1 depends on the nature of the regional knowledge base, let us note that the effect at stake increases over time. Consistent with the general evidence on the temporal unfolding of innovation processes following their stimulus (Rondé and Hussler 2005; Fritsch and Slavtchev 2011)—which reflects the iterative nature of these processes, their uncertainty, and complexity, in this case also related to regulatory and approval processes—a more stringent regional regulation gradually translates into higher EI. After 5 years, *ceteris paribus*, a 10 per cent increase in regional EU ETS stringency at time t is associated with an increase in EI of over half a percentage point (0.54 per cent)—that is, 0.20 percentage points more than the effect observed after 1 year (0.33 per cent). The results of the distributed lag model (Table B.3 in Supplementary Appendix B) support the findings of a positive relationship between ETS stringency and EI, as well as the magnitude of the effect (0.66 per cent EI increase for a 10 per cent increase in ETS stringency) in the long run. It should be noted, however, that the high correlation between the lags of the ETS stringency indicator raises problems of multicollinearity in the distributed lag models, imposing caution on the results. Nevertheless, we were able to partially address this problem by using different model specifications that omit consecutive lags, allowing us to speak of a robust long-run effect.¹⁴

The test of H1 yields particularly interesting results when accounting for the nature of the knowledge base in regions hosting regulated installations, specifically by considering their relative specialization in environmental technologies (RTA). Table 2 shows that the interaction term between ETS and RTA turns out to be negative and significant. Regions that are already specialized in the development of environmental technologies appear to be less responsive to the EI inducement effect of a

13. All models were tested for serial correlation using the Durbin–Watson and Wooldridge tests, and for heteroskedasticity using the Breusch–Pagan test. Given the moderate degree of cross-sectional dependence, standard errors have also been corrected using the Driscoll and Kraay (1998) method. The results remain very similar and robust.

14. Results of the baseline specification (with consecutive lags) of the distributed lag models are reported in Table B.3 in Supplementary Appendix B (additional model specifications are available from the authors upon request).

Table 1. Regional environmental innovation and ETS stringency for different time lags.

<i>Dependent variable: Environmental patents per 100,000 inhabitants</i>					
	Lag 1 (1)	Lag 2 (2)	Lag 3 (3)	Lag 4 (4)	Lag 5 (5)
ETS indicator, t-1	0.033** (0.015)				
ETS indicator, t-2		0.036** (0.015)			
ETS indicator, t-3			0.049*** (0.012)		
ETS indicator, t-4				0.053*** (0.014)	
ETS indicator, t-5					0.054*** (0.013)
Non-regional inst. share	−0.083*** (0.017)	−0.097*** (0.018)	−0.109*** (0.021)	−0.108*** (0.028)	−0.081*** (0.029)
REPS non-market	0.056** (0.026)	0.077*** (0.022)	0.085*** (0.023)	0.091*** (0.025)	0.102*** (0.033)
Knowledge complexity	0.028*** (0.009)	0.037*** (0.009)	0.034*** (0.009)	0.032*** (0.008)	0.022*** (0.008)
Human capital	0.194** (0.091)	0.228*** (0.083)	0.293*** (0.048)	0.345*** (0.043)	0.331*** (0.043)
R&D knowledge stock	0.111*** (0.027)	0.119*** (0.026)	0.141*** (0.029)	0.174*** (0.037)	0.195*** (0.058)
Population density	−0.971** (0.436)	−0.941* (0.505)	−1.060* (0.546)	−1.347*** (0.509)	−1.774*** (0.423)
GDP per capita	0.198* (0.111)	0.180* (0.104)	0.100 (0.080)	0.034 (0.103)	0.016 (0.187)
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2447	2283	2121	1953	1785
R ²	0.958	0.960	0.962	0.964	0.965
Adjusted R ²	0.958	0.960	0.962	0.964	0.965
F Statistic	13.166*** (df = 8; 2252)	14.801*** (df = 8; 2089)	15.145*** (df = 8; 1927)	15.803*** (df = 8; 1760)	13.966*** (df = 8; 1593)

Note. * $P < .1$; ** $P < .05$; *** $P < .01$.

Heteroskedasticity, serial correlation, and cross-sectional dependence consistent standard errors [Driscoll and Kraay (1998) correction] in parentheses.

more stringent ETS. Examining the net marginal effect of ETS stringency in specialized regions (denoted as RTA regions in Table 2)—by summing the main ETS coefficient and the interaction term, and testing its significance using the delta method—we find that the net effect remains positive across all model specifications and becomes statistically significant from lag 3 onward. This indicates that higher ETS stringency continues to induce EI also in specialized regions. For example, after 5 years, ceteris paribus, a 10 per cent increase in regional EU ETS stringency at time t is associated with an increase in EI of 0.68 per cent in non-specialized regions, compared to a 0.31 per cent increase in specialized ones. As discussed in Section 2, these results may reflect the fact that in such regions, policy stringency can be accommodated through existing technological capabilities, thereby reducing the need for additional innovation efforts. This introduces an important specification in the test of our H1, which appears confirmed, but to a lower extent for regions specialized in environmental technologies.

Table 2. Regional environmental innovation and ETS stringency for different time lags: interaction between ETS and RTA in environmental technologies.

<i>Dependent variable: Environmental patents per 100,000 inhabitants</i>					
	Lag 1 (6)	Lag 2 (7)	Lag 3 (8)	Lag 4 (9)	Lag 5 (10)
ETS indicator, t-1	0.046** (0.018)				
ETS indicator, t-2		0.050** (0.021)			
ETS indicator, t-3			0.068*** (0.019)		
ETS indicator, t-4				0.068*** (0.017)	
ETS indicator, t-5					0.068*** (0.019)
RTA	-0.013 (0.015)	-0.017 (0.015)	-0.020 (0.017)	-0.031* (0.017)	-0.043** (0.018)
Non-regional inst. share	-0.081*** (0.017)	-0.095*** (0.018)	-0.105*** (0.022)	-0.106*** (0.028)	-0.082*** (0.028)
REPS non-market	0.057** (0.026)	0.078*** (0.023)	0.086*** (0.024)	0.093*** (0.027)	0.106*** (0.035)
Knowledge complexity	0.028*** (0.009)	0.037*** (0.009)	0.035*** (0.008)	0.032*** (0.008)	0.023*** (0.008)
Human capital	0.176** (0.089)	0.211*** (0.080)	0.275*** (0.044)	0.326*** (0.036)	0.319*** (0.036)
R&D knowledge stock	0.114*** (0.029)	0.124*** (0.028)	0.148*** (0.030)	0.182*** (0.038)	0.200*** (0.059)
Population density	-0.955** (0.425)	-0.923* (0.487)	-1.026* (0.525)	-1.313*** (0.486)	-1.727*** (0.397)
GDP per capita	0.206* (0.110)	0.186* (0.102)	0.107 (0.077)	0.040 (0.101)	0.020 (0.183)
ETS indicator, t-1 x RTA	-0.033*** (0.009)				
ETS indicator, t-2 x RTA		-0.032*** (0.012)			
ETS indicator, t-3 x RTA			-0.043*** (0.013)		
ETS indicator, t-4 x RTA				-0.044*** (0.011)	
ETS indicator, t-5 x RTA					-0.037* (0.022)
Net effect in RTA regions	0.013 (0.015)	0.018 (0.011)	0.025*** (0.007)	0.024*** (0.009)	0.031*** (0.011)
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2447	2283	2121	1953	1785
R ²	0.958	0.960	0.962	0.964	0.965
Adjusted R ²	0.958	0.960	0.962	0.964	0.965
F Statistic	11.159*** (df = 10; 2250)	12.440*** (df = 10; 2087)	12.945*** (df = 10; 1925)	13.542*** (df = 10; 1758)	12.146*** (df = 10; 1591)

Note. * $P < .1$; ** $P < .05$; *** $P < .01$.

Heteroskedasticity, serial correlation, and cross-sectional dependence consistent standard errors [Driscoll and Kraay (1998) correction] in parentheses.

4.2 Inter-regional spillovers of ETS stringency

Turning to H2, Table 3 reports the results from the proximity-lagged (SLX-type) panel models with time lags of 1–5 years. At the outset, let us note that the controls for the production function of green knowledge we have considered affect a region's EI from spatially proximate regions (marked with SLX); this is consistent with inter-regional effects documented for standard technologies in recent studies (e.g. Balland and Boschma 2021; Obschonka et al. 2023).¹⁵ These effects appear to operate also in the

Table 3. Regional environmental innovation and ETS stringency for different time lags: spillover models.

<i>Dependent variable: Environmental patents per 100,000 inhabitants</i>					
	Lag 1 (x = 1) (11)	Lag 2 (x = 2) (12)	Lag 3 (x = 3) (13)	Lag 4 (x = 4) (14)	Lag 5 (x = 5) (15)
ETS indicator, t-x	0.038*** (0.013)	0.038*** (0.013)	0.049*** (0.012)	0.051*** (0.013)	0.052*** (0.017)
Spatial spillover, t-x	0.026 (0.055)	0.103** (0.051)	0.131** (0.056)	0.191*** (0.069)	0.216** (0.092)
Trade spillover, t-x	0.023*** (0.006)	0.024*** (0.007)	0.024*** (0.007)	0.027*** (0.007)	0.028*** (0.007)
Co-patent spillover, t-x	0.008 (0.028)	-0.001 (0.030)	-0.005 (0.032)	-0.032 (0.035)	-0.020 (0.039)
Non-regional inst. share	-0.088*** (0.026)	-0.105*** (0.030)	-0.116*** (0.031)	-0.118*** (0.034)	-0.098*** (0.033)
REPS non-market	0.052** (0.023)	0.069*** (0.018)	0.073*** (0.018)	0.078*** (0.020)	0.098*** (0.030)
Knowledge complexity	0.026*** (0.010)	0.035*** (0.008)	0.032*** (0.008)	0.030*** (0.009)	0.022** (0.008)
Human capital	0.133* (0.075)	0.146* (0.081)	0.200*** (0.070)	0.257*** (0.039)	0.263*** (0.043)
Human capital SLX	1.101*** (0.382)	0.862** (0.384)	0.856** (0.392)	0.583 (0.392)	0.412 (0.468)
R&D knowledge stock	0.173*** (0.035)	0.180*** (0.037)	0.198*** (0.049)	0.222*** (0.057)	0.244*** (0.058)
R&D knowledge stock SLX	-2.763*** (0.681)	-2.215*** (0.801)	-1.845*** (0.675)	-1.504*** (0.458)	-1.691*** (0.541)
Population density	-0.681** (0.312)	-0.510 (0.334)	-0.576 (0.401)	-0.861* (0.439)	-1.302*** (0.372)
GDP per capita	0.238** (0.107)	0.291*** (0.097)	0.221** (0.109)	0.171 (0.125)	0.152 (0.198)
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2447	2283	2121	1953	1785
R2	0.959	0.961	0.963	0.964	0.966
Adjusted R2	0.959	0.961	0.963	0.964	0.966
F Statistic	11.696*** (df = 13; 2247)	12.272*** (df = 13; 2084)	11.824*** (df = 13; 1922)	12.110*** (df = 13; 1755)	10.503*** (df = 13; 1588)

Note. * $P < .1$; ** $P < .05$; *** $P < .01$.

Heteroskedasticity, serial correlation, and cross-sectional dependence consistent standard errors [Driscoll and Kraay (1998) correction] in parentheses.

15. Non-focal regressors (R&D and human capital) are lagged only spatially for the sake of econometric parsimony, as spatial proximity represents the standard spillover channel for them.

production of green knowledge across regions, particularly for human capital. By contrast, the spatial lag of the R&D knowledge stock is unexpectedly negative. Innovation in environmental technologies in the focal region appears to diminish when closer regions have a thicker knowledge base. This might suggest that competition effects among proximate regions more than compensate for the effects of R&D spillovers. Alternatively, EI-enabling factors complementary to R&D may concentrate in closer regions with a wider (R&D) knowledge base, crowding out EI in the focal region.

As for our focal regressor, the EU ETS indicator is again positive and significant across all specifications, with values similar to the baseline model (Table 1). When we account for inter-regional spillovers, and for those of the other regressors, the direct ETS effect remains significant and of comparable magnitude, providing further support for H1.

Turning to the test of H2, as expected, a more stringent ETS in a given region generates spillover effects on EI in geographically proximate regions, though only after 2 years. Robustness checks show these spillovers are spatially bounded (i.e., valid up to a certain spatial distance), in line with broader findings in the geography of innovation literature (Rodríguez-Pose and Crescenzi 2008; Carlini and Kerr 2015). Nonetheless, the results highlight that geographical proximity constitutes a key channel through which regions' EI benefits from stricter C&T policies implemented elsewhere.

Interestingly, ETS-induced EI effects also spill over to regions that are closer to the focal region in terms of trade linkages. This suggests that proximity along inter-regional value chains is an additional channel through which regions can benefit from the C&T policies of their economic partners in terms of EI. By contrast, we find no evidence of ETS-induced EI spillovers through intangible inter-regional linkages, such as cross-regional co-patenting. While somewhat unexpected, this finding is nevertheless insightful, as it may suggest that the spillovers in question are predominantly embodied—namely, they are more likely to be transmitted through channels such as trade relationships, supply-chain linkages, or physical proximity—rather than through disembodied mechanisms like knowledge diffusion. This may reflect the fact that responding to a stricter ETS often requires transferring or adapting specific technologies, practices, or production processes that are more easily shared through tangible inter-regional interactions.

4.3 Robustness checks

To ensure robustness of our results, we conduct a range of supplementary analyses, with the corresponding output tables presented in [Supplementary Appendix C](#), unless indicated otherwise.

One major issue that our analysis may face is potential endogeneity of our focal explanatory variable, namely the stringency of the EU ETS. Despite controlling for unobserved heterogeneity through various strategies, our setting remains potentially exposed to reverse causality. That is, while a more stringent ETS induces EI, regions with higher EI may, in turn, face reduced policy stringency over time, due to their comparatively lower emissions. Estimating the effect of EU ETS stringency on EI without addressing this issue could let us underestimate the true effect because part of the variation in stringency is itself a response to prior innovation. To address this issue, we use a Bartik instrument (Bartik IV)—a shift-share instrument—based on external industry trends (shifts), which are considered independent of regional economic conditions and confounders, and on predetermined regional industry shares. External industry shifts can be viewed as a measure of policy size and regional industry shares as a measure of exposure, translating exogenously into the region. Interacting these two elements creates the Bartik IV (Goldsmith-Pinkham et al. 2020; Breuer 2022). For construction in our case, we use fixed regional shares ($R_{r,s}$) of FAAs for each sector s (C, D, X)¹⁶ in region r , based on the period 2005–2007 (EU ETS Phase 1). The shift is measured by yearly EU-wide trends ($T_{s,t}$) of FAAs for each sector s in each year t (from 2008

16. We group installations by their NACE classifications into: (i) Electricity, gas, steam and air conditioning supply (Class D, representing 35 per cent of all installations); (ii) Manufacturing (Class C, 50 per cent); and (iii) Residual industries (Class X, 15 per cent). This sectoral aggregation is motivated by the need to avoid too few observations in the classes and aligns with the industry typologies to which the EU ETS applies (see [Supplementary Appendix A](#)).

onward) at the EU level. By multiplying the fixed regional shares $R_{r,s}$ with the yearly EU-wide shift $T_{s,t}$ and aggregating across sectors, we obtain the region-year Bartik IVs for the period 2008–2020 ($IV_{r,t} = \sum_s R_{r,s} \times T_{s,t}$).¹⁷ We include these Bartik IVs and our controls, as well as region and time fixed effects, in the first stage of a two-stage least squares estimation (first-stage estimates reported in [Supplementary Table C.14](#)), instrumenting for ETS stringency in our panel setting.

The constructed Bartik IV appears to be a strong and valid instrument. The results of the second-stage regressions for different time lags are presented in [Table 4](#). Due to strong collinearity with industry shares in regions with a small number of installations, we exclude the “non-regional installation share” variable from the main specifications to preserve identification. However, we also estimate models that include this variable after excluding extreme values, and the results remain robust ([Supplementary Table C.15](#)).

We find significant effects for the IV variable, supporting our findings regarding H1. Again, the effect increases over time, reaching its highest value after five years. Fitting the distributed lag model with the constructed Bartik IVs supports the findings of a considerable long-run effect of ETS stringency on regional EI ([Supplementary Table C.16](#)). Taken together, we provide evidence that more stringent ETS regulation at the regional level leads to higher EI in that region (with a significant long-run effect). While the magnitude of the instrumented ETS coefficients may appear moderate, their interpretation as elasticities highlights a relevant EI impact: a 10 per cent increase in ETS stringency is associated with an increase of about 0.6 per cent to 1.1 per cent in environmental patents per 100,000 inhabitants, depending on the time lag considered. This effect is comparable to, or even larger than, other classic innovation drivers, such as the R&D stock, in several model specifications. Such increases are notable given the generally high variability in environmental patenting rates across regions and over time, where even small percentage changes can reflect substantial shifts in innovative activity. Thus, ETS stringency emerges not only as statistically significant but also as economically relevant, offering a durable lever for regional EI. As expected, when comparing the IV estimates to those from the non-instrumented model ([Table 1](#)), we find that the conventional OLS specification systematically underestimates the effect of ETS stringency. Depending on the lag, the IV coefficients are between 1.8 and 2.5 times larger than the corresponding OLS estimates. Being both larger in size and more persistent over time, the instrumented ETS estimates confirm that properly addressing endogeneity is crucial to uncover the full inducement potential of ETS on EI.

We apply the same setting to test H2, using our constructed Bartik IV in combination with the corresponding continuous weight matrices (spatial, trade, co-patenting) to instrument the spillover channels. Due to multicollinearity among the instruments—arising from their shared construction based on EU-wide trends ($T_{s,t}$) of FAAs multiplied with regional sectoral shares ($R_{r,s}$) of FAAs—we estimate each spillover channel in separate first- and second-stage regressions. While this was not an issue in the standard spillover models, where the spillover variables are independently constructed, it poses a challenge in the IV setting because all instruments are derived from the same underlying variation. All second-stage results support H2, with positive and significant effects for the trade and spatial channels, and no effect for the co-patenting channel ([Supplementary Tables C.17–C.19](#)).

To ensure further robustness of our results, we conduct a range of supplementary analyses. Starting with H1, we re-test it using a different dependent variable than regional EI density, which better captures the cumulative development of new environmental technologies across regions. We use the stock of environmental patents, constructed via the perpetual inventory method with a 15 per cent annual depreciation rate. [Supplementary Table C.1](#) shows that, despite some changes in the controls, ETS remains significant and positive across all five lags. Furthermore, we add additional firm-level controls for firm

17. An appropriate time to split the shifts and shares would also be between the second and third Phase (2012/2013), when major changes to the EU ETS were introduced. However, this would overly restrict our sample, resulting in a small sample size. Nevertheless, our annual setting still captures these changes and their inherited shifts.

Table 4. Regional environmental innovation and ETS stringency for different time lags: Bartik IV models.

<i>Dependent variable: Environmental patents per 100,000 inhabitants</i>					
	Lag 1 (16)	Lag 2 (17)	Lag 3 (18)	Lag 4 (19)	Lag 5 (20)
IV ETS indicator, t-1	0.096*** (0.035)				
IV ETS indicator, t-2		0.092** (0.041)			
IV ETS indicator, t-3			0.079** (0.037)		
IV ETS indicator, t-4				0.058** (0.028)	
IV ETS indicator, t-5					0.109*** (0.022)
REPS non-market	0.049* (0.025)	0.067** (0.032)	0.105*** (0.022)	0.115*** (0.023)	0.124*** (0.033)
Knowledge complexity	0.030*** (0.008)	0.021*** (0.008)	0.021 (0.017)	0.016 (0.012)	0.004 (0.012)
Human capital	0.412*** (0.071)	0.353*** (0.065)	0.275*** (0.041)	0.205*** (0.024)	0.242*** (0.041)
R&D knowledge stock	0.175*** (0.041)	0.220*** (0.072)	0.154** (0.067)	0.099 (0.061)	0.023 (0.059)
Population density	-1.292** (0.569)	-1.740*** (0.468)	-2.017*** (0.450)	-2.001*** (0.535)	-1.794*** (0.608)
GDP per capita	0.083 (0.124)	0.050 (0.237)	0.305 (0.189)	0.480*** (0.114)	0.591*** (0.107)
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2011	1833	1657	1484	1306
R ²	0.960	0.962	0.964	0.967	0.969
Adjusted R ²	0.960	0.962	0.964	0.967	0.969
F Statistic	16.558*** (df = 7; 1813)	15.192*** (df = 7; 1637)	12.985*** (df = 7; 1462)	9.847*** (df = 7; 1290)	8.002*** (df = 7; 1113)

Note. * $P < .1$; ** $P < .05$; *** $P < .01$.

Heteroskedasticity, serial correlation, and cross-sectional dependence consistent standard errors [Driscoll and Kraay (1998) correction] in parentheses.

size and emissions market shares (Supplementary Table C.2). The results are robust, and we additionally find that installations belonging to large EU ETS firms induce greater spillovers, whereas market shares play no significant role. Moreover, we test other ETS indicators to assess the role of a firm's headquarters in the unfolding of EU ETS spillover effects (Supplementary Tables C.4 and C.5).¹⁸ We find no significant effect in the firm's headquarters region, supporting our argument that spillovers primarily occur where installations are located. We further find supporting evidence for this by disentangling this effect, which we argue is influenced by regional and inter-regional firms being headquartered in the same region with potentially contrasting effects on regional EI. Specifically, we find a positive effect only for regional firms operating exclusively within one region, while no such effect is observed for inter-regional firms

18. We use the term "headquarters" here for simplicity, referring to the national firm's account-holder location, which may not always strictly correspond to the company's overall corporate headquarters. Typically, domestic firms use their national headquarters as the account holder, while multinational firms rely on local subsidiaries or branches for compliance in the respective country.

headquartered there. This suggests that EU ETS spillovers primarily unfold in the regions where installations are located, rather than in the headquarters region (of inter-regional firms).

To further validate H1, we implement robustness checks that account for specific data characteristics. First, we address the potential influence of extreme values by applying percentile-based trimming: we retain the central 90 per cent of observations and symmetrically exclude outliers. This improves robustness against skewed distributions, and the results remain stable ([Supplementary Table C.8](#)). Second, we re-estimate the models on different time subsets to control for policy adjustments and carbon-price fluctuations. The results remain consistent across all time splits ([Supplementary Tables C.9–C.13](#)).

To validate the H1 findings on the RTA interaction effect, we estimate several model variants, including alternative time windows, minimum patent thresholds, and a time-invariant specification based on pre-EU ETS patent stocks. Results remain robust across all specifications. As an additional robustness check, we split the sample by regional carbon intensity. Specifically, we introduce a dummy variable for dirty regions, defined as those with a CO₂ intensity (CO₂/GDP) in 2005 above the sample mean ([Supplementary Table C.21](#)). This split is motivated by the observation that dirty regions are typically not specialized in EI. Consistent with our main findings, the interaction effect is stronger in dirty regions.

Turning to H2, we re-test the spatial channel using alternative spatial neighbor matrices, as the literature suggests strong distance decay effects ([Rodríguez-Pose and Crescenzi 2008](#)). We first apply Queen's contiguity ([LeSage 1999](#)), whereby regions are considered neighbors if they share at least one border point. Second, we define neighbors by centroid distances with thresholds of 200, 300, and 400 km. Interestingly, the results hold only for direct neighbors and the 200 km threshold, suggesting that the EU ETS-induced spillovers are spatially bounded and mirror findings from the literature on knowledge spillovers. We also validate H2 by redefining the proximity-lag variables of ETS stringency using binary (rather than continuous) weight matrices for the other two proximity dimensions ([Supplementary Tables C.22–C.25](#)). For trade and co-patenting linkages, we define binary connections by relative advantage: regions are linked if observed bilateral flows exceed expected flows computed via a proportional-allocation approach (the product of total trade or co-patenting activity, normalized by the total volume of flows in the matrix). Each matrix is then row-standardized to construct the corresponding proximity lags. The results confirm our main findings: spatial- and trade-related spillovers of ETS stringency remain positive and statistically significant, while the co-patenting-based proximity continues to display no significant effect.

5. Conclusions

Although mainly designed at the supranational or national level, the implementation of climate policies is subject to important regional (subnational) effects. With respect to C&T policies, this has mainly been investigated by examining their effect on greenhouse gas emissions across regions. Conversely, this regional perspective has so far been absent from the otherwise abundant literature on the effect of C&T policies on the development of environmental technologies. This gap is particularly relevant, as the regional distribution of C&T-regulated installations is markedly uneven, and its effects are shaped by spatial mechanisms that may attenuate—or even offset—the expected impact of ETS on regional EI.

By addressing this gap, we shed light on these spatial mechanisms by considering the inter-regional ownership structure of regulated installations—which may enable regions to shift regulatory pressure—and the role of the regional knowledge base, which may influence whether policy stringency is met through existing rather than new environmental technologies. Furthermore, we address an additional gap in the literature by investigating whether, and to what extent, the effects of regional ETS stringency on EI spill over to other regions. In particular, we explore the channels through which these spillovers may occur among regions, distinguishing between tangible forms of proximity—such as geographical proximity and trade linkages—and intangible ones, notably co-inventive, knowledge-based collaborations.

From an empirical perspective, we offer the first comprehensive analysis of the relationship between the local stringency of C&T policies and regional EI within the framework of the EU Emissions Trading System, covering the implementation period from 2005 to 2020. Drawing on and regionalizing installation-level data from the EU ETS central reporting tool, we propose an original indicator of ETS stringency at the regional level. We then econometrically test whether the regional variability of this ETS-stringency indicator can account for the regional variability in the development of EIs and for EI spillovers among proximate regions.

The results we have obtained are interesting and have important policy implications. First, our findings reinforce the value of C&T policies like the EU ETS not only as tools to reduce emissions, but also as effective levers to promote EI at the regional level. In particular, we show that the positive effect of regional ETS stringency at a given point in time unfolds gradually and increases over (a 5-year) time. This dynamic response highlights the importance of a long-term perspective when evaluating the innovation impacts of environmental regulation: the full benefits of a more stringent ETS are not immediate, but build up over time, arguably as firms adapt and respond to it through innovation. Crucially, this positive effect emerges despite spatial mechanisms that could potentially counteract it, such as the possibility for multi-regional firms to reallocate emissions and compliance efforts to installations in other regions. This confirms that the ETS is a reliable and effective policy instrument, capable of stimulating innovation even in the presence of such dampening forces. Still, our evidence of a negative local EI effect from the presence of ETS-regulated installations belonging to firms operating across regions highlights the risk of regulatory externalization. Policymakers should therefore consider mechanisms to better align regulatory responsibility with the location of EI outcomes: for example, by adjusting ETS allocation criteria or introducing complementary monitoring of inter-regional firm behavior.

Second, since the marginal EI effect of ETS stringency is lower in regions already specialized in environmental technologies, policy efforts in such areas should also focus on maintaining specialization and leadership in EI. This could involve supporting the scaling and commercialization of existing EI while fostering knowledge spillovers to less advanced regions. At the same time, ETS stringency can serve as a powerful lever to stimulate EI in non-specialized regions—a potential that deserves greater policy attention.

Third, the identification of inter-regional spillovers in the EI effects of the ETS—particularly those occurring through geographical and trade-related proximity—suggests that regional governments should adopt proactive strategies to strengthen their absorptive capacity to leverage and amplify these effects. In particular, as ETS spillovers on EI are not conveyed through inter-regional knowledge co-creation (e.g. co-invention), but rather through more tangible connections, regional governments should reinforce economic and infrastructural linkages over pure innovation-network strategies when the goal is to benefit from nearby ETS-induced innovation.

Finally, our results point to the need for coordinated governance across regional, national, and EU levels to ensure that ETS externalities—both positive and negative—are managed effectively. Climate innovation strategies should integrate spatial considerations more explicitly, for instance by linking inter-regional green clusters or joint innovation programs to ETS regulation. In this respect, the use of revenues generated through ETS auctions represents a concrete policy lever to reinforce the innovation dynamics identified in this article. In line with the double-dividend rationale of ecological tax reforms, carbon pricing revenues can be allocated to support strategic investments in innovation, R&D, and skills development. Directing auction revenues toward regional innovation efforts could help leverage ETS-induced innovation by supporting business networks, supply-chain R&D projects, and worker training in environmental technologies, particularly for SMEs.

As is usually the case, the paper is not free from limitations. The main issue is the non-strictly-causal nature of the relationship we detect between regional EI and the regional stringency of a C&T policy. We have implemented procedures to attenuate the potential endogeneity of our focal regressor. Firstly, we have lagged the latter in a spatial panel and controlled for unobservables in its relationship with the

former. Furthermore, we have applied a Bartik IV approach, which provides supportive evidence for the causal nature of this effect. However, a full solution requires a different identification strategy.

Another limitation of our study is that, as anticipated, the empirical setting we use does not allow us to measure the third-party spillover effects of ETS stringency on EI or to show how this effect unfolds in detail at the regional level. Here, too, a more in-depth analysis is needed to examine the interactions of regulated installations with other regional actors.

Last but not least, another limitation concerns our reliance on a fully parametric specification in the econometric analysis. While offering interpretability and alignment with our theoretical framework, this strategy may not adequately capture complex interactions or heterogeneous effects across regions. Future research should explore semi-parametric or non-parametric approaches that allow for greater flexibility in modeling the potentially non-linear and spatially varying relationship between ETS stringency and EI. In line with this, recent work illustrates how moving beyond fully parametric specifications can yield additional insights. In particular, [Soberon et al. \(2025\)](#) show that the significance and magnitude of carbon pricing effects may differ across parametric and non-parametric specifications, and find that carbon pricing has economy-wide effects on CO₂ emissions beyond sectors directly covered by the EU ETS, varying with countries' economic specialization, green technological intensity, and policy histories. [Musolesi et al. \(2025\)](#) further show that environmental policy effects may be endogenous to historically accumulated knowledge stocks and R&D spillovers. Together, these findings underscore the value of more flexible approaches for capturing heterogeneous, non-linear, and dynamically evolving policy impacts.

Future research could also build on some of the insights emerging from these results, exploring them in greater depth and extending the analysis in new directions. First, it would be interesting to investigate other spatial and regional mechanisms in addition to those we have focused on, which could interfere with the inducement effects of a higher local ETS stringency on regional EI, such as regional disparities in access to sustainable finance for implementing EI, or local lock-in effects due to existing carbon-intensive industrial structures. Conversely, since we found evidence of a stronger effect of ETS stringency on EI in regions not (yet) specialized in environmental technologies, it would be interesting to investigate whether the policy's inducement effect could be strong enough for these regions to specialize in environmental technologies, thereby linking our research question to the literature on regional diversification in the environmental realm ([Montresor and Quatraro 2020](#); [Santoalha and Boschma 2021](#); [Bagayev et al. 2025](#)). Second, the evidence we found on inter-regional EI spillovers of the ETS driven by trade relationships could be further explored by investigating whether the effect varies across regions depending on their upstream or downstream position in global value chains relative to their trade partners. In this respect, the introduction of the EU Carbon Border Adjustment Mechanism (CBAM) in 2026 deserves attention as a policy tool that aligns the carbon price of selected imports with the EU ETS to curb carbon leakage ([Magacho et al. 2024](#); [Cammeo et al. 2025](#); [Morone and Alfino 2025](#)). Given our finding that trade-connected EU regions innovate more when stringency in the focal region increases, similar effects may extend beyond the EU. This might hold for both innovation and adoption of ETS-induced environmental technologies, and such dynamics are discussed as the "innovation channel" of carbon leakage ([Cameron and Baudry 2023](#)). CBAM may strengthen this channel, with potentially widespread effects for the global development of environmental technologies. Accordingly, future research should be extended to trade relationships with non-EU regions to assess whether effects hold or differ for regions without ETS regulation.

Third, future research should also investigate how policy mixes—where regional or national authorities layer carbon taxes or other pricing instruments alongside C&T—may bias or re-scale the estimated effects of ETS stringency on innovation, given the growing coexistence of instruments across jurisdictions and the geographically heterogeneous impacts of carbon pricing ([OECD 2023](#)). In this context, an important avenue for future research is to examine how differences in the spatial allocation and use of ETS auction revenues across regions interact with carbon pricing to shape innovation outcomes.

Fourth, it would be interesting to investigate whether the effects of local ETS stringency on EI differ across types of environmental technologies, and whether similar patterns hold under other C&T systems beyond the EU ETS.

Acknowledgements

Previous versions of this article were presented at the Kiel Institute for the World Economy workshop “The role of public research and innovation measures on mitigating climate change” (May 2023), at Regional Studies Association’s Annual Conference (June 2023), the RSA-YSI Young Scholars’ Academy on Regional Studies (June 2023) and the German Congress for Geography (September 2023). The authors have benefited greatly from feedback received from the participants of these events, in particular from comments by Giovanni Marin, Antoine Dechezleprêtre, Aliénor Cameron and Ron Boschma. A previous version of this article received the 2023 RSA Nathaniel Lichfield Award.

Supplementary data

[Supplementary data](#) is available at *Journal of Economic Geography* online.

Conflict of interest statement. The authors declare no conflicts of interest.

Funding

We acknowledge financial support from the German Federal Ministry of Research, Technology and Space (BMFTR 031B1281).

References

- Abrell, J. (2021) Database for the European Union Transaction Log. *Database*.
- Acs, Z. J., Anselin, L., and Varga, A. (2002) ‘Patents and Innovation Counts as Measures of Regional Production of New Knowledge’. *Research Policy*, 31: 1069–85.
- Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and van Reenen, J. (2016) ‘Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry’, *Journal of Political Economy*, 124: 1–51.
- Almon, S. (1965) ‘The Distributed Lag Between Capital Appropriations and Expenditures’, *Econometrica*, 33: 178–196.
- Ambec, S., Cohen, M. A., Elgie, S., and Lanoie, P. (2013) ‘The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness?’, *Review of Environmental Economics and Policy*, 7: 2–22.
- Arellano, M. (1987) ‘Computing Robust Standard Errors for Within-Groups Estimators’, *Oxford Bulletin of Economics and Statistics*, 49: 431–4.
- Audretsch, D. B., and Feldman, M. P. (2004) ‘Knowledge Spillovers and the Geography of Innovation’, in J. V. Henderson and J.-F. Thisse (eds) *Handbook of Regional and Urban Economics*, pp. 2713–39. Amsterdam: Elsevier.
- Bagayev, I., Kogler, D. F., and Lochard, J. (2025) ‘Does Environmental Regulation Drive Specialisation in Green Innovation?’, *Journal of Environmental Economics and Management*, 130: 103101.
- Baldwin, J. G., and Wing, I. S. (2013) ‘The Spatiotemporal Evolution of US Carbon Dioxide Emissions: Stylized Facts and Implications for Climate Policy’, *Journal of Regional Science*, 53: 672–89.
- Balland, P.-A., and Boschma, R. (2021) ‘Complementary Interregional Linkages and Smart Specialisation: An Empirical Study on European Regions’, *Regional Studies*, 55: 1059–70.
- Balland, P.-A., Boschma, R., Crespo, J., and Rigby, D. L. (2019) ‘Smart Specialization Policy in the European Union: Relatedness, Knowledge Complexity and Regional Diversification’, *Regional Studies*, 53: 1252–68.

- Baltagi, B. H. (2008) *Econometric Analysis of Panel Data*. New York, NY: Wiley.
- Baltagi, B. H. (2011) 'Distributed Lags and Dynamic Models', in B. H. Baltagi (ed.) *Econometrics*, pp. 131–47. Berlin, Heidelberg: Springer.
- Barbieri, N., Marzucchi, A., and Rizzo, U. (2020) 'Knowledge Sources and Impacts on Subsequent Inventions: Do Green Technologies Differ from Non-Green Ones?', *Research Policy*, 49: 103901.
- Barbieri, N., Marzucchi, A., and Rizzo, U. (2023) 'Green Technologies, Interdependencies, and Policy', *Journal of Environmental Economics and Management*, 118: 102791.
- Bartram, S. M., Hou, K., and Kim, S. (2022) 'Real Effects of Climate Policy: Financial Constraints and Spillovers', *Journal of Financial Economics*, 143: 668–96.
- Bel, G., and Joseph, S. (2018) 'Policy Stringency Under the European Union Emission Trading System and Its Impact on Technological Change in the Energy Sector', *Energy Policy*, 117: 434–44.
- Bolea, L., Duarte, R., Hewings, G. J., Jiménez, S., and Sánchez-Chóliz, J. (2022) 'The Role of Regions in Global Value Chains: An Analysis for the European Union', *Papers in Regional Science*, 101: 771–95.
- Bolton, P., Lam, A., and Muûls, M. (2025) 'Do Carbon Prices Affect Stock Prices?', *Journal of Financial Research*, 1–35. <https://doi.org/10.1111/jfr.12472>
- Bontemps, C., Simioni, M., and Surry, Y. (2008) 'Semiparametric Hedonic Price Models: Assessing the Effects of Agricultural Nonpoint Source Pollution', *Journal of Applied Econometrics*, 23: 825–42.
- Borghesi, S., Cainelli, G., and Mazzanti, M. (2015a) 'Linking Emission Trading to Environmental Innovation: Evidence from the Italian Manufacturing Industry', *Research Policy*, 44: 669–83.
- Borghesi, S., Crespi, F., D'Amato, A., Mazzanti, M., and Silvestri, F. (2015b) 'Carbon Abatement, Sector Heterogeneity and Policy Responses: Evidence on Induced Eco Innovations in the EU', *Environmental Science & Policy*, 54: 377–88.
- Boschma, R. (2005) 'Proximity and Innovation: A Critical Assessment', *Regional Studies*, 39: 61–74.
- Breuer, M. (2022) 'Bartik Instruments: An Applied Introduction', *Journal of Financial Reporting*, 7: 49–67.
- Brunnermeier, S. B., and Cohen, M. A. (2003) 'Determinants of Environmental Innovation in US Manufacturing Industries', *Journal of Environmental Economics and Management*, 45: 278–93.
- Cainelli, G., Mazzanti, M., and Montresor, S. (2012) 'Environmental Innovations, Local Networks and Internationalization', *Industry and Innovation*, 19: 697–734.
- Calel, R. (2020) 'Adopt or Innovate: Understanding Technological Responses to Cap-and-Trade', *American Economic Journal: Economic Policy*, 12: 170–201.
- Calel, R., and Dechezleprêtre, A. (2016) 'Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market', *Review of Economics and Statistics*, 98: 173–91.
- Cameron, A., and Baudry, M. (2023) 'The Case for Carbon Leakage and Border Adjustments: Where Do Economists Stand?', *Environmental Economics and Policy Studies*, 25: 435–69.
- Cameron, A., and Garrone, M. (2024) 'Carbon Intensity and Corporate Performance: A Micro-Level Study of EU ETS Industrial Firms', HAL Working Paper hal-04705368, version 1, <https://hal.science/hal-04705368>, accessed 23 Sept. 2024.
- Cammeo, J., Ferrari, A., Borghesi, S., and Dokken, T. (2025) 'Understanding and Assessing CBAM: Vulnerability and Impacts in the EU. SPES', Working Paper; 2025/7.2; Florence School of Regulation.
- Cardot, H., and Musolesi, A. (2021) 'Assessing Spillover Effects of Spatial Policies with Semiparametric Zero-Inflated Models and Random Forests', in A. Daouia and A. Ruiz-Gazen (eds) *Advances in Contemporary Statistics and Econometrics*, pp. 319–38. Cham: Springer International Publishing.
- Carlino, G., and Kerr, W. R. (2015) 'Agglomeration and Innovation', in G. Duranton, V. Henderson, and W. Strange (eds) *Handbook of Regional and Urban Economics*, pp. 349–404. Amsterdam: Elsevier.
- Cattani, L., Montresor, S., and Vezzani, A. (2025) 'Firms' Eco-Innovation and Industry 4.0 Technologies in Urban and Rural Areas', *Regional Studies*, 59: 2243984. <https://doi.org/10.1080/00343404.2023.2243984>
- Consoli, D., Marin, G., Marzucchi, A., and Vona, F. (2016) 'Do Green Jobs Differ from Non-Green Jobs in Terms of Skills and Human Capital?', *Research Policy*, 45: 1046–60.
- Costantini, V., Crespi, F., and Palma, A. (2017) 'Characterizing the Policy Mix and Its Impact on Eco-Innovation: A Patent Analysis of Energy-Efficient Technologies', *Research Policy*, 46: 799–819.
- Crescenzi, R., Rodríguez-Pose, A., and Storper, M. (2007) 'The Territorial Dynamics of Innovation: A Europe-United States Comparative Analysis', *Journal of Economic Geography*, 7: 673–709.

- Cui, C. X., Hanley, N., McGregor, P., Swales, K., Turner, K., and Yin, Y. P. (2017) 'Impacts of Regional Productivity Growth, Decoupling and Pollution Leakage', *Regional Studies*, 51: 1324–35.
- D'Amato, A., Mazzanti, M., and Nicolli, F. (2021) 'Green Technologies and Environmental Policies for Sustainable Development: Testing Direct and Indirect Impacts', *Journal of Cleaner Production*, 309: 127060.
- De Benedictis, L., and Taglioni, D. (2011) 'The Gravity Model in International Trade', in L. De Benedictis, and L. Salvatici (eds) *The Trade Impact of European Union Preferential Policies*, pp. 55–89. Berlin, Heidelberg: Springer.
- Dechezleprêtre, A., Neumayer, E., and Perkins, R. (2015) 'Environmental Regulation and the Cross-Border Diffusion of New Technology: Evidence from Automobile Patents', *Research Policy*, 44: 244–57.
- De Marchi, V. (2012) 'Environmental Innovation and R&D Cooperation: Empirical Evidence from Spanish Manufacturing Firms', *Research Policy*, 41: 614–23.
- Driscoll, J. C., and Kraay, A. C. (1998) 'Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data', *The Review of Economics and Statistics*, 80: 549–60. <https://doi.org/10.1162/003465398557825>
- Du, G., Yu, M., Sun, C., and Han, Z. (2021) 'Green Innovation Effect of Emission Trading Policy on Pilot Areas and Neighboring Areas: An Analysis Based on the Spatial Econometric Model', *Energy Policy*, 156: 112431.
- Elhorst, J. P. (2014) 'Spatial Panel Models', in M. Fischer and P. Nijkamp (eds) *Handbook of Regional Science*, pp. 1637–52. Berlin, Heidelberg: Springer.
- European Commission (2005) EU Action Against Climate Change: EU Emissions Trading an Open Scheme Promoting Global Innovation. <http://ec.europa.eu/environment/climat/pdf/emissiontrading2en.pdf>, accessed 13 Jan. 2024.
- European Commission (2022) Unionsregister. https://ec.europa.eu/clima/eu-action/eu-emissions-trading-system-eu-ets/union-registry_de, accessed 21 Dec. 2022.
- Eurostat (2022) Eurostat database. <https://ec.europa.eu/eurostat/data/database>, accessed 23 Oct. 2022.
- Flori, A., and Spelta, A. (2025) 'Carbon Trade Biases and the Emerging Mesoscale Structure of the European Emissions Trading System Network', *Nature Communications*, 16: 5199.
- Fowlie, M., Holland, S. P., and Mansur, E. T. (2012) 'What Do Emissions Markets Deliver and to Whom? Evidence from Southern California's NOx Trading Program', *American Economic Review*, 102: 965–93.
- Fritsch, M., and Slavtchev, V. (2011) 'Determinants of the Efficiency of Regional innovation systems', *Regional Studies*, 45: 905–18.
- Fusillo, F. (2023) 'Green Technologies and Diversity in the Knowledge Search and Output Phases: Evidence from European Patents', *Research Policy*, 52: 104727.
- Fusillo, F., Montresor, S., Burlina, C., and Palma, A. (2024) 'Regional Technological Diversification and the Global Network of Embodied R&D: Evidence from the Exposure of European Regions', *Regional Studies*, 58: 1410–24. <https://doi.org/10.1080/00343404.2023.2269205>
- Fusillo, F., Quatraro, F., and Usai, S. (2022) 'Going Green: The Dynamics of Green Technological Alliances', *Economics of Innovation and New Technology*, 31: 362–86.
- Ghisetti, C., Marzocchi, A., and Montresor, S. (2015) 'The Open Eco-Innovation Mode. An Empirical Investigation of Eleven European Countries', *Research Policy*, 44: 1080–93.
- Ghisetti, C., and Quatraro, F. (2013) 'Beyond Inducement in Climate Change: Does Environmental Performance Spur Environmental Technologies? A Regional Analysis of Cross-Sectoral Differences', *Ecological Economics*, 96: 99–113.
- Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020) 'Bartik Instruments: What, When, Why, and How', *American Economic Review*, 110: 2586–624.
- Greunz, L. (2003) 'Geographically and Technologically Mediated Knowledge Spillovers Between European Regions', *The Annals of Regional Science*, 37: 657–80.
- Griliches, Z. (1979) 'Issues in Assessing the Contribution of Research and Development to Productivity Growth', *The Bell Journal of Economics*, 10: 92–116.
- Halleck Vega, S., and Elhorst, J. P. (2015) 'The SLX Model', *Journal of Regional Science*, 55: 339–63.
- Hicks, J. (1932) *The Theory of Wages*. London: Macmillan.
- Hoffmann, V. H. (2007) 'EU ETS and Investment Decisions: The Case of the German Electricity Industry', *European Management Journal*, 25: 464–74.

- Horbach, J., Rammer, C., and Rennings, K. (2012) 'Determinants of Eco-Innovations by Type of Environmental Impact—The Role of Regulatory Push/Pull, Technology Push and Market Pull', *Ecological Economics*, 78: 112–22.
- Huang, S., and Koutroumpis, P. (2023) 'European Multi Regional Input Output Data for 2008–2018', *Scientific Data*, 10: 218.
- ICAP (2025) *Emissions Trading Worldwide: Status Report 2025*. Berlin: International Carbon Action Partnership.
- IEA (2021) *World Energy Outlook 2021*, IEA, Paris.
- IPCC (2022) *Climate Change 2022: Mitigation of Climate Change: Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY, USA: Cambridge University Press.
- Jaffe, A. B., and Palmer, K. (1997) 'Environmental Regulation and Innovation: A Panel Data Study', *Review of Economics and Statistics*, 79: 610–9.
- Jaffe, A. B., Newell, R. G., and Stavins, R. N. (2002) 'Environmental Policy and Technological Change', *Environmental and Resource Economics*, 22: 41–70.
- Jaffe, A. B., Newell, R. G., and Stavins, R. N. (2003) 'Technological Change and the Environment', in K. G. Mäler, and J. R. Vincent (eds) *Handbook of Environmental Economics*, pp. 461–516. Amsterdam: Elsevier.
- Jaffe, A. B., Newell, R. G., and Stavins, R. N. (2005) 'A Tale of Two Market Failures: Technology and Environmental Policy', *Ecological Economics*, 54: 164–74.
- Johnstone, N., Haščić, I., and Popp, D. (2010) 'Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts', *Environmental and Resource Economics*, 45: 133–55.
- Kerr, S., and Newell, R. G. (2003) 'Policy-Induced Technology Adoption: Evidence from the U.S. Lead Phasedown', *Journal of Industrial Economics*, 51: 317–343.
- Knight, E. R. W. (2011) 'The Economic Geography of European Carbon Market Trading', *Journal of Economic Geography*, 11: 817–41.
- Knox-Hayes, J. (2009) 'The Developing Carbon Financial Service Industry: Expertise, Adaptation and Complementarity in London and New York', *Journal of Economic Geography*, 9: 749–77.
- Kruse, T., Dechezleprêtre, A., Saffar, R., and Robert, L. (2022) 'Measuring Environmental Policy Stringency in OECD Countries: An Update of the OECD Composite EPS Indicator', OECD Economic Department Working Papers, (1703), 0_1-56.
- Lanjouw, J. O., and Mody, A. (1996) 'Innovation and the International Diffusion of Environmentally Responsive Technology', *Research Policy*, 25: 549–71.
- LeSage, J. P. (1999) *The Theory and Practice of Spatial Econometrics*, 28 pp. Toledo, OH: University of Toledo.
- LeSage, J., and Pace, R. K. (2009) *Introduction to Spatial Econometrics*. New York: Chapman and Hall/CRC.
- Liu, Z., and Sun, H. (2021) 'Assessing the Impact of Emissions Trading Scheme on Low-Carbon Technological Innovation: Evidence from China', *Environmental Impact Assessment Review*, 89: 106589.
- Losacker, S., Hansmeier, H., Horbach, J., and Liefner, I. (2023) 'The Geography of Environmental Innovation: A Critical Review and Agenda for Future Research', *Review of Regional Research*, 43: 291–316.
- Magacho, G., Espagne, E., and Godin, A. (2024) 'Impacts of the CBAM on EU Trade Partners: Consequences for Developing Countries', *Climate Policy*, 24: 243–59.
- Mangiante, G. (2024) 'The Geographic Effects of Carbon Pricing', *European Economic Review*, 168: 104825.
- Mariani, M. S., Vidmer, A., Medo, M., and Zhang, Y.-C. (2015) 'Measuring Economic Complexity of Countries and Products: Which Metric to Use?', *The European Physical Journal B*, 88: 1–9.
- Mascia, D. V., and Onali, E. (2024) 'Keep Calm and Carry on Emitting: Cap-and-Trade Rules, Local Emissions and Growth', *Regional Studies*, 58: 220–37.
- Miller, S. (2014) 'Indirectly induced innovation: consequences for environmental policy analysis', *Mimeograph*, University of California, Santa Barbara.
- Montresor, S., and Quatraro, F. (2020) 'Green Technologies and Smart Specialisation Strategies: A European Patent-Based Analysis of the Intertwining of Technological Relatedness and Key Enabling Technologies', *Regional Studies*, 54: 1354–65.
- Morone, P., and Alfino, A. (2025) 'Impact of the EU Carbon Border Adjustment Mechanism on the Global South', *Discover Sustainability*, 6: 315.

- Musolesi, A., Golinelli, D., and Mazzanti, M. (2025) 'Modelling Green Knowledge Production and Environmental Policies with Semiparametric Panel Data Regression Models', *Empirical Economics*, 68: 327–52.
- Nagaoka, S., Motohashi, K., and Goto, A. (2010) 'Patent Statistics as an Innovation Indicator', in B. Hall, and N. Rosenberg (eds) *Handbook of the Economics of Innovation*, pp. 1083–127. Amsterdam: North Holland.
- Naqvi, A. (2021) 'Decoupling Trends of Emissions Across EU Regions and the Role of Environmental Policies', *Journal of Cleaner Production*, 323: 129130.
- Newell, R. G. (2010) 'The Role of Markets and Policies in Delivering Innovation for Climate Change Mitigation', *Oxford Review of Economic Policy*, 26: 253–69.
- Newell, R. G., Jaffe, A. B., and Stavins, R. N. (1999) 'The Induced Innovation Hypothesis and Energy-Saving Technological Change', *The Quarterly Journal of Economics*, 114: 941–75.
- Obschonka, M., Tavassoli, S., Rentfrow, P. J., Potter, J., and Gosling, S. D. (2023) 'Innovation and Inter-City Knowledge Spillovers: Social, Geographical, and Technological Connectedness and Psychological Openness', *Research Policy*, 52: 104849.
- OECD (2023) *Effective Carbon Rates 2023: Pricing Greenhouse Gas Emissions Through Taxes and Emissions Trading (OECD Series on Carbon Pricing and Energy Taxation)*. Paris: OECD Publishing. <https://doi.org/10.1787/b84d5b36-en>
- Orsatti, G., Quatraro, F., and Pezzoni, M. (2020) 'The Antecedents of Green Technologies: The Role of Team-Level Recombinant Capabilities', *Research Policy* 49: 103919.
- Peters, M., Schneider, M., Griesshaber, T., and Hoffmann, V. H. (2012) 'The Impact of Technology-Push and Demand-Pull Policies on Technical Change—Does the Locus of Policies Matter?', *Research Policy*, 41: 1296–308.
- Popp, D. (2002) 'Induced Innovation and Energy Prices', *The American Economic Review*, 92: 160–80.
- Popp, D. (2019) 'Environmental Policy and Innovation: A Decade of Research', *International Review of Environmental and Resource Economics*, 13: 265–337.
- Porter, M. E., and van der Linde, C. (1995) 'Toward a New Conception of the Environment-Competitiveness Relationship', *Journal of Economic Perspectives*, 9: 97–118.
- Quatraro, F., and Scandura, A. (2019) 'Academic Inventors and the Antecedents of Green Technologies: A Regional Analysis of Italian Patent Data. *Ecological Economics*, 156: 247–63.
- Requate, T. (2005) 'Dynamic Incentives by Environmental Policy Instruments—A Survey', *Ecological Economics*, 54: 175–95.
- Rodríguez-Pose, A., and Crescenzi, R. (2008) 'Research and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe', *Regional Studies*. 42: 51–67.
- Rogge, K. S., and Hoffmann, V. H. (2010) 'The Impact of the EU ETS on the Sectoral Innovation System for Power Generation Technologies—Findings for Germany', *Energy Policy*, 38: 7639–52.
- Rogge, K. S., Schneider, M., and Hoffmann, V. H. (2011) 'The Innovation Impact of the EU Emission Trading System—Findings of Company Case Studies in the German Power Sector', *Ecological Economics*, 70: 513–23.
- Rondé, P., and Hussler, C. (2005) 'Innovation in Regions: What Does Really Matter?', *Research Policy*, 34: 1150–72.
- Santoalha, A., and Boschma, R. (2021) 'Diversifying in Green Technologies in European Regions: Does Political Support Matter?', *Regional Studies*, 55: 182–95.
- Scotti, F., Flori, A., Crescenzi, R. P., and Pammolli, F. (2024) 'Demand-Pull and Technology-Push Environmental Innovation: A Policy Mix Analysis on EU ETS and EU Cohesion Policy', *Climate Policy*, 25: 153–70.
- Schmalensee, R., Joskow, P. L., Ellerman, A. D., Montero, J. P., and Bailey, E. M. (1998) 'An Interim Evaluation of Sulfur Dioxide Emissions Trading', *Journal of Economic Perspectives*, 12: 53–68.
- Schmalensee, R., and Stavins, R. N. (2017) 'Lessons Learned from Three Decades of Experience with Cap and Trade', *Review of Environmental Economics and Policy*, 11: 59–79.
- Soberon, A., Mazzanti, M., Musolesi, A., and Rodríguez-Poo, J. M. (2025) 'Efficient Estimation of a Partially Linear Panel Data Model with Cross-Sectional Dependence. *Journal of Multivariate Analysis*, 206: 105393.

- Stavins, R. N. (2003) 'Experience with Market-Based Environmental Policy Instruments', in K. G. Mäler and J. R. Vincent (eds) *Handbook of Environmental Economics*, vol. 1, pp. 355–435. Amsterdam: Elsevier.
- Teixidó, J., Verde, S. F., and Nicolli, F. (2019) 'The Impact of the EU Emissions Trading System on Low-Carbon Technological Change: The Empirical Evidence', *Ecological Economics*, 164: 106347.
- Valentini, E., and Vitale, P. (2019) 'Optimal Climate Policy for a Pessimistic Social Planner', *Environmental and Resource Economics*, 72: 411–43.
- Wang, H., Chen, Z., Wu, X., and Nie, X. (2019) 'Can a Carbon Trading System Promote the Transformation of a Low-Carbon Economy Under the Framework of the Porter Hypothesis? —Empirical Analysis Based on the PSM-DID Method', *Energy Policy*, 129: 930–8.
- Weller, S. (2012) 'The Regional Dimensions of the 'Transition to a Low-Carbon Economy': The Case of Australia's Latrobe Valley', *Regional Studies*, 46: 1261–72.
- WIPO (2019) *World Intellectual Property Report 2019: The Geography of Innovation: Local Hotspots, Global Networks*. Geneva: World Intellectual Property Organization.
- Wooldridge, J. M. (2010) *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.
- Zhang, S., Wang, Y., Hao, Y., and Liu, Z. (2021) 'Shooting Two Hawks with One Arrow: Could China's Emission Trading Scheme Promote Green Development Efficiency and Regional Carbon Equality?', *Energy Economics*, 101: 105412.
- Zhao, M., and Islam, M. (2017) 'Cross-Regional R&D Collaboration and Local Knowledge Spillover', *Geography, Location, and Strategy*, 36: 343–85.