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Do R&D Spillovers Support Low-carbon Transition?

FIRM-LEVEL EVIDENCE FROM FINNISH ENERGY-INTENSIVE MANUFACTURING

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Abstract

A structural shift from fossil fuel-based energy systems to renewable, sustainable energy sources critically depends on research and development (R&D) activities at the firm-level. This study examines the contribution of R&D spillovers from other firms to greenhouse gas (GHG) emissions in Finnish energy-intensive manufacturing industries. We link firm-level GHG emissions to financial and innovation data for 230 firms in the pulp and paper, chemicals, non-metallic minerals, and basic metals industries over 2000–2019. We derive emissions-generating functions based on a directional distance function framework, and estimate them using shape-constrained semiparametric regression. Our key result is that R&D spillovers have a strong statistically significant association with the firm-level GHG emissions. However, the signs and magnitudes of the spillovers differ across industries. In the chemical industry, intra-industry R&D spillover is associated with lower emissions, whereas in the pulp and paper and the basic metals industries, intra-industry R&D spillover is associated with higher emissions. These results demonstrate that R&D spillovers do not self-evidently lower emissions, but can also contribute to higher emissions. Our findings also reveal an important channel of inter-industry R&D spillovers through material flows, highlighting the pivotal role of the chemical industry for the GHG abatement in the pulp and paper production and non-metallic minerals industry.

Tiivistelmä

Tukevatko t&k-heijastevaikutukset vähähiilistä siirtymää? Yritystason näyttö suomalaisesta energiaintensiivisestä teollisuudesta

Siirtymä fossiilisiin polttoaineisiin perustuvista energiajärjestelmistä uusiutuviin ja kestäviin energialähteisiin edellyttää tutkimus- ja kehittämistoimintaa (t&k) yritystasolla. Tässä tutkimuksessa tarkastellaan muiden yritysten t&k-toiminnan aikaansaamien heijastevaikutusten yhteyttä kasvihuonekaasupäästöihin suomalaisessa energiaintensiivisessä teollisuudessa. Yhdistämme yritystason kasvihuonekaasupäästöt taloudellisiin ja innovaatiotoimintaa kuvaaviin tilastoaineistoihin, jotka kattavat yhteensä 230 yritystä paperi- ja selluteollisuudessa, kemianteollisuudessa, ei-metallisten mineraalituotteiden valmistuksessa sekä metallien jalostuksessa vuosina 2000–2019. Johdamme tuotantoteoriaan perustuvan päästömallin, joka voidaan estimoida semiparametristen menetelmien avulla ilman rajoittavia funktiomuotoa koskevia oletuksia. Keskeinen tulos on, että t&k-heijastevaikutuksilla on vahva ja tilastollisesti merkitsevä yhteys yritystason kasvihuonekaasupäästöihin. T&k-heijastevaikutusten suunta ja voimakkuus vaihtelevat kuitenkin toimialoittain. Kemianteollisuudessa toimialan sisäinen t&k-heijastevaikutus on yhteydessä alhaisempiin päästöihin, kun taas paperi- ja selluteollisuudessa sekä metallien jalostuksessa toimialan sisäinen t&k-heijastevaikutus on yhteydessä korkeampiin päästöihin. Tulokset osoittavat, etteivät heijastevaikutukset automaattisesti johda päästöjen vähenemiseen, vaan ne voivat joissakin tapauksissa myös lisätä päästöjä. Lisäksi havaitsemme materiaalivirtojen kautta välittyvän merkittävän toimialojen välisen heijastevaikutuksen, mikä korostaa kemianteollisuuden keskeistä roolia kasvihuonekaasupäästöjen vähentämisessä paperi- ja selluteollisuudessa sekä ei-metallisten mineraalituotteiden valmistuksessa.

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1 Introduction

Low-carbon energy transition refers to the shift from fossil fuel-based energy systems to renewable and sustainable energy sources, aimed at achieving significant reductions in greenhouse gas (GHG) emissions to mitigate climate change and promote sustainable development. Technological innovation is considered central to enable this transition. However, the role of technology transfer and spillover of clean innovations across firms remain poorly understood.

The economics of innovation spillovers has a long tradition in productivity research since the late 1970s. Influential studies such as Griliches (1979) and Jaffe (1986) have demonstrated that firms benefit not only from their own innovation activities, but also from knowledge generated by others in their technological environment. Bernstein and Nadiri (1989) provided empirical evidence on intra-industry spillovers using dynamic cost function models. Subsequent work has shown that the magnitude of spillover effects depends critically on a firm's absorptive capacity (Cohen and Levinthal, 1989) and on technological or geographic proximity (Griffith et al., 2004). Bloom et al. (2013) further quantify these effects, showing that social returns to research and development (R&D) are substantially higher than private ones once spillover effects are accounted for. These findings establish that external knowledge environments play a central role in shaping firm-level productivity. However, the question of whether external knowledge environments that drive productivity growth can also influence GHG emissions remains open.

Previous literature on clean innovation has largely focused on direct firm-level R&D, green patents, or responses to environmental regulation (Jaffe and Palmer, 1997; Porter and van der Linde, 1995; Lanoie et al., 2011). For example, Dechezlepretre et al. (2014) provide evidence based on patent citations that clean technologies generate stronger spillovers than polluting ones. Recent cross-country studies, such as Rahko and Alola (2024) and Mamkhezri and Khezri (2024), indicate that R&D spillovers across countries contribute to lower GHG emissions, while Pio and Gonçalves (2024) find that domestic R&D capital and spillovers coincide with lower emissions across sectors. Aldieri et al. (2022) argue that international diffusion of environmental innovation contributes to green growth. However, these studies operate at aggregate levels and cannot identify how external knowledge flows interact with production decisions and emission outcomes of firms.

At the firm-level, potential spillover mechanisms, such as those operating through labor mobility (Song et al., 2003), supplier-customer networks (Nollen, 2020), or trade channels (Copeland and Taylor, 2004), are often mentioned but rarely examined jointly with environmental outcomes. One notable exception is Fujii et al. (2016), who analyze environmental productivity in the Chinese manufacturing sector, identifying firms that combine higher output with lower emissions. However, this study focuses on firms' internal innovation rather than external R&D spillovers. To our knowledge, there are no prior studies on whether knowledge diffusion mechanisms that enhance productivity also affect emissions.

To address the research gaps identified above, we empirically examine the influence of R&D spillovers on firm-level GHG emissions in four energy-intensive manufacturing industries in Finland, a high-income, innovation-rich country that has an ambitious national target to achieve carbon neutrality by 2035. We focus on the pulp and paper, chemicals, non-metallic minerals, and basic metals industries, which are globally among the largest sources of industrial GHG emissions (e.g., Joyo et al., 2025).

Our first contribution is to assemble a unique register-based panel dataset of Finnish manufacturing firms during the period 2000–2019, which includes five types of information: i) annual financial statements data that can be used to calculate value added as well as labor and capital inputs; ii) firm-level GHG emissions collected for the implementation of the EU Emissions Trading System (EU ETS); iii) detailed data about innovation inputs such as R&D expenditures; iv) firm characteristics, such as firm age, foreign ownership, and export status; and v) three phases of the EU ETS, which capture changes in the regulatory environment over time. Our dataset covers 230 firms during the period 2000–2019. The observed sample of firms accounted for almost 80 percent of the GHG emissions of the Finnish energy-intensive manufacturing sector over the study period.

Our second contribution is to empirically estimate how R&D spillovers influence firm-specific GHG emissions, conditional on inputs, firm characteristics, and changes in the regulation over time. To this end, we adapt the approach by Griliches (1979) and Jaffe (1986) to the present setting. More specifically, we construct an intra-industry R&D externality variable as the R&D intensity (i.e., the ratio of R&D expenditure to total revenue) of all other firms within the same two-digit industry. In principle, this variable is exogenous to firms in the sense that it is not directly affected by firms' own R&D activity, and hence, it is less prone to reverse causality and simultaneity bias than firms' internal R&D decisions. Obviously, there can be knowledge spillovers across firms that indirectly affect R&D activities of other firms in the same industry (consider, for example, a patent race). The purpose of the R&D externality variable is to capture horizontal diffusion of innovations through such mechanisms as technological benchmarking, supplier relationships, and labor mobility.

The third contribution of this paper is to develop a novel estimation framework to capture the direct and spillover contributions of R&D activities on emissions. We first derive industry-specific emissions-generating functions based on the multi-output production theory and the directional distance functions. We then estimate the emissions-generating functions using a semi-parametric variant of the convex nonparametric least squares (CNLS) estimator (Johnson and Kuosmanen, 2011, 2012). This approach is free from restrictive functional form assumptions regarding the emissions-generating technology, but at the same time, we maintain useful regularity conditions such as monotonicity and concavity. This semi-parametric estimation framework also enables us to correct for the sample selection bias using the Heckman two-step procedure.

The rest of the paper proceeds as follows. Section 2 reviews related literature. Section 3 outlines the empirical framework. Section 4 describes the data. Section 5 presents results. Section 6 concludes with policy implications.

2 Literature review

Understanding how innovation diffuses across firms and affects environmental performance is central to debates on low-carbon energy transition. Not surprisingly, a very large number of studies have shed light on the themes of this study. The purpose of this section is to briefly review three research streams to frame our contribution: productivity spillovers, environmental regulation and innovation, and the emerging literature linking innovation to emissions outcomes.

2.1 R&D spillover effects on productivity

As noted in the introduction, it is well established in economics that R&D and innovation spillovers through external knowledge flows can significantly enhance firm-level productivity (Griliches, 1979; Jaffe, 1986; Bloom et al., 2013). Spillovers can occur through multiple channels, including labor mobility and knowledge embodied in skilled workers (Song et al., 2003), vertical linkages between suppliers and customers, informal knowledge exchange through industry networks (Nollen, 2020), and technological proximity that facilitates imitation and adaptation. Crucially, firms with higher absorptive capacity (typically those investing in their own R&D) are better positioned to recognize, assimilate, and exploit external knowledge (Cohen and Levinthal, 1989; Griffith et al., 2004).

The extensive literature on R&D spillovers has focused almost exclusively on productivity effects, leaving possible effects on GHG emissions and other environmental externalities largely unexplored. Whether the same mechanisms that enhance productivity also facilitate emission reductions remains an open empirical question.

2.2 Environmental regulation, innovation, and the Porter Hypothesis

Another stream of literature examines how environmental regulation affects innovation and firm competitiveness. Porter and van der Linde (1995) argued that well-designed regulation can stimulate innovation that offsets compliance costs, potentially enhancing competitiveness – the so-called Porter Hypothesis. Early empirical tests yielded mixed results. Jaffe and Palmer (1997) found that environmental compliance expenditures are associated with increased R&D spending, consistent with regulation-induced innovation, though they could not establish whether this innovation improved performance. Lanoie et al. (2011) provided more supportive evidence, showing that stricter environmental policies coincide with improved business performance in certain contexts. Ambec et al. (2013) offer a comprehensive review, highlighting that empirical support depends critically on regulatory design, industry characteristics, and innovation capacity.

Initial evaluations of the EU ETS, the world's largest carbon pricing mechanism, found limited short-run impacts during early phases. Petrick and Wagner (2014) detected no significant effects on German manufacturing competitiveness in Phase I, while Calel and Dechezleprêtre (2016) found weak but positive innovation effects among regulated firms. Marin et al. (2018) and Löschel et al. (2019) similarly documented modest impacts on productivity and emissions during Phases I and II (2005–2012), attributing this to generous free allocation and relatively low carbon prices.

These studies primarily examine how regulation affects internal firm innovation (own R&D spending, patenting, or process improvements) rather than whether external knowledge environments facilitate regulatory compliance or emission reductions. Our analysis extends this literature in two ways: by examining outcomes throughout Phase III (2013–2019), when tighter caps and reduced free allocation may have generated stronger incentives, and by investigating whether industry-level R&D spillovers interact with carbon pricing to shape emission outcomes.

2.3 Innovation, spillovers, and emissions outcomes

Recent research has begun to examine the effects of innovation on emissions directly, though primarily at aggregate or sectoral levels. Dechezlepretre et al. (2014) use patent citation data to show that clean technologies generate larger and more valuable knowledge spillovers than polluting technologies, suggesting that green innovation has particularly strong social returns. At the country level, Rahko and Alola (2024) and Mamkhezri and Khezri (2024) demonstrate that R&D spillovers across national borders are more strongly associated with CO_2 reductions than domestic R&D alone, highlighting the importance of international knowledge diffusion. Pio and Gonçalves (2024) find similar patterns in a sectoral analysis, showing that both domestic R&D capital and cross-sector spillovers coincide with lower emissions. Aldieri et al. (2022) argue that international diffusion of environmental innovation contributes to green growth by enabling emission reductions without sacrificing productivity.

Despite these advances, micro-level evidence on how external R&D environments affect firm-level emissions remains scarce. Fujii et al. (2016) represent a notable exception: they use directional distance functions to evaluate environmentally sensitive productivity in Chinese manufacturing, identifying firms that combine higher output with lower emissions. However, their analysis focuses on firms' own innovation activities (measured by R&D intensity and patent counts) rather than on external knowledge spillovers. Other potential spillover channels (labor mobility, supplier networks, trade) are often mentioned in theoretical discussions but rarely examined empirically in conjunction with environmental outcomes.

This gap is significant because the theoretical relationship between spillovers and emissions is ambiguous. If R&D spillovers facilitate the adoption of cleaner production technologies, as suggested by the clean innovation literature, they could reduce emissions. Conversely, if spillovers primarily enhance scale and output, they might increase absolute emissions even if efficiency improves. Traditional production theory often assumes a trade-off between desirable and undesirable outputs: producing more value may inherently require more pollution (e.g., Chung et al., 1997). Whether this trade-off persists in innovation-intensive environments, or whether knowledge diffusion enables technological substitutability, where emissions constrain rather than enable output, remains an open empirical question.

2.4 Positioning and contribution

Our study bridges the productivity spillover literature and the environmental innovation literature by directly estimating how industry-level R&D spillovers relate to firm-level emissions. To our knowledge, no prior study has quantified how external, industry-wide R&D knowledge affects firm-level emission performance after controlling for production scale and technology. Existing work either focuses on productivity spillovers without environmental outcomes (Bloom et al., 2013), examines aggregate emissions without firm-level detail (Rahko and Alola, 2024; Mamkhezri and Khezri, 2024), or analyzes firm-level environmental performance without measuring external knowledge environments (Fujii et al., 2016).

We build on the theoretical and methodological foundation of productivity estimation with undesirable outputs (Chambers et al., 1996, 1998; Chung et al., 1997). Our semi-parametric estimation approach following Johnson and Kuosmanen (2011, 2012) enables flexible modeling without imposing restrictive functional forms, while maintaining economic regularity conditions. Our empirical design also aligns with recent evaluations of emissions trading systems (Marin et al., 2018; Löschel et al., 2019), though environmental policy evaluation is not our primary focus.

By incorporating intra-industry R&D spillovers into reduced-form regression equations derived from the directional distance function framework, we estimate how external knowledge environments relate to firm-level emissions. This allows us to assess whether emissions and output behave as technological substitutes or complements, and whether these relationships evolve across different phases of the EU ETS implementation. The analysis provides new micro-level evidence on how industry-level knowledge diffusion relates to emission outcomes, with production performance serving as a complementary check that emission reductions do not compromise economic viability.

3 Theory and methods

This section outlines the empirical framework used to examine how innovation and environmental regulation are associated with firm-level emissions. We model the production of desirable (value added) and undesirable (GHG emissions) outputs in a nonparametric setting. This approach allows us to estimate how contextual factors, such as intra-industry R&D spillovers and the EU ETS participation, are associated with emission outcomes without imposing specific functional forms.

3.1 Production technology and reduced-form functional representations

The most general representation of a multi-output production technology is the production possibility set:

$$T = \{(L, K, y, b) \mid (L, K) \text{ can produce } (y, b)\}, \tag{1}$$

where L denotes labor input (full-time equivalents), K is capital input (real fixed assets), y is desirable output (value added in 2015 prices), and b is undesirable output (GHG emissions). We assume that technology T satisfies free disposability of inputs and desirable outputs and weak disposability of undesirable outputs. This means that the association between y and b can be either positive or negative.

The directional distance function (DDF) (Chambers et al., 1996, 1998) provides a convenient functional representation of the production set T. The DDF can be defined as:

$$\text{DDF} = \max\left\{\delta \mid (L - \delta g^L,\ K - \delta g^K,\ y + \delta g^y,\ b - \delta g^b) \in T\right\}, \tag{2}$$

where the direction vector $g = (g^L, g^K, g^y, g^b)$ determines the direction of input contraction and output expansion. By varying g, we obtain different reduced-form models that capture how emissions and output relate to production inputs and external conditions.

3.1.1 Emissions-generating function

For empirical estimation of the DDF, the direction vector g must be specified *a priori* (e.g., Kuosmanen and Johnson, 2017; Kuosmanen and Zhou, 2021). Since we are primarily interested in the influence of R&D spillovers on GHG emissions, we set $g = (0, 0, 0, 1)$. In this case, the DDF reduces to:

$$\text{DDF} = \max \{\delta \mid (L, K, y, b - \delta) \in T\} . \tag{3}$$

Taking the undesirable output as the dependent variable and interpreting the DDF as an error term (see Kuosmanen and Johnson, 2017), the DDF formulation (3) is equivalent to the following reduced-form emissions-generating model:

$$b_{it} = EG(L_{it}, K_{it}, y_{it}) + \delta_{it}, \tag{4}$$

where subscripts i and t denote individual firms and years, respectively. We will henceforth refer to the function EG as the emissions-generating function.

In this study, we are primarily interested in the associations between R&D activities and GHG emissions on the one hand, and between GHG emissions and value added on the other. Therefore, we posit a semiparametric specification of the emissions-generating function:

$$EG(L_{it}, K_{it}, y_{it}) = EI(L_{it}, K_{it}) + \gamma \ln y_{it}, \tag{5}$$

where EI is a monotonic increasing and concave function that captures the associations of the GHG emissions with the labor and capital inputs. Note that we do not assume any specific functional form for EI. The coefficient γ can be interpreted as the semi-elasticity of value added on GHG emissions. This semiparametric specification enables us to capture the association between GHG emissions and value added in a single coefficient, which can be positive or negative.

Following Johnson and Kuosmanen (2011, 2012), we next introduce a vector of contextual variables $\mathbf{z}_{it}$ that include observed firm characteristics, R&D inputs, and the EU ETS phases. Note that these variables are not part of the emissions-generating function as such, but if omitted, the effects of contextual variables are attributed to the error term δ_{it}. However, if the contextual variables correlated with output, labor, or capital, omitting $\mathbf{z}_{it}$ can cause endogeneity bias. Therefore, it is generally advisable to include observed contextual variables explicitly in the semiparametric regression model.

Introducing the contextual variables to our semiparametric specification, our primary regression equation of interest can be stated as:

$$b_{it} = EI(L_{it}, K_{it}) + \gamma \ln y_{it} + \boldsymbol{\mu}'\mathbf{z}_{it} + \varepsilon_{it}. \tag{6}$$

Notably, the coefficients $\boldsymbol{\mu}$ capture how R&D inputs, R&D spillovers, and the EU ETS phases relate to emission levels. Importantly, this semiparametric, partial linear model also enables us to test for the statistical significance of coefficients γ, $\boldsymbol{\mu}$, of which we are primarily interested in, while at the same time we can model the labor and capital inputs in a fully nonparametric fashion, respecting the properties of the production theory.

3.1.2 Production function

To gain further insight, we also consider a more conventional production function model, which can be analogously derived from the general DDF by setting $g = (0, 0, 1, 0)$. In this case, the DDF can be stated as:

$$\text{DDF} = \max \{\delta \mid (L, K, y + \delta, b) \in T\}. \tag{7}$$

Thus, we can write the reduced-form production function model as:

$$y_{it} = GF(L_{it}, K_{it}, b_{it}) + \delta_{it}, \tag{8}$$

where GF denotes the *green production function* that indicates how much value added can be produced by the given labor and capital inputs and GHG emissions, and δ_{it} is interpreted as the error term.

Next, introducing contextual variables $\mathbf{z}_{it}$ and assuming separability between the GHG emissions and the labor and capital inputs, we obtain the following semiparametric partial linear production function model:

$$y_{it} = F(L_{it}, K_{it}) + \gamma \ln b_{it} + \boldsymbol{\mu}'\mathbf{z}_{it} + \varepsilon_{it}, \tag{9}$$

where F is a conventional production function that satisfies monotonicity and concavity, and coefficient γ is the semi-elasticity of GHG emissions on value added. Note that we do not assume any specific parametric functional form for F. Further, note that semi-elasticity γ can be positive or negative: a positive γ indicates high value added is correlated with high GHG emissions, whereas a negative γ suggests that higher value added is associated with lower emissions, in line with the Porter Hypothesis.

Regression models (6) and (9) represent parallel perspectives on the same technology set T, derived by using two alternative specifications of the direction vector g in the DDF. Equation (6) constitutes our primary specification, examining how innovation and regulation relate to emission outcomes. Equation (9) serves as a robustness check: if spillovers enable cleaner production, firms with lower emissions should not sacrifice output, conditional on inputs. Both equations use the same contextual variables $\mathbf{z}_{it}$ and are estimated under identical regularity conditions, ensuring internal consistency.

3.2 Semiparametric regression subject to shape constraints

We estimate models (6) and (9) using the semi-parametric CNLS regression (Johnson and Kuosmanen, 2011, 2012). This estimator is well-suited to our setting for three reasons. First, it respects key economic regularity conditions (monotonicity and concavity in inputs) implied by the production theory. Second, this approach can accommodate contextual variables such as R&D spillovers, the EU ETS participation, and selection corrections in an additive manner. Third, it avoids restrictive functional form assumptions that could bias the estimated relationships. Unlike commonly used parametric specifications such as Cobb-Douglas or translog, CNLS does not impose a predetermined structure on how emissions and output relate to inputs and contextual factors. This flexibility is valuable when the production technology may vary across firms or over time. While fully structural estimation is not our goal, the CNLS framework provides a theoretically sound way to estimate how contextual drivers are associated with productive performance.

More specifically, the emissions-generating model (6) is estimated by solving the following quadratic programming (QP) problem:

$$\min_{\alpha,\beta,\gamma,\boldsymbol{\mu},\varepsilon} \sum_t \sum_i \varepsilon_{it}^2 \tag{10}$$

subject to

$$\begin{gathered} b_{it} = \alpha_{it} + \beta_{it}^L L_{it} + \beta_{it}^K K_{it} + \gamma \ln y_{it} + \boldsymbol{\mu}' \mathbf{z}_{it} + \varepsilon_{it}, \\ \alpha_{it} + \beta_{it}^L L_{it} + \beta_{it}^K K_{it} \leq \alpha_{hs} + \beta_{hs}^L L_{it} + \beta_{hs}^K K_{it} \quad \forall i, h, \ \forall t, s \quad \text{(concavity)}, \\ \beta_{it}^L \geq 0, \quad \beta_{it}^K \geq 0 \quad \forall i, t \quad \text{(monotonicity)}. \end{gathered}$$

The first set of constraints of (10) is a linearized version of the emissions-generating model (6). In this specification, the true but unknown EI is approximated by a piecewise linear function. Note that the intercepts and the coefficients of labor and capital are not constants, but observation-specific. The system of inequality constraints in (10) effectively imposes concavity and monotonicity of EI (see Kuosmanen, 2008, for further details).

The production function model (9) is estimated analogously by solving the QP problem:

$$\min_{\alpha,\beta,\gamma,\boldsymbol{\mu},\varepsilon} \sum_t \sum_i \varepsilon_{it}^2 \tag{11}$$

subject to

$$\begin{gathered} y_{it} = \alpha_{it} + \beta^L_{it} L_{it} + \beta^K_{it} K_{it} + \gamma \ln b_{it} + \boldsymbol{\mu}'\mathbf{z}_{it} + \varepsilon_{it}, \\ \alpha_{it} + \beta^L_{it} L_{it} + \beta^K_{it} K_{it} \le \alpha_{hs} + \beta^L_{hs} L_{it} + \beta^K_{hs} K_{it} \quad \forall i, h, \ \forall t, s \quad \text{(concavity)}, \\ \beta^L_{it} \ge 0, \quad \beta^K_{it} \ge 0 \quad \forall i, t \quad \text{(monotonicity)}. \end{gathered}$$

Both models are estimated under identical structural constraints across the two specifications. This unified treatment enables us to assess the relationships between emissions, output, and external factors in a way that is both data-driven and grounded in production theory.

We estimate the emissions-generating model and the production function model separately for the four emission-intensive industries considered, but we also estimate the models for the pooled sample of all four industries. All CNLS regressions are estimated in Python using the `pyStoNED` package (Dai et al., 2024) and MOSEK optimization software. We apply an additive specification subject to the variable returns to scale, conforming with formulations (10) and (11). Standard errors for the linear coefficients γ, $\boldsymbol{\mu}$ are computed using heteroskedasticity-robust estimators.

3.3 Sample selection correction

Firm-level data on emissions and R&D activities are not systematically reported by all firms. If the likelihood of reporting correlates with firms' productive performance, our estimates could suffer from the sample selection bias. Following Kuosmanen et al. (2023), we address this issue using Heckman's (1979) two-step correction procedure, which adjusts for data availability bias and persistent unobserved heterogeneity (e.g., managerial quality, compliance culture).

Let $E_{it} = 1$ if firm i reports positive emissions in year t, and 0 otherwise. The first-stage probit model is:

$$\Pr(E_{it} = 1) = \Phi(\beta_0 + \beta_1 L_{it} + \beta_2 \text{matint}_{it} + \beta_3 \text{age}_{it} + \gamma_t + \delta_j)\,, \tag{12}$$

where matint_{it} is the material intensity, defined as the ratio of real intermediate inputs to real turnover, captures the importance of energy- and material-intensive inputs in production, age_{it} controls for organizational maturity, and γ_t, δ_j are year and two-digit industry fixed effects. The Inverse Mills Ratio (IMR) for emission reporting is:

$$\lambda^E_{it} = \frac{\phi(x'_{it}\hat{\beta})}{\Phi(x'_{it}\hat{\beta})}, \tag{13}$$

computed only for firms with $E_{it} = 1$, capturing the conditional expectation of unobserved factors influencing reporting.

For R&D reporting, define $RD_{it} = 1$ if firm i reports R&D expenditure in year t. The probit model is:

$$\Pr(RD_{it} = 1) = \Phi(\beta_0 + \beta_1 L_{it} + \beta_2 VA_{i,t-1} + \beta_3 \text{age}_{it} + \beta_4 CIS_t + \gamma_t + \delta_j)\,, \tag{14}$$

where lagged value added $VA_{i,t-1}$ proxies for financial capacity, and CIS_t controls for Community Innovation Survey years when reporting intensity increased. The resulting IMR, λ_{it}^{RD}, adjusts for selective R&D reporting.

Both correction terms, λ_{it}^{E} and λ_{it}^{RD}, are included in the CNLS estimation as contextual variables. This ensures that observed associations between innovation, regulation, and performance reflect underlying structural relationships rather than selection into reporting. The estimated coefficients from the first-stage probit models are reported in Appendix A.

4 Data

We construct a firm-level panel linking GHG emissions (in CO_2-equivalent), financial accounts, and innovation variables for Finnish manufacturing firms over 2000–2019. GHG emissions are obtained from Statistics Finland, which compiles installation-level reports submitted under the EU ETS. These installation records are linked to firm identifiers, allowing emissions to be measured at the firm-year level. The inclusion of the early 2000s provides a pre-ETS baseline prior to carbon pricing introduction in 2005.

Financial data are drawn from Statistics Finland's Financial Statement Data Panel, which provides harmonized income-statement and balance-sheet variables based on administrative tax records. Innovation inputs are obtained from the annual R&D Statistics, including intramural and extramural R&D expenditures and R&D personnel. Additional firm characteristics, such as the share of Science, Technology, Engineering, and Mathematics (STEM) workers, foreign ownership, export status, labor input, and capital stock, are derived from matched employer-employee registers and other administrative datasets.

The analysis focuses on four emission-intensive manufacturing industries (NACE Rev. 2 code in parentheses):

- pulp and paper (17)
- chemicals and chemical products (20)
- non-metallic minerals (23) (including bricks, cement, ceramics, concrete, and glass)
- basic metals (24) (including manufacture and casting of iron, steel, aluminum, and copper)

Over 2000–2019, the sample comprises 230 unique firms and 2,300 firm-year observations from these sectors, which together account for 78.7 percent of total manufacturing GHG emissions in Finland. These industries are characterized by capital-intensive production, large stationary installations covered by the EU ETS, and thermodynamically constrained technologies, making them particularly suitable for studying how innovation and regulation relate to emission outcomes.

4.1 Emission patterns and R&D intensity by industry

Figure 1 illustrates the intertemporal development of GHG emissions in the sample firms between 2000 and 2019, grouped by industry. The figure also depicts a parallel development in other energy-intensive manufacturing. The four industries considered exhibit distinct trajectories.

The chemical industry exhibited the largest proportional decline, with emissions falling from around 2.8 million tonnes in the mid-2000s to roughly 1.2 million tonnes by 2019, reflecting shifts toward less energy-intensive production and efficiency improvements. The Finnish chemical industry has a stated goal to achieve carbon neutrality by year 2045 (Gabrielli et al., 2023). The basic metals industry, the largest emitter of GHG in this sample, exhibited a sustained decline from approximately 6.8 million tonnes of CO_2-equivalents in 2000 to about 3 million tonnes in 2019. The pronounced contraction after 2008 coincided with reduced activity in primary steel production and the modernization of remaining facilities.

The pulp and paper industry displayed a more modest reduction from roughly 4.3 to 2.8 million tons, achieved through process improvements and structural adjustments following declining demand for graphic paper products. Emissions from the non-metallic minerals industry, which are closely linked to construction activity, peaked in 2008 and declined thereafter, stabilizing at lower levels in the post-crisis period. Finally, emissions from other energy-intensive manufacturing (not included in our firm-level sample) remained relatively stable over the period, highlighting the heterogeneity of smaller and less carbon-intensive sectors. Corresponding trends in real value added are reported in Appendix B.

For comparison, Figure 2 similarly illustrates the development of R&D intensity in the sample firms grouped by industry. Among the industries considered, the chemical industry had the largest R&D intensity by a large margin. In 2000–2001, the R&D expenditures of the chemical industry were more than five percent relative to the turnover, but since 2005, the R&D intensity fluctuated around three percent. At the aggregate level, Finland's R&D expenditures were approximately three percent of the GDP during this period. Currently, Finland's national target is to increase R&D intensity to four percent by year 2030.

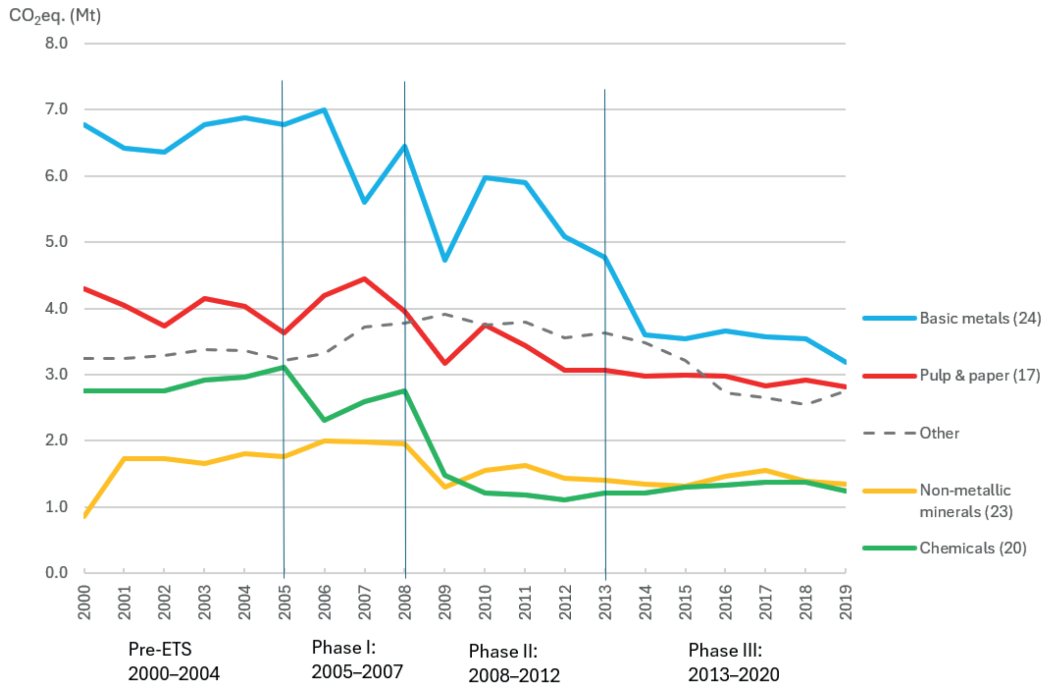

Figure 1: Development of GHG emissions by industry in Finnish energy-intensive manufacturing during 2000–2019. Vertical lines indicate the EU ETS phase transitions (2005, 2008, 2013).

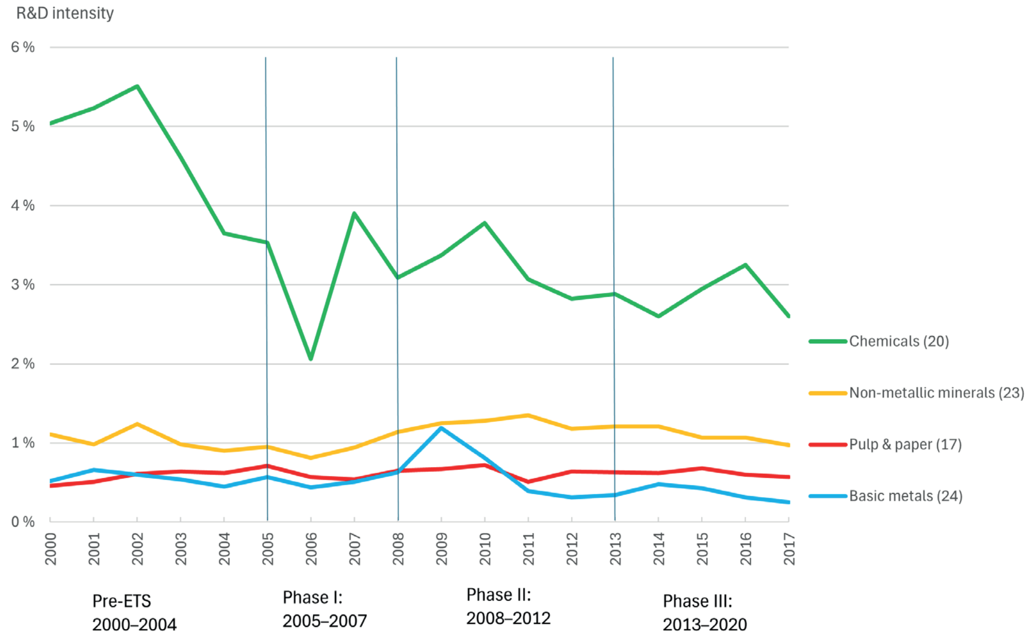

Figure 2: Development of R&D intensity by industry in Finnish energy-intensive manufacturing during 2000–2019. Vertical lines indicate the EU ETS phase transitions (2005, 2008, 2013).

Except for the chemical industry, the R&D intensity of three other emission-intensive manufacturing industries lagged far below the national R&D target. Figure 2 reveals some temporal fluctuations in the R&D intensity over time, but there was no clear growth trend or temporal association with the EU ETS phases.

In summary, the GHG emissions decreased most notably in the basic metals and chemical industries, while pulp and paper and non-metallic minerals industries exhibited more modest decrease in emissions. The R&D intensity was highest in the chemical industry, with major fluctuations during the study period. The R&D intensity in the other three industries considered was rather low. These key patterns are worth keeping in mind when interpreting our regression results.

4.2 Contextual variables and exogeneity assumptions

In addition to production inputs and outputs, the empirical analysis incorporates contextual variables $\mathbf{z}_{it}$ capturing firm characteristics and operating conditions relevant for explaining variation in emissions and output. Following Johnson and Kuosmanen (2011, 2012), these variables influence firm performance conditional on input use but are not themselves part of the production technology. They capture systematic heterogeneity across firms that would otherwise be attributed to inefficiency or unobserved noise.

The contextual variables fall into three groups:

1. **Firm-level innovation indicators:** These include logarithmic measures of intramural and extramural R&D intensity (i.e., R&D expenditure / total revenue) and the share of R&D personnel. The share of STEM workers is included as a proxy for absorptive capacity and firms' ability to implement or adapt advanced technologies.

2. **Industry-level knowledge spillovers:** To capture the broader innovation environment, we construct an intra-industry R&D spillover measure, defined as the R&D intensity of all other firms in the same two-digit industry, excluding the focal firm's own R&D. This variable reflects horizontal knowledge diffusion through channels such as labor mobility, supplier-customer links, and technological imitation. Both firm-level R&D intensity and the spillover variable capture R&D activity without distinguishing between environmentally targeted and other forms of innovation. Consequently, the spillover measure reflects general within-industry knowledge diffusion rather than explicitly green technologies. Cross-sector spillovers are examined separately in Section 5.3.

3. **Environmental policy exposure:** Policy variation is captured by dummy variables for the EU ETS phases: Phase I (2005–2007), Phase II (2008–2012), and Phase III (2013–2019), with the pre-ETS period (2000–2004) serving as the reference category. The timing and content of these phases are determined at the EU level and apply uniformly across covered installations, making them plausibly exogenous to individual firm performance. Additional controls include firm age,

export status, foreign ownership, and material intensity, together with year and industry fixed effects, where specified.

It is worth noting that the contextual variables differ in terms of their exogeneity. R&D spillovers and the EU ETS phase indicators are not directly dependent on firm-level decisions: recall that R&D spillovers exclude a firm's own R&D by construction, and the EU ETS phases are determined by supranational regulation rather than micro-level performance. By contrast, firm-level R&D decisions are inherently endogenous, as more productive or innovation-oriented firms may self-select into R&D activity.

4.3 Descriptive statistics

Table 1 reports the sample averages and standard deviations of the main variables separately for each industry. The right-most column reports the averages and standard deviations for the pooled sample of all four industries.

The sample exhibits substantial heterogeneity in production scale and emissions, reflecting differences between capital-intensive heavy industries and smaller firms. Innovation inputs are highly skewed, with a small number of firms accounting for a large share of total R&D expenditure. Additional firm characteristics, policy indicators, and selection-correction terms used in the estimations are described above and reported in the regression tables.

Table 1: Sample means (standard deviations in parentheses) of model variables by industry.

	Pulp & paper (17)		Chemicals (20)		Non-metallic (23)		Basic metals (24)		All industries	
Variable	Mean (SD)	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)	N
Panel A. Innovation inputs (firm-level)										
STEM workers (share)	0.04 (0.03)	491	0.08 (0.06)	781	0.03 (0.03)	456	0.03 (0.03)	572	0.05 (0.05)	2,300
R&D employees (share)	0.03 (0.03)	362	0.11 (0.13)	511	0.03 (0.03)	289	0.03 (0.03)	307	0.06 (0.09)	1,469
Intramural R&D (M€, 2015)	4.54 (9.85)	362	6.57 (18.36)	511	1.18 (1.48)	289	2.13 (5.33)	307	4.08 (12.33)	1,469
Extramural R&D (M€, 2015)	0.83 (2.19)	362	0.22 (0.79)	511	0.07 (0.21)	289	0.16 (0.45)	307	0.33 (1.24)	1,469
Panel B. Policy variables										
Pre-ETS (dummy)	0.29 (0.46)	491	0.20 (0.40)	781	0.28 (0.45)	456	0.27 (0.45)	572	0.26 (0.44)	2,300
EU ETS Phase I	0.16 (0.37)	491	0.14 (0.35)	781	0.17 (0.37)	456	0.17 (0.38)	572	0.16 (0.37)	2,300
EU ETS Phase II	0.23 (0.42)	491	0.26 (0.44)	781	0.25 (0.43)	456	0.25 (0.43)	572	0.25 (0.43)	2,300
EU ETS Phase III	0.31 (0.46)	491	0.39 (0.49)	781	0.30 (0.46)	456	0.30 (0.46)	572	0.34 (0.47)	2,300
Financial crisis (dummy)	0.04 (0.21)	491	0.05 (0.21)	781	0.05 (0.23)	456	0.05 (0.22)	572	0.05 (0.22)	2,300
Panel C. Firm characteristics and production structure										
Material intensity (ratio)	4.35 (6.22)	491	3.28 (46.05)	781	2.57 (3.09)	456	3.57 (12.33)	572	3.44 (27.71)	2,300
Value added (M€, 2015)	130.96 (280.05)	491	35.23 (63.80)	781	25.07 (24.19)	456	45.04 (143.08)	572	56.09 (157.68)	2,300
Fixed assets (M€, 2015)	1195.1 (3323.4)	491	121.99 (318.01)	781	45.21 (61.98)	456	111.28 (293.54)	572	333.25 (1616.5)	2,300
Labor (FTE)	965.11 (1866.9)	491	266.57 (442.64)	781	265.75 (264.54)	456	459.27 (1034.5)	572	463.46 (1079.8)	2,300
Emissions (1,000 tons CO_2e)	143.62 (257.50)	491	49.87 (157.84)	781	68.52 (182.10)	456	186.01 (764.41)	572	107.44 (421.33)	2,300
Firm age (years)	12.37 (7.33)	491	14.29 (8.24)	781	13.97 (7.48)	456	14.07 (8.58)	572	13.73 (8.02)	2,300
Foreign-owned (dummy)	0.21 (0.41)	491	0.52 (0.50)	781	0.53 (0.49)	456	0.27 (0.44)	572	0.40 (0.49)	2,300
Exporting firm (dummy)	0.97 (0.17)	491	0.94 (0.24)	781	0.87 (0.33)	456	0.87 (0.34)	572	0.91 (0.28)	2,300
Panel D. Selection correction										
IMR (emissions)	0.20 (0.14)	491	0.37 (0.16)	781	0.42 (0.19)	456	0.29 (0.16)	572	0.33 (0.18)	2,300
IMR (R&D)	0.37 (0.24)	306	0.57 (0.26)	387	0.60 (0.19)	224	0.72 (0.37)	215	0.55 (0.29)	1,132

Notes: Monetary variables are expressed in millions of euros (M€) and deflated to 2015 prices using GDP deflators. CO_2eq. denotes carbon dioxide equivalents. FTE stands for Full-Time Equivalent. Firm-level data were accessed and processed within Statistics Finland's secure FIONA remote environment under a restricted data-use license.

5 Results

This section presents estimates from the emissions-generating model and the production function model, examining how innovation inputs, intra-industry knowledge spillovers, and environmental policy relate to firm-level emissions and economic performance in Finnish manufacturing. We begin with the emissions-generating model introduced in Section 5.1.

5.1 Emissions-generating model

Table 2 reports the CNLS estimates of the emissions-generating model, where GHG emissions are modeled as a function of innovation inputs, knowledge spillovers, environmental policy, and production structure, conditional on firm scale. The results are shown separately for the four emission-intensive industries and for the pooled sample.

The main finding of Table 2 is that there were statistically significant intra-industry R&D spillover associations across all carbon-intensive manufacturing industries, except for non-metallic minerals. Recall from Figure 1 that the GHG emissions of the non-metallic minerals industry showed only a modest decline. However, the signs and magnitudes of R&D spillovers differ notably across industries.

In the chemical industry, the R&D spillover is negative, which means that R&D spillovers are associated with lower GHG emissions. Recall from Figure 1 that the chemical industry exhibited the largest proportional decrease in the GHG emissions. In contrast, the R&D spillovers are associated with higher GHG emissions in the pulp and paper and the basic metals industries, as well as in the pooled sample. These results suggest that knowledge spillovers do not self-evidently contribute to the emissions abatement, but indeed, R&D spillovers can also result in an increase in emissions.

In sharp contrast, firm-level R&D intensity displays systematic negative associations with GHG emissions. Both intramural and extramural R&D intensities are negatively associated with the emissions, although the coefficients of intramural R&D are larger and statistically significant. These findings seem to suggest that firms devote own R&D resources for developing clean innovations and process technologies, but appear to be reluctant to share these innovations with their competitors.

Since our R&D intensity variables are in the logarithmic scale while the GHG emissions are in levels, the estimated coefficients can be interpreted as semi-elasticities. In the chemical industry, for example, the coefficient of R&D spillover of approximately -430 implies that a one percent increase in the R&D intensity of other firms in this industry is associated with 4.3 thousand tonnes lower GHG emissions (*ceteris paribus*). The magnitude of this R&D spillover is more than ten times larger than that of the intramural R&D intensity: a one percent increase in firm's intramural R&D intensity is associated with only 0.4 thousand tonnes lower GHG emissions.

Table 2: Estimated coefficients from the emissions-generating model.

	Pulp & paper (17)	Chemicals (20)	Non-metallic (23)	Basic metals (24)	All 4 industries
A. Innovation environment					
ln(intra-industry R&D spillover)	1657.8**	-429.7**	459.4	7636.2***	978.4***
	(832.9)	(173.5)	(432.1)	(2081.7)	(273.3)
B. Innovation inputs (firm-level)					
STEM workers (share)	10888.7***	-5965.1**	-5073.2**	9369.4	3127.4**
	(4042.2)	(907.7)	(2401.6)	(20188.3)	(1333.8)
R&D workers (share)	5530.3**	82.7	4577.0*	13761.9	183.2
	(2653.9)	(224.1)	(2462.4)	(16294.7)	(572.6)
ln(intramural R&D intensity)	-293.4***	-38.4*	-59.0	-340.0**	-132.3***
	(81.2)	(21.1)	(47.9)	(164.1)	(37.1)
ln(extramural R&D intensity)	-14.5	-0.005	-10.7	-112.8	-39.2***
	(12.5)	(6.84)	(9.05)	(83.0)	(10.2)
C. Policy variables					
ETS Phase I	-86.8	-110.7	-51.3	73.3	412.0*
	(226.6)	(138.7)	(156.9)	(1593.2)	(242.6)
ETS Phase II	-305.3	204.3	-142.2	-1404.7	161.3
	(241.1)	(128.9)	(183.3)	(1664.0)	(213.5)
ETS Phase III	-75.8	557.7***	-378.2	1794.3	448.3*
	(263.4)	(154.5)	(216.8)	(1724.7)	(230.1)
D. Firm characteristics and production structure					
Material intensity (ratio)	-882.9***	-1871.0***	-5088.3***	-1968.0	-1658.7***
	(176.8)	(362.3)	(781.9)	(3164.7)	(561.3)
ln(value added)	-1583.7***	-86.0	-1721.5***	-2393.5***	-2013.2***
	(187.0)	(78.7)	(151.4)	(999.5)	(240.2)
ln(firm age)	66.7	-1023.5***	443.0***	-28.3	-401.3**
	(107.9)	(82.7)	(115.5)	(597.6)	(86.8)
Foreign-owned (dummy)	-129.3	51.5	481.1***	6419.5***	687.5***
	(143.5)	(85.1)	(128.8)	(1331.4)	(103.6)
Exporting firm (dummy)	2030.6***	390.0	146.8	3423.6	1024.9***
	(634.9)	(248.7)	(196.8)	(3689.4)	(363.1)
Industry fixed effects	No	No	No	No	Yes
E. Selection correction					
IMR (emissions)	3494.2**	8704.9***	1633.8*	2872.7	2750.0***
	(1410.6)	(788.1)	(962.7)	(9396.3)	(975.3)
IMR (R&D)	-889.2	5816.7***	146.9	20200.8***	1423.7
	(1341.3)	(573.7)	(820.0)	(3770.3)	(904.7)
Financial crisis (dummy)	-921.1**	-469.3***	-464.0*	-9164.0***	-892.5**
	(316.5)	(163.9)	(238.6)	(3126.8)	(356.2)
N	303	381	224	213	1,122

Notes: Robust standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Emissions are measured in thousand tonnes of CO_2-equivalents. The reference category for the EU ETS phases is the pre-ETS period (2000–2004).

The share of STEM workers reflects firm's absorptive capacity, which is important for the diffusion of knowledge and innovations. Table 2 indicates that the share of STEM workers has a significant positive association with the GHG emissions in the pulp and paper industry, where the R&D spillover was also positive. In contrast, the share of STEM workers has a negative coefficient in the chemical industry, where the R&D spillover was similarly negative. This suggests that the STEM workers have an important role in the diffusion of knowledge and innovations, both cleaner products and processes, but also spillovers that contribute to higher emissions. The same logic does not directly apply to the designated R&D personnel, which is directly involved in firms' own R&D activities.

The association between the GHG emissions and the EU ETS phases proves surprisingly weak in light of Figure 1 . The only significant coefficient can be found in the chemical industry in Phase III, and even in this case, the coefficient has a positive sign, pointing towards an increase in emissions. In contrast, the dummy variable for the financial crisis has a significant negative association with emissions across all industries. Based on these results, it seems that the Finnish emissions-intensive manufacturing firms could easily meet the tigheter emissions standards during the period known as the Great Recession, and hence, the emissions reductions directly attributable to the EU ETS phases appear to be negligible at best.

Interestingly, higher material intensity is strongly associated with lower emissions across all industries. High material intensity could reflect low profit margins, a low share of in-house production, and dependence on outside suppliers. Since our sample consists of Finnish firms in emissions-intensive manufacturing industries subject to the EU regulations, the negative association between the material intensity and GHG emissions could indicate a possibility to outsource emissions to suppliers.

A good news is that the association between value added and the GHG emissions is negative and statistically significant in all industries except for the chemical industry. Our results do not imply a trade-off between emission abatement and value added growth: clean innovations and efficient processes enable firms to generate more value added with less emissions, instead of forcing a choice between environmental and economic performance. In other words, environmental and economic outcomes can be improved simultaneously.

Regarding other firm characteristics, the firm age has somewhat ambiguous association with the GHG emissions, with a significant negative association in the chemical industry (older firms have lower emissions) and a positive one in the non-metallic minerals industry (newer firms have lower emissions). Foreign-owned and exporting firms tend to exhibit higher emissions in several specifications. Finally, the selection correction terms prove statistically significant in most specifications, highlighting the importance of modeling the sample selection explicitly.

5.2 Production function model

Table 3 presents analogous CNLS estimates of the more conventional production function model, where the dependent variable is now value added. The results serve two purposes. First, they validate our empirical framework by reproducing well-established productivity spillover patterns. Second, they assess whether spillover-associated emission reductions coincide with output losses, providing a direct test of whether innovation-driven decarbonization involves an economic trade-off.

Table 3: Estimated coefficients from the production function model.

	Pulp & paper (17)	Chemicals (20)	Non-metallic (23)	Basic metals (24)	All 4 industries
A. Innovation environment					
ln(intra-industry R&D spillover)	4753.8***	678.73***	36.75*	1030.8***	732.63***
	(1117.5)	(114.06)	(20.97)	(259.2)	(146.95)
B. Innovation inputs (firm-level)					
STEM workers (share)	-731.9	571.25**	-282.86**	6485.5*	428.79
	(4249.3)	(242.55)	(134.34)	(3313.6)	(482.52)
R&D workers (share)	2721.0	-257.77	566.57***	1793.0	32.71
	(3424.4)	(208.22)	(164.77)	(2063.7)	(194.43)
ln(intramural R&D intensity)	-285.3***	-21.58	-1.35	-47.90**	-46.37***
	(84.60)	(16.07)	(1.74)	(22.06)	(13.38)
ln(extramural R&D intensity)	-27.87**	7.10***	-0.47	-26.28**	-18.52***
	(13.77)	(2.45)	(0.45)	(11.23)	(4.89)
C. Policy variables					
ETS Phase I	-147.25	281.84***	5.54	-25.12	77.81
	(385.66)	(66.40)	(7.35)	(200.5)	(145.92)
ETS Phase II	-285.86	282.46***	0.58	-164.8	63.19
	(353.35)	(68.76)	(9.76)	(214.6)	(117.33)
ETS Phase III	131.16	396.22***	4.18	4214.9	162.37
	(330.25)	(74.45)	(11.74)	(216.6)	(117.11)
D. Firm characteristics and production structure					
ln(emissions)	-255.63***	22.83***	-1.87	-340.5***	-88.53***
	(55.96)	(6.99)	(1.55)	(53.14)	(14.29)
ln(firm age)	201.20	-113.91***	-40.56***	-105.2	-117.58***
	(163.69)	(30.94)	(5.20)	(77.55)	(31.82)
Foreign-owned (dummy)	275.83	89.68***	29.31***	987.0***	329.71***
	(185.13)	(26.40)	(5.74)	(170.0)	(47.39)
Exporting firm (dummy)	572.30	-33.17	-11.43	385.8	225.99*
	(387.00)	(63.42)	(14.98)	(380.5)	(118.52)
Industry fixed effects	No	No	No	No	Yes
E. Selection correction					
IMR (emissions)	5914.4***	1269.39***	655.61***	88.49	906.49**
	(1625.3)	(284.34)	(59.68)	(1108.0)	(369.02)
IMR (R&D)	3752.7***	1756.56***	316.95***	3177.4***	2387.47***
	(1077.1)	(213.54)	(50.82)	(480.2)	(256.65)
Financial crisis (dummy)	-697.06*	-168.28**	-28.07***	-1272.7***	-289.76*
	(416.41)	(67.97)	(7.88)	(386.8)	(162.29)
N	305	385	224	215	1,130

Notes: Robust standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Value added is measured in million euros in 2015 prices. The reference category for the EU ETS phases is the pre-ETS period (2000–2004).

Intra-industry R&D spillovers systematically exhibit a positive, economically meaningful, and statistically significant association with value added across all industries (for non-metallic minerals, the association is almost significant). These findings further confirm the importance of R&D spillovers established in the economic literature. Recall that the estimated coefficients can be interpreted as semi-elasticities. In the basic metals industry, the estimated R&D spillover of approximately 1,030 implies that a one percent increase in the R&D intensity of other firms in the same industry is associated with 10.3

million euros higher value added, holding everything else constant. The magnitude of this spillover association is approximately equal to 22 percent of the average yearly value added in this industry.

Firm-level R&D intensities display a markedly different pattern. Both intramural and extramural R&D intensities are generally negatively associated with contemporaneous value added. R&D activities divert resources away from production and yield returns only with a lag. Moreover, the results of Table 2 suggest that intramural R&D activities are more likely to be associated with emissions reductions, possibly driven by tighter regulatory standards. This contrast between strong, positive R&D spillover associations with value added and weak or negative own-firm R&D associations reinforces the view that external knowledge diffusion plays a more important role for short-run economic returns than firms' own R&D activity.

Workforce composition associations remain mixed, similar to the emissions-generating model. A higher share of STEM workers has a significant association with higher value added only in the chemical industry. Similarly, a higher share of R&D personnel is positively related to value added only in non-metallic minerals. These results indicate that highly skilled labor can enhance economic performance in some specific industries, but not broadly across all industries.

The EU ETS phases have a positive association with value added in the chemical industry, but associations are statistically insignificant in all other industries as well as in the pooled sample. This result provides further support for our conclusions based on Table 2 that the Finnish emissions-intensive manufacturing firms could easily meet the tigheter emissions standards without a significant economic burden. The positive coefficients of the chemical industry provide some limited support for the Porter Hypothesis, which suggests that environmental regulation can induce efficiency gains and innovation that ultimately enhance competitiveness.

The GHG emissions enter the production function model with a negative coefficient in most industries, including the pooled sample. In other words, higher emissions are associated with lower value added. Chemicals constitute a notable exception, where emissions are positively related to value added. In this industry, emissions appear to be an unavoidable byproduct. Recall from Table 2 that the GHG emissions are also negatively associated with the material intensity.

5.3 Inter-industry spillovers and temporal dynamics

The spillover measure used in the baseline estimations (Sections 5.1–5.2) captures R&D conducted by other firms within the same two-digit industry, reflecting intra-industry R&D spillovers and horizontal knowledge diffusion among technologically proximate producers. This approach conforms with a large body of literature emphasizing the localized nature of knowledge spillovers. At the same time, it remains unclear whether R&D originating in technologically related upstream or downstream sectors, that is, inter-industry spillovers, also influences firms' emissions or output performance.

Inter-industry spillovers are knowledge flows between technologically related sectors through supplier-customer relationships and complementary technologies. We define the following linkages based on input-output relationships:

1) The pulp and paper and chemical industries are mutually interlinked; chemical inputs are used in pulp and paper production, and conversely, byproducts of the pulp and paper industry are used as intermediates in the chemical industry (Gabrielli et al., 2023; Joyo et al., 2025).

2) The chemical industry also provides intermediate inputs to the non-metallic minerals industry, for example, through chemical additives used in cement manufacturing.

3) The non-metallic minerals and basic metals are mutually interlinked, for example, through refractory materials that are essential for metal smelting and shared high-temperature processing technologies.

To incorporate these inter-industry linkages, we estimate the emissions-generating and production function models for the pooled sample of all four emissions-intensive manufacturing industries, introducing inter-industry spillovers and temporal dynamics. For each firm-year observation, we calculate the inter-industry spillover as the sum of total R&D expenditures in related industries (one or two industries depending on the focal firm's sector), normalized by the total turnover of all other firms in the focal firm's own industry, to isolate knowledge intensity from industry scale effects. This measure captures a firm's exposure to external R&D conducted in complementary sectors.

Table 4 reports the results for the four alternative specifications. Column I includes only intra-industry R&D spillovers, replicating the baseline findings for the pooled model reported in Tables 2 and 3. Column II extends the intra-industry spillovers with lagged spillovers from periods $t-1$ and $t-2$. Column III includes only inter-industry R&D spillovers, and column IV is the same model with lagged spillovers. Column V includes both intra- and inter-industry spillovers simultaneously. Column VI is the most general specification that includes the contemporaneous associations and two lags for both intra-industry and inter-industry spillover measures.

For emissions generation, R&D spillovers originating within a firm's own industry are systematically positive and statistically significant across all specifications. In contrast, the inter-industry spillover terms are systematically negative and significant across all model specifications. These findings highlight the pivotal role of the chemical industry as the potential source of spillovers for both the non-metallic minears and pulp and paper industries. Our results suggest that the chemical industry provides emissions decreasing spillovers, not only within the chemical industry itself (Table 2), but also through inter-industry spillovers to the pulp and paper and non-metallic minerals industries. As a specific example, Gabrielli et al. (2023) note that the pulp and paper industry also provides sustainable carbon-neutral material for the synthesis of many valuable chemicals. One such example is the UPM biorefinery in Lappeenranta, where black liquor waste from pulp and paper manufacturing is converted into renewable diesel. The negative inter-industry spillover is large and highly significant, whether included alone or jointly with intra-industry spillovers.

Table 4: Intra- and inter-industry spillover associations.

	(I) Intra	(II) Intra+Lags	(III) Inter	(IV) Inter+Lags	(V) Intra+Inter	(VI) Full model
Panel A: Emissions-generating model						
ln(intra spillover), t	978.4***	1150.2***			1381.0***	943.9**
	(273.3)	(292.2)			(284.2)	(457.6)
ln(intra spillover), $t-1$		39.27**				449.1
		(16.16)				(510.2)
ln(intra spillover), $t-2$		16.34				1425.9***
		(14.99)				(454.7)
ln(inter spillover), t			-1390.0***	-1154.1***	-1951.8***	-999.3**
			(355.1)	(407.6)	(354.6)	(458.4)
ln(inter spillover), $t-1$				-440.7		116.0
				(434.7)		(516.4)
ln(inter spillover), $t-2$				-950.8**		-439.9
				(405.1)		(434.8)
N	1122	971	973	973	1122	647
Panel B: Production function model						
ln(intra spillover), t	732.63***	734.5***			948.0***	513.3***
	(146.95)	(145.1)			(167.8)	(197.7)
ln(intra spillover), $t-1$		13.90**				316.7
		(5.93)				(232.9)
ln(intra spillover), $t-2$		1.36				836.9***
		(5.39)				(210.4)
ln(inter spillover), t			-811.2***	-561.9**	-1027.2***	-423.2*
			(195.5)	(225.3)	(212.4)	(230.3)
ln(inter spillover), $t-1$				-301.3		-81.98
				(242.3)		(262.3)
ln(inter spillover), $t-2$				-644.6***		-284.6
				(228.1)		(215.5)
N	1130	977	1132	979	1130	651
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

A similar pattern emerges for the production function model: intra-industry spillovers are positive and highly significant, while inter-industry spillovers are systematically negative. Of course, in the production function model, positive spillovers are desirable, whereas negative spillovers are not. Since the inter-industry spillovers largely originate from the chemical industry in this analysis, the negative inter-industry spillovers suggest that the cleaner chemical intermediates are also more expensive, which would explain a decreasing effect on the value added in pulp and paper production and in non-metallic minerals.

The temporal analysis reveals that the spillovers tend to display strong temporal persistence. In most cases, the lagged spillovers have the same sign as the contemporaneous spillovers. The lagged spillovers tend to be smaller in magnitude and statistically insignificant in most cases. However, two notable exceptions are observed. In the most general specification VI, the two-period lagged intra-industry R&D spillover is large, positive, and highly significant both in the emisions-generating and production function models. However, this lagged spillover appears only in combination with the inter-industry spollovers, and does not emerge in specification II that only includes intra-industry spillovers. Conversely, we observe a significant two-period lagged inter-industry spillover in model specification IV, which becomes insignificant in specification VI that also includes intra-industry spillovers. While we cannot rule out delayed spillovers, these patterns may suggest that the two-period lagged spillovers could arise from multicollinearity.

Taken together, the results highlight the importance of inter-industry spillovers through intermediate inputs in the supply chain. In contrast to the previous empirical literature that emphasizes the technological proximity, our results indicate that inter-industry spillovers on GHG emissions can be of similar magnitude or even greater than intra-industry spillovers. In particular, the chemical industry has played a pivotal role as a source of emissions decreasing spillovers, considering both intra-industry and inter-industry spillovers. Tighter emissions standards in other industries also benefitted the chemical industry: recall from Table 3 that the EU ETS phases had a significant positive association with the value added of the chemical industry firms.

6 Discussion and conclusion

In this study, we examined the association between R&D spillovers and firm-level GHG emissions in four emission-intensive Finnish manufacturing industries using a unified production-theoretic framework. By estimating emissions-generating and production function models with shape-constrained semiparametric regression corrected for sample selection, we shed new light on the role of R&D spillovers in the emission abatement. Our three key results can be summarized as follows.

Our first key result is that R&D spillovers are not only important for productivity growth, but also have a strong statistically significant association with the firm-level GHG emissions. However, the signs and magnitudes of the R&D spillovers differ across industries. In the chemical industry, intra-industry R&D spillover was associated with lower emissions, whereas in the pulp and paper and the basic metals industries, intra-industry R&D is associated with higher emissions. These results demonstrate that technology spillovers do not automatiocally result in lower emissions, but can also contribute to an increase in emissions.

Second, our results suggest that effective GHG abatement seems to require active R&D engagement at the firm-level. In all model specifications considered, firms' own R&D intensity had a negative association with the GHG emissions. However, the economic incentives may favor free-riding on R&D and copying innovations developed by other firms. In the production function model, we found that the R&D spillovers from other firms had a large positive association with value added, whereas firms' own R&D intensity had a negative association with value added. Indeed, the external societal benefits of R&D activity, including environmental benefits, form the primary motivation for public R&D support, whether through R&D tax allowances or directed R&D subsidies.

Third, our findings revealed an important channel of inter-industry R&D spillovers through material flows, which thus far has not attracted enough attention in the literature. The chemical industry had a far higher R&D intensity than the other three emission-intensive industries considered. Our results indicate that emission-reducing R&D spillovers from the chemical industry were not confined to that industry, but also contributed to GHG abatement in the pulp and paper and non-metallic minerals industries.

These results have several policy implications. As Finland pursues its national goal of increasing its R&D intensity to four percent of the GDP, it is important to bear in mind potential spillover effects on emissions, which could be positive or negative. Targeted subsidies can be used to incentivize firms to engage in R&D activities to develop cleaner technologies. Innovation policies, such as public R&D programs, could be designed to facilitate knowledge diffusion between firms in the same industry as well as across different industries. Platforms that foster collaborative research, sector-specific technology roadmaps, and labor mobility, such as Finland's SHOK centers or EU Horizon industry clusters, could be especially effective for facilitating diffusion of emission-reducing technological innovations.

The main limitation of this study is that we cannot utilize a natural or quasi-expetimental research design, but have to rely on statistical correlations. In contrast to many previous studies, we carefully refer to the estimated R&D spillovers as statistical associations rather than causal effects. Despite the lack of causal claims, we do believe that the statistical associations reveal interesting patterns that can help to develop more credible causal identification strategies in future research. Another obvious limitation is that our analysis is restricted to four emission-intensive manufacturing industries in the context of a high-income, innovation-rich country. The findings may not be generalizable to other countries with weaker institutional capacity.

This study opens several interesting avenues for future research. First, future research could pursue causal identification strategies, such as exploiting sectoral differences in the EU ETS policy, or exogenous shocks to public R&D programs. Second, examining whether similar dynamics hold in other countries would test the generalizability of our findings. Third, investigating more specifically the channels through which intra- and inter-industry spillovers operate (e.g., labor mobility, supplier networks, or technological imitation) would help to deepen our understanding of knowledge-diffusion mechanisms. Fourth, exploring how spillover-emission associations vary with firm characteristics, such as absorptive capacity or export orientation, could inform more targeted policies.

This study contributes to both the innovation and environmental economics literature by providing the first micro-level evidence on how industry-level knowledge diffusion relates to firm-level emission outcomes. While prior work has documented productivity spillovers (Bloom et al., 2013) or examined aggregate emission patterns (Rahko and Alola, 2024; Mamkhezri and Khezri, 2024), no previous study has estimated how external, industry-wide R&D environments affect firm-level emissions after controlling for production scale and technology. By demonstrating that, under the right conditions, such as localized innovation ecosystems and credible regulation, firms in emission-intensive industries can reduce emissions while maintaining or improving productivity, our findings suggest a pathway toward sustainable industrial transitions. These results from Finland's advanced manufacturing sector indicate that fostering sectoral innovation networks and maintaining stable and predictable carbon pricing could be key policy instruments for achieving emission reductions without sacrificing economic performance.

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Appendix A.

Table A1: Probit selection models for emission and R&D reporting.

Variable	(I) Emission reporting	(II) R&D reporting
Labor (FTE)	0.00165***	0.000533
	(0.000402)	(0.000615)
Material intensity (I/VA)	0.00011	–
	(0.000712)	
Lagged value added	–	0.00903*
		(0.00464)
Firm age	-0.0210**	-0.00526
	(0.00963)	(0.00918)
CIS year	–	0.0336
		(0.193)
Year dummies	Yes	Yes
Industry (2-digit) dummies	Yes	Yes
Log-likelihood	-1,349.15	-1,398.01
Wald χ^2	47.98	47.56
p-value	0.0038	0.0012
Pseudo R^2	0.088	0.142
N	2,910	2,386

Notes: Clustered standard errors are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix B.

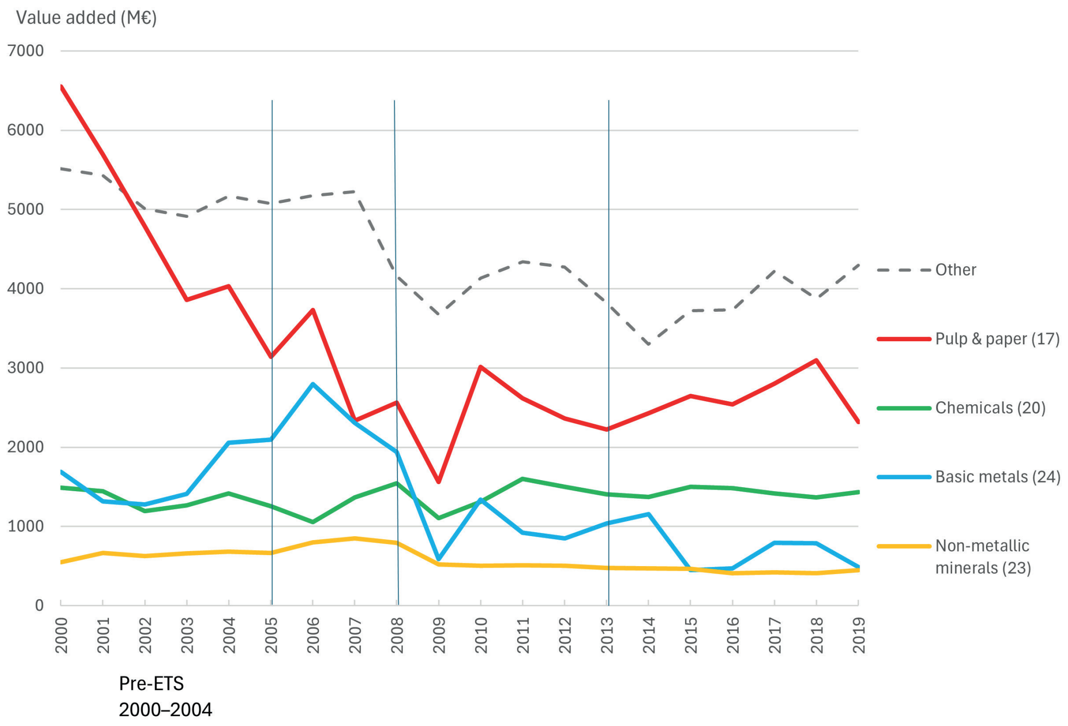

Figure B.1: Real value added by industry in Finnish energy-intensive manufacturing, 2000–2019 (2015 prices).

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