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WORKING PAPER

Green on paper? The effect of green patents on EU ETS firms

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On 29 January 2025, the European Commission unveiled the Competitiveness Compass, a set of policy guidelines that highlights the need to align industrial decarbonization and long-term competitiveness. While existing literature recognizes the importance of innovation to develop or scale up low-carbon technologies, the link between firm-level green inventions and their real-world impacts on technological change, efficiency and emission levels has largely been overlooked. This paper investigates this relationship in the context of heavy industry firms regulated by the European Union Emissions Trading System from 2013 to 2020. In a first stage, efficiency and technological progress are assessed using a Technological Frontier Analysis, applied to emissions data from the EU Transaction Log and financial and operational data from ORBIS. In a second stage, a firm-level panel econometric model evaluates the effects of green patenting---measured using PATSTAT data---on firms' efficiency and technological progress. The results reveal a paradox: firms engaging in green patenting are, on average, less likely to contribute to technological change in their sector than non-green-patenting firms. This suggests that carbon-intensive technological lock-in may constrain the transformative impact of green innovation, allowing firms using conventional technologies to achieve greater performance gains from their innovative activities.

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Executive summary

On 29 January 2025, the European Commission unveiled the Competitiveness Compass, a set of policy guidelines aimed at "reigniting economic dynamism in Europe" (European Commission, 2025b). A central pillar of this initiative is the creation of a joint road map that aligns industrial decarbonization with long-term competitiveness. Designing effective policies that promote green innovation and industrial decarbonization while maintaining competitiveness requires a nuanced understanding of how these objectives interact, of the policy instruments capable of shaping their alignment, and of how industrial production systems function (Dakpo et al., 2016; Diesing et al., 2025; Morfeldt & Silveira, 2014).

Building on this need for a better understanding of industrial production systems in view of decarbonization, this paper contributes to research on directed technical change and the impact of the EU's carbon market, the EU ETS, on heavy industry by addressing a key gap in the literature: the missing link between green inventions and actual firm-level decarbonization and production outcomes. While prior studies have established that the EU ETS has spurred low-carbon patenting activity (Calel, 2020; Calel & Dechezleprêtre, 2014), and others have assessed general trends in technical change within EU~ETS sectors Dzemydaité & Naruševičius, 2023; Morfeldt & Silveira, 2014), there remains limited evidence on whether such patented inventions have translated into measurable emission reductions or efficiency gains.

This study complements existing literature by jointly analyzing technical and climate efficiency at the firm level among industrial firms regulated under the EU ETS' third phase (2013–2020). Applying a Technological Frontier approach, the analysis goes beyond identifying innovation signals to evaluate whether firms that engage in low-carbon patenting are also those that shift or approach the technological frontier. In a second step, patent data is added to run a firm-level panel econometric analysis in which a firm's distance to the frontier is explained by firm characteristics and patenting behavior.

Key Findings:

- **Efficiency dispersion is uneven across EU ETS sectors.** Sectors like paper, chemicals, and non-metallic minerals display significant heterogeneity in their firms' efficiency levels, highlighting a large potential for efficiency gains among laggards, while firms in sectors such as cement and steel produced via electric arc furnaces (EAF) are more uniform.
- **Technological progress is driven by a small number of firms within each sector.** This suggests the presence of a strong leader–laggard dynamic.
- **Green patenting does not directly imply improvements in firm-level efficiency,** even when the measure of efficiency includes both emission and output in its measure. This counterintuitive result could be explained by brown technological lock-in: firms diverting resources from brown innovation to green innovation lose out to firms that are pushing the technological frontier faster by continuing their investments in brown technologies.

Ultimately, achieving deep decarbonization in heavy industries will require a dual focus on accelerating technological breakthroughs among sectoral leaders while ensuring broader diffusion of innovations and process changes across lagging firms. Policymakers must also look beyond patent-based metrics and prioritize direct evidence of emission reductions when evaluating the effectiveness of climate regulations.

1 Introduction

On 29 January 2025, the European Commission unveiled the Competitiveness Compass, a set of policy guidelines aimed at "reigniting economic dynamism in Europe" (European Commission, 2025b). A central pillar of this initiative is the creation of a joint road map that aligns industrial decarbonization with long-term competitiveness. This vision was formalized in the Clean Industrial Deal, which identifies heavy industry as one of two priority sectors requiring policy intervention to support the EU's climate and competitiveness objectives (European Commission, 2025a). These recent policy developments underscore the challenge policymakers are facing to design decarbonization policies without harming the industrial sector's competitiveness in a globally fragmented climate policy context.

A major barrier preventing heavy industry from significantly decarbonizing without policy intervention is that most low-carbon technologies are either not yet market-ready or are more expensive than their business-as-usual counterparts (Diesing et al., 2025; International Energy Agency, 2024; IPCC, 2023). This highlights the need for investments in low-carbon innovation to develop or scale up the industrial technologies needed for the transition. The EU's carbon market—the EU Emissions Trading Scheme (EU ETS)—recognizes this and aims to spur low-carbon innovation through market-based incentives (European Parliament and Council, 2003).

Designing effective policies that promote green innovation and industrial decarbonization while maintaining competitiveness requires a nuanced understanding of how these objectives interact, and of the policy instruments capable of shaping their alignment. A deeper grasp of industrial production systems can allow policymakers to design interventions that are both well-targeted and efficient—ensuring that they support climate goals while remaining compatible with the physical science and security requirements inherent to many industrial processes and products (Dakpo et al., 2016; Diesing et al., 2025; Morfeldt & Silveira, 2014).

Building on this need for a better understanding of industrial production systems in view of decarbonization, this paper contributes to the research on directed technical change and the impact of the EU ETS in heavy industry by addressing a key gap in the literature: the missing link between green inventions and actual firm-level decarbonization and production outcomes. While prior studies have established that the EU ETS has spurred low-carbon patenting activity (Calel, 2020; Calel & Dechezleprêtre, 2014), and others have assessed general trends in technical change within EU ETS sectors (Dzemydaitė & Naruševičius, 2023; Morfeldt & Silveira, 2014), there remains limited evidence on whether such patented inventions have translated into measurable emission reductions or efficiency gains.

This study complements and extends the existing literature by jointly analyzing technical and climate efficiency at the firm level among industrial firms regulated under the EU ETS' third phase (2013–2020). Applying a Technological Frontier approach, the analysis goes beyond identifying innovation signals to evaluate whether firms that engage in low-carbon patenting are also those that shift or approach the technological frontier. In doing so, the paper provides new insights into the effectiveness of patented inventions to transform heavy industry production systems. This can help policymakers to better target innovation policies towards firms that have not been able to innovate so far and investment policies towards firms that struggle to transform their inventions into tangible efficiency gains.

The choice of employing a Technological Frontier Analysis (TFA) stems from this methodology's capacity to model the joint production of industrial products (like cement or steel) and emissions. This reflects the fact that emissions are an inevitable and undesirable by-product of industrial processes (Färe et al., 2005). This paper uses data on firm-level emissions from the EU Transaction Log and on financial and operational data from ORBIS to run a TFA via a deterministic linear-quadratic minimization program. The TFA is applied to a sample of around 900 firms in 17 heavy industry sectors. This yields a measure of sector-level technological frontiers. These frontiers represent the best available performance within a sector. A firm's distance to the frontier is taken as a measure of its relative efficiency within its sector. In a second step, patent data is added and used to run a firm-level panel econometric analysis in which a firm's distance to the frontier is explained by firm characteristics and patenting behavior.

The TFA in this paper highlights two main insights into EU ETS sectors' efficiency and technological patterns. First, the level of dispersion in firm-level efficiency varies widely across sectors. Sectors like paper, chemicals, and non-metallic minerals display significant heterogeneity in their firms' efficiency levels, while firms in sectors such as cement and steel produced via electric arc furnaces (EAF) are more uniform. Second, technological frontier displacement—used here as a proxy for technological progress—is highly concentrated among a few firms, often the same ones year after year. These findings reveal the uneven pace of progress and point to the potential of targeted policies to boost lagging firms.

Our second-stage econometric analysis finds that firms that file green patents become less efficient than their competitors. The most plausible explanation for this is that brown innovation in heavy industry benefits from decades of research and technological lock-in, while green innovation has a large research gap to make up for. As a result, firms diverting resources from brown innovation to green innovation lose out to firms that are pushing the technological frontier faster by continuing their investments in brown technologies. This is in line with the mechanisms of innovation path dependency as theorized by Acemoglu et al. (2012) and empirically studied by Aghion et al. (2016). We highlight further research avenues that could be pursued to strengthen this claim in our discussion.

The rest of this paper is organized as follows. Section 2 reviews the literature that relates to innovation, the EU ETS, and technical efficiency. Section 3 presents the theoretical framework of technological frontiers as it is applied in this paper. Section 4 and Section 5 respectively present the data and empirical approach that are used. Section 6 presents the results from our two-stage analysis, which Section 7 discusses. Finally, Section 8 concludes and presents avenues for future research.

2 Related literature

2.1 Directed technical change

One of the core objectives of the EU ETS is to "encourage the use of more energy-efficient technologies", as outlined in its founding directive (European Parliament and Council, 2003). Since the market's launch in 2005, policy reforms have further institutionalized this objective and leveraged the transition from free allocation of allowances to auctioning as the default allocation mode. These reforms include (1) the earmarking of some of the revenues from auctioning allowances to the Innovation Fund, which channels funds into large-scale low-carbon projects, and (2) requirements that Member States reinvest national ETS revenues into climate adaptation and mitigation, with a focus on research and innovation (European Commission, 2023; European Parliament and Council, 2024).

This objective is in line with the idea known as directed technical change, which posits that the direction of innovation responds to economic incentives (Hicks, 1932). In the case of climate change mitigation, instruments like the EU ETS create incentives for firms to reduce their emissions by imposing a price on carbon (Porter & van der Linde, 1995). This type of directed technical change is a necessary (but insufficient) condition to meet climate objectives (Bataille et al., 2018; IPCC, 2023). However, decades of climate inaction have entrenched a brown technological lock-in—a situation where industrial systems, infrastructure, and knowledge bases are deeply embedded in fossil-fuel technologies. This lock-in creates structural inertia which makes it difficult for green innovation to compete without targeted support. Empirical studies have found evidence of carbon-intensive technology lock-in in the automobile (Aghion et al., 2016) and chemicals industries (Janipour et al., 2020) for instance. To break this cycle, complementary policies like innovation subsidies are essential (Acemoglu et al., 2012).

2.2 Trends in EU ETS sectors' technical change

Some studies document technical change trends in EU ETS-regulated sectors without making a causal claim about the policy's impacts. The most comprehensive multi-sector analysis of this sort, Baudry and Faure (forthcoming), applies a linear-quadratic minimization framework to nine four-digit NACE sectors (iron and steel, cement, flat glass, hollow glass, ceramic tiles, ceramic bricks, pulp, paper, and chemicals) from 2012–2021. Calibrating sector-specific annual frontiers for 249 EU ETS firms, they categorize sectors as exhibiting non-directed technological change (iron and steel, flat and hollow glass, ceramic tiles, and chemicals), weakly directed technical change—meaning that firms reduced their carbon intensity but increased total emissions through output growth (cement, pulp, ceramic bricks)—or indeterminate technological change due to a high level of heterogeneity between firms (paper).

Sector-specific papers further study these trends. For iron and steel, Morfeldt and Silveira (2014) use a DEA-based Malmquist index to distinguish technical change (innovation-driven efficiency gains) from energy efficiency (firms' average distance to best practices) across 15 EU countries from 1992–2010. While technological progress occurred, energy efficiency gaps widened between frontier and lagging producers. In the Swedish pulp and paper sector, Bostian et al. (2018) find productivity declines between 2002 and 2008 when emissions are accounted for in the DEA frontier. For chemicals, Dzemydaitė and Naruševičius (2023) highlight robust technological progress (2000–2019) measured via Stochastic Frontier Ananlysis (SFA). Oggioni et al. (2011) attribute stable efficiency gains in EU cement (2005–2008) to advanced kilns and alternative fuels but do not disentangle EU ETS incentives from other drivers. Overall, there is little recent evidence on firm-level technical change across all heavy industry sectors covered by the EU ETS.

2.3 Has the EU ETS caused directed technical change?

A separate strand of literature evaluates whether the EU ETS *caused* directed technical change, with two main approaches. The first group assesses the EU ETS' impact on TFA-based measures of technological progress, while the second group does so on proxies of technological progress, namely patents and investments in research and development.

Within the first group, Löschel et al. (2019) perform a difference-in-differences analysis on 473 EU ETS-regulated firms and 35,122 non-EU ETS firms in Germany (2003–2012). They apply an SFA to estimate sector-specific economic efficiency frontiers for the entire period. Efficiency improvements are measured as the reduction of a firm's distance to the frontier over time. While EU ETS firms initially lagged in efficiency, their median distance to the frontier decreased by 2012—notably in the paper sector—while non-ETS firms showed no improvement. The authors show that the EU ETS improved economic efficiency. However, their methodology only allows them to measure general technological progress, without commenting on its direction with regards to emission efficiency. Contrary to this result, Lundgren et al. (2015) assess 90 Swedish firms (1998–2008) and find that CO_2 taxes and the EU ETS had negligible or negative effects on productivity, but that fossil fuel prices spurred stronger incentives for efficiency gains through technological progress. They are able to decompose efficiency gains from technological change by computing a Luenberger Total Factor Productivity indicator. This indicator defines technological change as the displacement of the technological frontier from one year to the next and efficiency gains as the change in firms' distance to the frontier from one year to the next.

Within the second strand of literature, researchers have exploited the EU ETS' installation-level inclusion criteria to assess the market's causal impact on patents or investments in research and development—used as proxies for technological change. Calel (2020) adopt this approach on a panel of British firms and find that the EU ETS has encouraged low-carbon patenting and spending in research and development between 2005 and 2012. Applying a similar approach on a panel of around 3,500 firms, Calel and Dechezleprêtre (2014) find that the EU ETS increased low-carbon patenting in regulated firms by as much as 10% from 2005 to 2009. While this research points in the direction of directed technical change induced by the EU ETS, there is one significant limitation: low-carbon patents indicate that a firm has invented a new process or product, but not that it has implemented this invention in its production process (making it an innovation), nor that this implementation has effectively reduced emissions or emission intensity.

This paper aims to complement the existing literature highlighted in this section by providing an analysis of technical change in EU ETS firms and by studying whether low-carbon patenting by EU ETS firms has led improvements in emission and production efficiency. We now turn to the theoretical framework that allows us to measure firm-level efficiency accounting both for technical and emission parameters.

3 Theoretical framework

3.1 Technological frontiers

We apply the theoretical framework of technological frontiers, first formalized by Shephard (1970) and later generalized by Chambers et al. (1998). A technological frontier represents a firm's maximum attainable output with a given set of inputs if the firm is fully efficient. A firm's inefficiency is therefore measured as its distance to the technological frontier. Following Färe et al. (2005), we examine a setting where firms produce both a desirable and an undesirable output.

General setup. We consider $\sum_{s=1}^{S} N_s$ firms in S sectors over T time periods (years). Firm i ($i = 1, ..., N_s$) in sector s ($s = 1, ..., S$) produces $O = 2$ types of outputs Y_o at time t ($t = 1, ..., T$): one good output Y_g (production of an industrial good such as cement) and one bad output Y_b (CO_2 emissions). The bad output is an undesirable side effect of production. The output of firm i at time t is a O-dimensional vector given by: $Y_{it} = (Y_{itg}, Y_{itb})' \in \Re_+^O$.

Firm i uses $Q = 3$ inputs X_q for its production: capital X_k, labor X_l, and material inputs X_m (which include energy and raw materials). The inputs used by firm i at time t are a Q-dimensional vector given by: $X_{it} = (X_{itk}, X_{itl}, X_{itm})' \in \Re_+^Q$.

Firm i transforms the vector of inputs X_{it} into the vector of outputs Y_{it} by using a production technology P that is common to all firms within a sector s (Färe et al., 2005). All the equations that follow are given for a specific sector s. To simplify notations, we forego the s subscript in the rest of this section.

Production technology. The production technology P is defined as:

$$P(X_{it}) = \{Y_{it} : X_{it} \text{ can produce } Y_{it}\} \tag{1}$$

This specification follows a set of standard neoclassical micro-economic assumptions, augmented to account for joint production of desirable and undesirable outputs (Färe et al., 2005; Shephard & Färe, 1974; Shephard, 1970). For notational simplicity, we omit firm i and time t subscripts when presenting these assumptions below, though all properties hold for each firm-period observation.

- **Inputs are strongly and freely disposable**, meaning that a firm cannot decrease its output level if it does not also decrease its input level:
$$\text{If } X' \geq X \text{ then } P(X') \subseteq P(X) \tag{2}$$
- **Null-jointness of Y_g and Y_b**, meaning that a firm cannot produce any level of the good output without also producing some amount of the bad output:
$$\text{If } (Y_g, Y_b) \in P(X) \text{ and } Y_b = 0 \text{ then } Y_g = 0 \tag{3}$$
- **Good and bad outputs together are weakly disposable**, meaning that for a given level of X, cutting down proportionally on Y_b and Y_g is technologically feasible (the decrease in Y_g represents the cost of cutting down on Y_b):
$$\text{If } (Y_g, Y_b) \in P(X) \text{ and } 0 \leq \zeta \leq 1 \text{ then } (\zeta Y_g, \zeta Y_b) \in P(X) \tag{4}$$
- **Good outputs are strongly disposable**, meaning that the firm can dispose of the good output at no cost:
$$\text{If } (Y_g, Y_b) \in P(X) \text{ and } (Y'_g, Y_b) \leq (Y_g, Y_b) \text{ then } (Y'_g, Y_b) \in P(X) \tag{5}$$

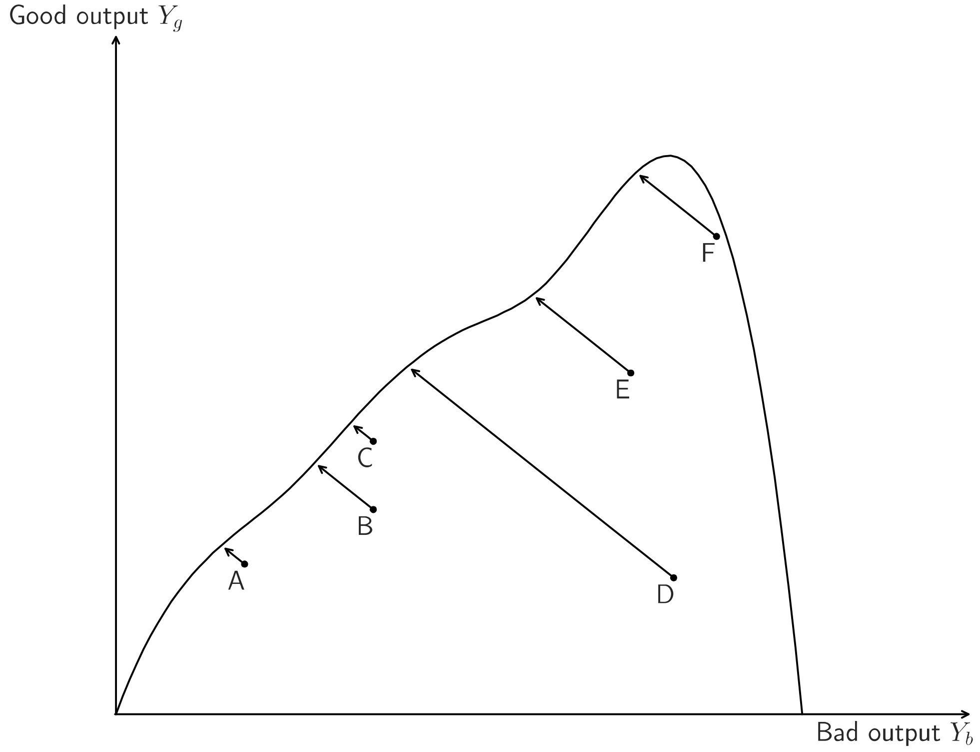
To further explain the characteristics of the technological frontier framework, we turn to a graphical representation (Figure 1). The technological frontier is represented by the solid line.[1] Firms' inputs have been normalized to an equal amount and each dot represents the level of good and bad outputs that each firm produces given this normalized amount of inputs.

3.2 Efficiency

Broadly speaking, efficiency can be understood as firms' capacity to use the lowest amount of inputs (resources) to produce the largest amount of outputs. In practice, efficiency is measured either as an input-oriented measure or an output-oriented measure. Input-oriented efficiency measures the extent to which a firm could reduce its use of inputs and still be able to produce the same level of output. Output-oriented efficiency is the opposite, meaning the extent to which a firm could expand

[1]The technological frontier has an inverse-U shape for three reasons: (1) the assumption of null-jointness of Y_g and Y_b imposes that it passes through $(0, 0)$; (2) it must be above or equal to all firms' outputs; (3) the assumption that Y_g is strongly disposable means that it passes through $(\max(Y_b), 0)$.

Figure 1: Representation of an output-oriented technological frontier



Source: Authors.

its level of output without using more inputs. Both measures are relative to the best-performing firms in a sector (Bogetoft & Otto, 2011).

In this paper, efficiency has to integrate both a good and a bad output. We therefore use an output-oriented measure of efficiency, defined as a firm's capacity to produce the largest amount of good outputs, while producing the smallest amount of bad outputs, with a fixed level of inputs.

To integrate both a good and a bad output, we use the concept of Shephard's distance applied to an output-oriented efficiency (Shephard, 1970). Shephard's distance measures how far each firm is from its sector's technological frontier. The further away a firm is from the frontier, the higher its inefficiency. The solid arrows going from the firm-level observations to the frontier in Figure 1 illustrate this measure of inefficiency. Formally, Shephard's distance is defined as a directional distance function

$$\overrightarrow{D_{it}}(X_{it}, Y_{itg}, Y_{itb}; v_g, -v_b) = \max\{\phi : Y_{itg} + \phi v_g; Y_{itb} - \phi v_b) \in P(X_{it})\} \tag{6}$$

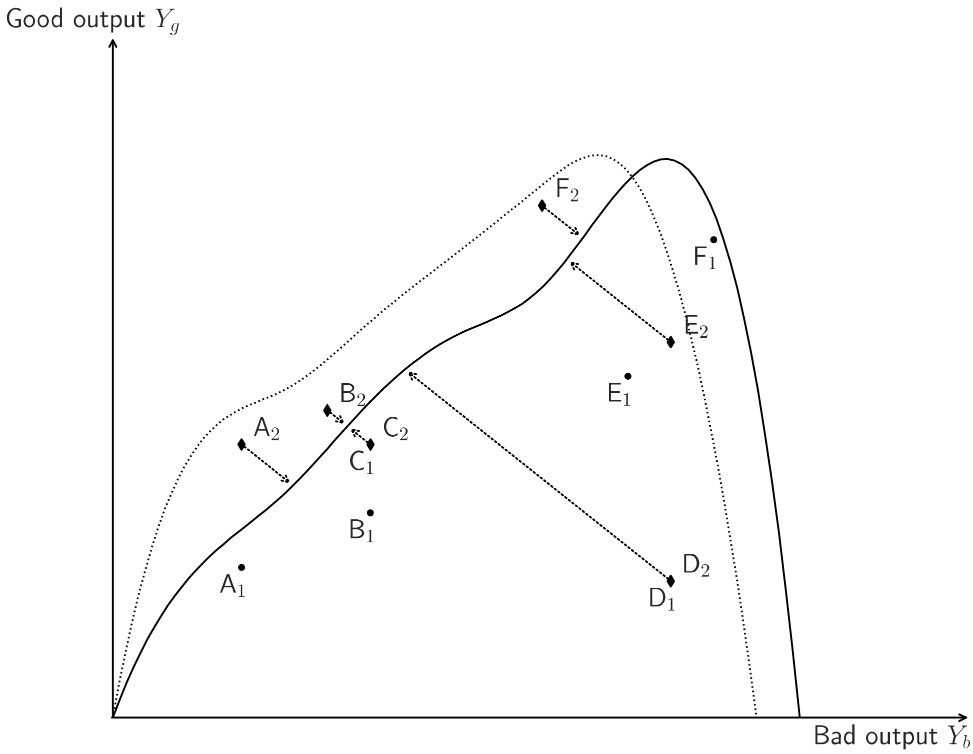
where ϕ represents the most the good output can grow (or the bad output can shrink) based on a plant's technology, moving in a specific direction defined by $v = (v_g, -v_b)$, where v represents the direction for good outputs (v_g) and bad outputs (v_b).

3.3 Technological progress

In this framework, technological progress occurs when the production frontier shifts upward from one period to the next (represented by the dashed frontier line in Figure 2). This shift reflects an expansion of production possibilities.

Our focus is on identifying the firm-level drivers of technological progress. Specifically, we aim to pinpoint which firms are responsible for pushing the frontier outward. To do this, we compute each firm's position relative to the $t-1$ frontier (represented as the diamonds in Figure 2) by evaluating its t-period inputs and outputs against the frontier's $t-1$ coefficients. This also allows us to compute a firm's distance to the $t-1$ frontier (represented as the dotted arrows in Figure 2). If a firm's production lies beyond the $t-1$ frontier, it has contributed to displacing the frontier outward in period t (for example, firms A, B and F in Figure 2) and has a negative value for its distance. If it lies below the frontier, it has not driven technological progress (for example, firms C, D and E in Figure 2) and has a positive value for its distance.

Figure 2: Representation of frontier displacement



Source: Authors.

4 Data

4.1 Data sources

Three main databases were merged to provide data on firm-level climate and economic variables: Moody's ORBIS database,[2] the EU Transaction Log (EUTL),[3] and the European Patent Office's (EPO) PATSTAT database.[4]

ORBIS is a proprietary dataset that includes around 550 million businesses throughout the world. It harmonizes financial information into a uniform global template, enabling comparisons between countries. The EUTL, managed by the European Commission, serves as the primary system for reporting and tracking all EU ETS compliance and transaction information. It provides public access to GHG emission compliance data for installations covered by the EU ETS. PATSTAT is a proprietary database compiled by the EPO. It provides patent data at the firm level from patent offices in major industrialized and developing countries and includes bibliographical and legal information.

4.2 Data preparation

4.2.1 Data cleaning

EUTL We use the data files provided by Abrell (2022).[5] We implement the following steps to clean these files for the purpose of our analysis. First, we remove all observations lacking company registration numbers and entries from the Swiss ETS (CH ETS). Second, we discard entries not reporting Operator Holding Accounts, as well as those with "Aircraft operator activities" as their installation activity. Finally, we exclude account holders without any corresponding installations.

ORBIS We follow recommendations from Gal (2013), Gopinath et al. (2017), and Kalemli-Ozcan et al. (2015) to ensure that we eliminate all observations without sufficient data quality from our sample. In particular, we drop all observations that meet the following criteria:

- Missing any of the following variables: total assets, turnover, sales, cost of employees, tangible fixed assets, material costs
- Any of the following variables are negative: total assets, number of employees, sales, tangible fixed assets, material costs, operating revenue

[2] https://www.moodys.com/web/en/us/capabilities/company-reference-data/orbis.html
[3] https://www.eea.europa.eu/data-and-maps/dashboards/emissions-trading-viewer-1
[4] https://www.epo.org/en/searching-for-patents/business/patstat
[5] Abrell (2022) scraped the data from the EUTL and compiled it into a relational database made up of various CSV files. These files, along with documentation on Abrell's work and output are available for download at the following website: https://www.euets.info/download/

- Any of the following variables are equal to zero: material costs, total assets, tangible fixed assets, number of employees or operating revenue

Additionally, we deflate all the data reported in euros in ORBIS. Following Curzi et al. (2021), we deflate turnover with Eurostat's output price index data series and tangible fixed assets with Eurostat's implicit deflator for fixed assets data series. Both of these data series come from national accounts data. Labor costs are deflated using Eurostat's labor cost index for wages and salaries data series. Material costs are deflated through a combined index, computed as the simple average of price indexes for natural gas and metals from the IMF, and electricity prices from Eurostat.[6]

Finally, following Cameron and Garrone (2024), we keep only firms whose main activity as stated by its ORBIS NACE code is an activity regulated by the EU ETS. This is to ensure better compatibility between ORBIS and EUTL data.

PATSTAT To assess the level of patented inventions among EU ETS firms, we exploit the EPO's PATSTAT database. Patents signal novel and significant advances over the current state of the art in technology and confer exclusive industrialization and commercial rights within the relevant jurisdiction.

To avoid double counting of the same invention filed in multiple jurisdictions, we rely on observations at the patent family level (defined as the INPADOC family classification).[7] Since our focus is on inventions within EU member states, we only consider patents filed with the EPO, or, in the absence of such, with a national office of an EU ETS country.

We define the date of invention as the filing date, which better reflects the timing of inventive activity than the grant date. We do not restrict the dataset to granted patents, to capture early-stage inventions and avoid truncation biases in recent years.

We construct two different measures of patent counts. One is a stock value and the other is a flow value. The stock value begins in the first year of our sample (2013) and is a cumulative count of the patents filed since then. We do not include the stock before 2013 because it does not vary over time and is therefore accounted for in our firm-level fixed effects. The patent flow value is the simple count of patents filed in a single year.

Patent families are classified either as "Low-carbon" or "Not low-carbon" in our data. This is determined based on the Cooperative Patent Classification (CPC) system. The EPO and the

[6]Data codes are the following for Eurostat data series: "NAMA_10_A64" for the output price index series, "NAMA_10_AN6" for the implicit deflator for fixed assets deflator series, "LC_LCI_R2_A" for the labor cost index data series, and "TEN00117" for the electricity price data series. All of these data series are provided for industry only (NACE code D) and by country and year. The IMF data for natural gas and metal price indexes are taken from the Primary Commodity Price Systems database. The natural gas data is provided as an EU average and the metal data is provided as a world average. Both are for all sectors of the economy.

[7]An extended patent family is a collection of patent documents covering a technology. The technical content covered by the applications is similar, but not necessarily the same. See Martinez (2010) and the EPO's website for a complete discussion on the use of patent families: https://www.epo.org/en/searching-for-patents/helpful-resources/first-time-here/patent-families/inpadoc

United States Patent and Trademark Office developed a tagging system that identifies patents linked to climate change mitigation technologies. The tagged patents are given a CPC code that begins with “Y02” (Angelucci et al., 2018). Patent families can have several associated CPC codes if they are related to several technical fields. As a result, a single patent family may be associated both with CPC codes starting with “Y02” and others that are not.

To avoid double counting these patent families, we count those with both “Y02” and non-“Y02” CPC codes as 0.5 Low-carbon and 0.5 Not Low-carbon. We refer to the category of Low-carbon patent families as green inventions and Not low-carbon patent families as brown inventions. We include a robustness test that counts patent families with both types of CPC codes as 1 in each category of inventions. Results for this test are reported in Appendix 11.

Finally, we also compute a variant of our stock count of patent families that includes a rate of depreciation of inventions. This is to account for the progressive loss of value of inventions as they grow older. Following the literature, we compute this with an annual depreciation rate of 5% (de Rassenfosse & Jaffe, 2018; Huang & Diewert, 2011). Results that use the depreciated patent family stock variable are reported in Appendix 11.

4.2.2 Matching databases at the firm level

The matching between ORBIS and the EUTL was conducted in previous work by Cameron and Ho (2024). The full procedure, as well as the resulting matched dataset, has been published by the European Commission and is available online.[8]

Turning to the PATSTAT–EUTL matching, no common unique identifiers exist between the two datasets. We therefore implement a matching protocol based on firm names and geographic information.

First, we extract all patent filings from firms located in countries participating in the EU ETS, between 1992 and 2020. We then construct a name-matching algorithm following Cameron and Ho (2024) that applies an N-gram similarity algorithm to compare firm names across PATSTAT and the EUTL, incorporating data on zip codes to improve the precision of matches. The resulting candidate matches are evaluated using a combination of automated similarity scores and complementary manual validation to ensure correspondence between legal entities.

We subsequently merge the outputs of the two separate matched databases (i) PATSTAT–EUTL, and (ii) EUTL–ORBIS. Upon inspection, we observed that in some cases, firm names from ORBIS—distinct from their EUTL counterparts—matched closely with PATSTAT applicant names. To account for this, we re-applied the N-gram algorithm to the subsample of ORBIS firms already matched to the EUTL but not matched in the original PATSTAT-EUTL procedure. This procedure results in a balanced panel of 872 firms that were observed between 2013 and 2020.

[8]The matching procedure and data can be accessed at https://single-market-economy.ec.europa.eu/single-market/services/economic-analysis/matching-eu-transaction-log-orbis-database_en?prefLang=sv

4.2.3 Sectoral classification

One of the fundamental assumptions in TFA is that firms within a given sector employ the same production technology, meaning they share a common production/technology set. This assumption is crucial because firm efficiency is assessed through benchmarking against other firms in the same sector. If firms differ in their outputs, production technologies, or input types, efficiency measurements may be biased (Walheer, 2024).

This assumption poses two challenges for empirical implementation. First, sectoral nomenclatures typically classify firms based on their economic activity or outputs, rather than the production technologies they use. This may not be a problem for sectors where production technologies for one output or activity are relatively homogeneous (e.g., paper production), but it is one in sectors that have several distinct production pathways (e.g., steel production). The second challenge is that, although using the most disaggregated nomenclature maximizes technological homogeneity within sectors, it also creates sectors that are too narrow for empirical analysis—for instance, at the 4-digit level, 21 NACE sectors contain only a single firm in our sample. We must thus strike a balance between achieving sufficient disaggregation to reflect homogeneous technological processes while avoiding excessive fragmentation that results in sectors that contain very few firms.

To determine the sectoral classification that best ensures technological homogeneity within sectors while avoiding over-fragmentation, we evaluate available nomenclatures using a Multiple Analysis of Variance (MANOVA).[9] There are four nomenclatures available in our dataset: 2-digit NACE codes, 3-digit NACE codes, 4-digit NACE codes, and installation activity codes from the EUTL. The indicators employed in the MANOVA are firms' capital intensity, labor intensity, material input intensity, and emission intensity.[10]

We begin with the most disaggregated nomenclature available—the 4-digit NACE codes—which achieves the best MANOVA scores across all test (brown bars in Figure 3). Sectors with fewer than 20 firms are subsequently merged with their closest parent NACE sector (orange bars in Figure 3).[11] While the 3-digit NACE classification (purple bars in Figure 3) and the EUTL installation activity nomenclature (red bars in Figure 3) both yield better scores than the new aggregated nomenclature for some of the test statistics, they suffer from the same issue as the 4-digit classification, with some sectors containing too few firms. Therefore, the final proposed nomenclature represents the most disaggregated classification in which all sectors contain at least 20 firms.

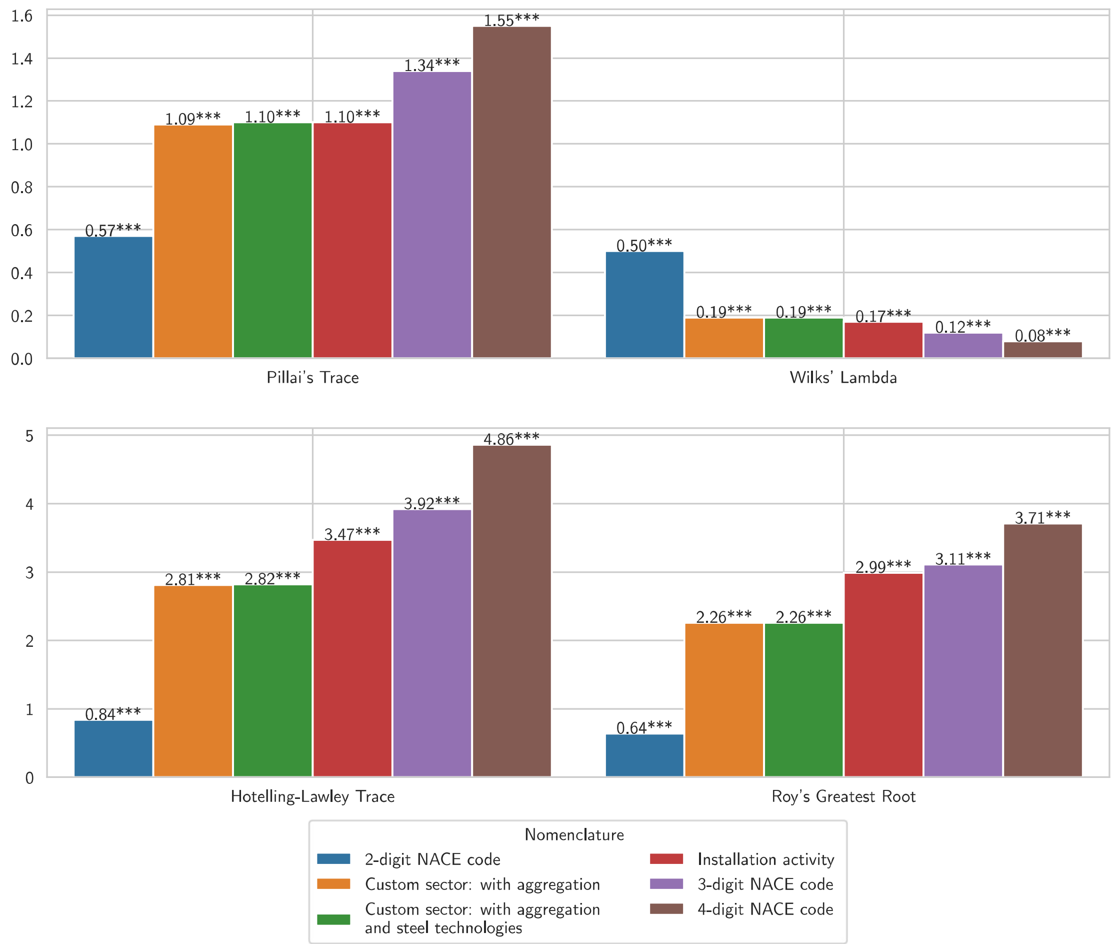
[9] We report results for the four most common MANOVA test statistics: Wilk's Lambda, Hotelling-Lawley's Trace, Roy's Greatest Root, and Pillai's Trace. While all assess group differences across dependent variables, they handle variability differently and rely on distinct data assumptions. Regardless of the test statistic used, the results of the nomenclature assessment remain broadly consistent.

[10] Capital intensity serves as a proxy for the machinery used in production (Bellocchi et al., 2023; Kaldor, 1957); labor intensity reflects skill and labor requirements (Acemoglu & Autor, 2011); material input intensity characterizes the type and quantity of inputs needed (Rigby & Essletzbichler, 1997); and emission intensity represents the emission profile associated with different production pathways (OECD, 2024).

[11] The complete list of these aggregations is provided in Appendix 9.

We refine this classification and address the first challenge described above by incorporating information on steel production technologies. Neither the NACE nor the EUTL installation activity classifications distinguish between steel firms operating electric arc furnaces and those using basic oxygen furnaces, despite the significant differences between these technologies (Cameron, 2025). To address this gap, we merge our dataset at the installation level with the Global Steel Plant Tracker database, which provides information on steel mill production technologies (Global Energy Monitor, 2024).[12] This additional classification step slightly enhances the MANOVA scores of the final nomenclature (green bars in Figure 3).

Figure 3: Results of MANOVA for sectoral classification



Note: Higher scores for Hotelling-Lawley's Trace, Roy's Greatest Root and Pillai's Trace indicate a higher level of differentiation between sectors, while the opposite is true for Wilk's Lambda (i.e. a lower score indicates a higher level of differentiation between sectors).
Source: Authors.

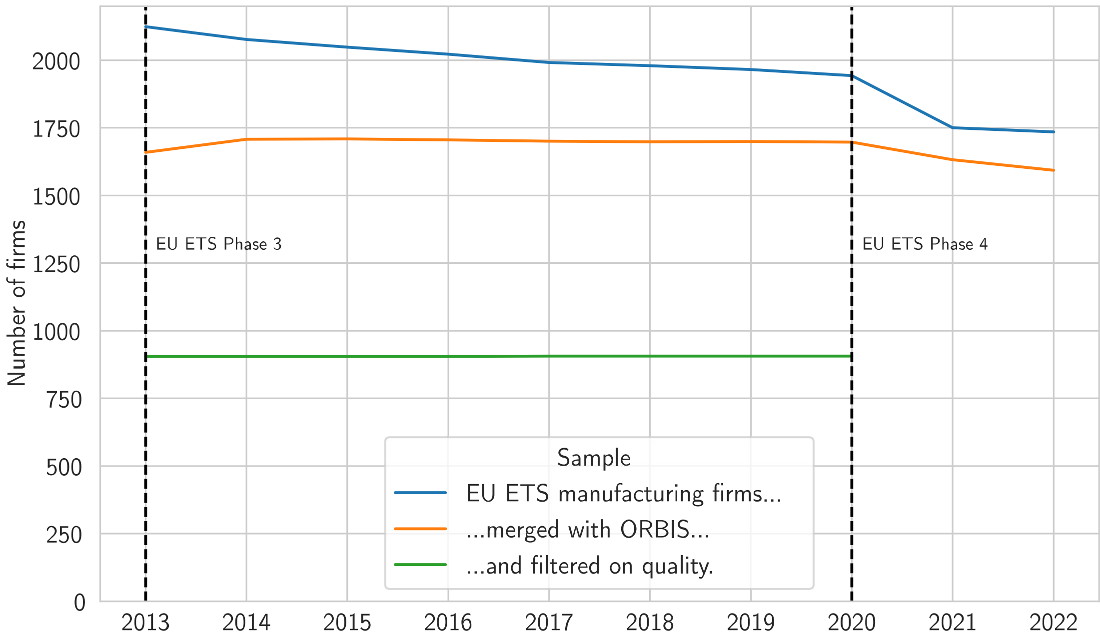
[12] These datasets are first matched based on geographic location, then manually verified using installation and company name similarities. Unmatched steel mills are categorized under "Unknown technology".

4.3 Data characteristics

4.3.1 Final sample

The sample in this study comprises heavy industry firms regulated under the EU ETS, which are not representative of all EU heavy industry firms. Due to the EU ETS inclusion criteria, the dataset disproportionately reflects the largest and most polluting firms in the sector (Cameron & Garrone, 2024). Data limitations further constrain the analysis: attrition occurs during the matching and cleaning processes (Figure 4). Observations prior to 2013 are excluded because data from ORBIS are unavailable for earlier years. The final sample we use in our analysis is a balanced panel of observations with sufficient data quality—meaning they are likely the largest firms, not a representative set.

Figure 4: Sample size at the different stages of data preparation



Source: Authors.

4.3.2 Descriptive statistics

The dataset spans 17 heavy industry sectors, which are heterogeneous in their sizes, and input and output structures (Table 1). In our sample, Paper & paperboard have the most firms (160 firms), followed by Ceramic tiles (100 firms), while Iron & steel via the EAF route and Pulp have the least (20 firms each). Basic chemicals (173M€) and Pulp (168M€) have the highest mean levels of capital, though with high volatility (standard deviation of up to 263M€), while Other metals (653M€) and Basic chemicals (467M€) have the highest levels of material inputs. Mean labor costs are highest in Chemical products (85M€), but with high dispersion (standard deviation of 442M€), suggesting heterogeneous firm sizes. Finally, Other metals (761M€) and Chemical products (724M€) have the highest mean level of output and Cement by far has the largest mean level of emissions (1203ktCO_2).

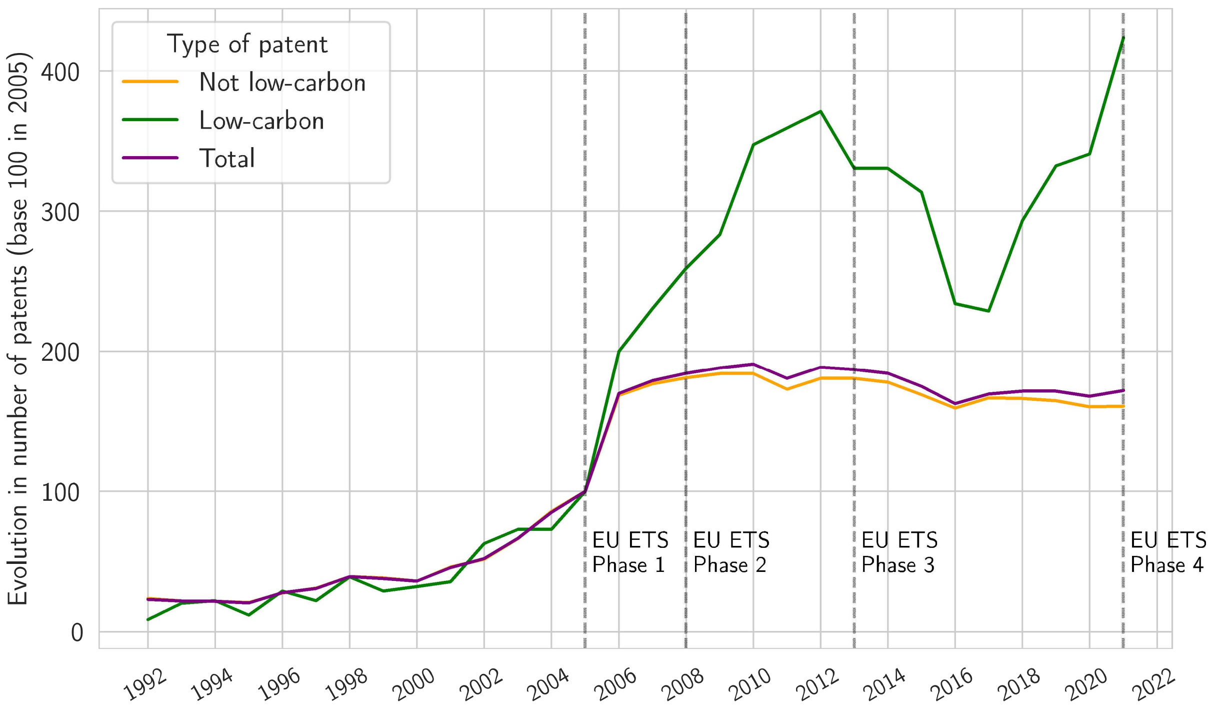
Table 1: Mean firm-level values by sector

Sector	N firms	Capital (M€)	Labor (M€)	Material inputs (M€)	Output (M€)	Emissions ($ktCO_2$)
Baked clay products	70	17.32	7.05	13.69	33.02	36.02
		[26.6]	[14.54]	[26.64]	[59.73]	[56.64]
Basic chemicals	34	173.1	45.46	467.17	638.58	343.87
		[179.55]	[74.98]	[772.15]	[920.29]	[426.65]
Cement	43	109.85	24.36	66.0	159.04	1202.57
		[98.6]	[26.58]	[78.3]	[134.12]	[901.93]
Ceramic tiles	96	27.66	10.27	22.57	55.29	34.17
		[39.47]	[12.18]	[37.37]	[66.38]	[41.34]
Chemical products	59	157.07	85.39	460.3	723.96	194.03
		[469.57]	[441.79]	[1754.72]	[2856.32]	[566.65]
Hollow glass	45	50.47	22.04	62.84	123.97	91.74
		[46.77]	[29.69]	[105.91]	[151.95]	[119.56]
Iron & steel - EAF	22	114.16	31.27	317.7	436.7	105.61
		[147.2]	[27.85]	[264.32]	[341.31]	[83.05]
Iron & steel - Unknown	32	63.77	23.07	148.49	210.51	74.11
		[58.57]	[24.81]	[117.36]	[166.72]	[77.7]
Lime & plaster	59	26.1	6.27	18.88	43.53	227.26
		[40.71]	[9.44]	[23.05]	[52.48]	[322.99]
Metal processing	45	75.23	33.68	176.02	255.0	48.79
		[80.9]	[52.98]	[216.37]	[296.44]	[67.33]
Other glass	42	71.14	19.87	63.15	126.56	98.0
		[69.48]	[20.22]	[68.37]	[119.06]	[108.52]
Other metals	29	108.39	34.04	653.1	761.11	73.0
		[125.14]	[43.85]	[1325.3]	[1393.81]	[97.21]
Other non-metallic minerals	48	43.31	14.46	48.71	97.46	101.88
		[56.86]	[18.66]	[64.75]	[117.78]	[216.48]
Paper & paperboard	160	68.66	18.4	89.02	160.94	47.83
		[187.06]	[39.08]	[194.17]	[345.87]	[93.75]
Paper & paperboard products	42	51.1	18.25	79.37	136.92	62.86
		[111.97]	[26.01]	[144.42]	[229.37]	[130.49]
Pulp	21	167.69	18.68	140.2	243.5	35.84
		[263.4]	[21.83]	[225.14]	[357.27]	[44.3]
Sanitary goods	26	53.79	25.86	126.36	200.39	30.26
		[49.44]	[34.39]	[171.52]	[225.07]	[31.93]

Note: Standard deviation in square brackets.
Source: Authors based on EUTL and ORBIS.

The data presented above has been matched to patent data from PATSTAT to explore the relationship between patenting, green patenting and technical progress. As discussed in Section 2, the existing literature finds that the EU ETS induced green patenting in regulated firms (Calel, 2020; Calel & Dechezleprêtre, 2014). As a purely descriptive check, we examine whether firms in our sample exhibit a similar trend. Figure 5 shows the evolution of patent families filed by these firms as an index with a base of 100 in 2005. It confirms that, following the introduction of the EU ETS, firms in our sample increased the number of low-carbon patent families they filed more than other types of patent families. This trend remained strong during the second and third phases of the EU ETS, with the exception of a noticeable dip in 2016–2017, followed by a sharp increase. This is only an indication of the evolution of patenting trends, not of the number of patent families that have been filed in each category. Many more non-low-carbon patent families have been filed, as illustrated by the fact that the total trend follows the non-low-carbon trend very closely.

Figure 5: Patenting trends in the sample



Source: Authors based on PATSTAT

5 Empirical approach

5.1 Choice of an approach for the Technological Frontier Analysis

Since the inception of TFA, many empirical methods have been developed to bring the theory to the data. In this subsection, we review the main TFA methods in economic literature and highlight their strengths and weaknesses. Finally, we argue for the choice of using a Minimization Program (MP) approach in this paper. Figure 6 describes the nomenclature of methodologies that have been applied for TFA and summarizes their main advantages and drawbacks.

Flexibility. These methodologies can first be classified as either parametric or non-parametric. This characterizes whether they make assumptions about the data process underlying the observed data. Non-parametric approaches are more flexible than their parametric counterparts because they do not impose assumptions on the functional form of the production function or on the distribution of the unknown parameters (Assaf & Josiassen, 2016). This can be an advantage when little is known about the true distribution of the data. Some parametric approaches can relax the restrictiveness of their distribution assumption, namely the Generalized Method of Moments (GMM) and Bayesian Inference (BI). GMM are relatively flexible because they only require moment conditions rather than assumptions about full probability distributions (Atkinson & Tsionas, 2018). BI can relax distribution assumptions by starting with noninformative priors (Fernández et al., 2000).

Outliers. While non-parametric methods offer flexibility, this advantage comes with heightened sensitivity to outliers. Due to this flexibility, a single highly efficient firm can disproportionately influence the frontier's shape. In contrast, parametric methods mitigate the impact of outliers by leveraging distributional assumptions, which aid in identifying and accounting for these outliers.

Statistical inference. Non-parametric methods do not rely on statistical inference and therefore do not allow for hypothesis testing or sensitivity analyses. Parametric methods are the opposite.

Multi-output setting. Non-parametric approaches are more easily applied to multi-output settings than parametric models (Assaf & Josiassen, 2016). This is because they are applied through mathematical programs that can easily be generalized to include multiple outputs. Additionally, these methods are very close to the theoretical underpinning of TFA. Some parametric methods are also adapted to multi-output settings, namely a Minimization Program (MP), GMM, and BI. On the other hand the use of Maximum Likelihood Estimation (MLE) is ill-suited for multiple outputs because it is an econometric method that can only have a single dependent variable (output). Researchers have proposed two options to work around this, as detailed below. However, neither of these options are consistent with the theoretical and empirical setting in the present paper, meaning MLE is excluded.

- Outputs are aggregated into a single variable, either with a ratio or a sum. For example, Robaina-Alves et al. (2015) use a ratio of a good output over a bad output as their dependent variable. The issue with this approach is that it fully departs from the theoretical framework of TFA and no longer allows for efficiency to be defined according to a frontier.

- A system of equations is estimated, with one equation for each output type. The efficiency term can be linked between these different equations via a copula function (Skevas, 2025). This model makes the explicit assumption that the different outputs are produced by distinct sub-technologies. While this can make sense for models whose outputs are different products (e.g.: one production technology to produce hats and another to produce shoes, or multi-crop farms in agriculture), this assumption does not reflect the setting in this paper. The bad outputs of industrial production are intrinsically linked to the production technology of the good outputs (e.g.: emissions from cement production are produced by the cement kiln).

Error term. Non-parametric and parametric deterministic methods do not include an error term and therefore attribute all noise in the data to firm-level inefficiency. This can be problematic for two reasons:

1. There are random effects that affect firms' production that are unrelated to their efficiency (e.g.: changing weather patterns and extreme events, changes in local policies, etc... (Atkinson & Tsionas, 2018)).
2. There are likely reporting errors and biases in the data we use (e.g.: Liu (2020) reports on issues with data consistency, survival and selection biases and misclassifications in ORBIS; the European Securities and Markets Authority (2022) identified consistency errors in the EUTL due to the absence of common entity identifiers).

Data availability. Most of the methodologies presented here can be applied via a distance function derived from a production function. This means they only need data on production volumes or values, as well as input and emission volumes or values. There is one exception however, namely GMM. GMM requires input and output price data as it relies on the estimation of a cost function with prices as instrumental variables (Atkinson & Tsionas, 2018). This data is very difficult to find given its commercial sensitivity, which forces us to exclude GMM.

Computational needs. DEA, Free Disposal Hull (FDH, which is a specific form of DEA with no assumption on the convexity of the distance function), MLE and GMM all have ready-to-use, optimized packages in statistical programming languages. These allow for computation of the distance function with fairly low computational needs. While MP is not available in the form of a ready-to-use package, it can be programmed in a mathematical computation program and requires low computational needs. The only exception is BI, which has extremely high computational needs given its reliance on high-iteration Monte Carlo simulations.

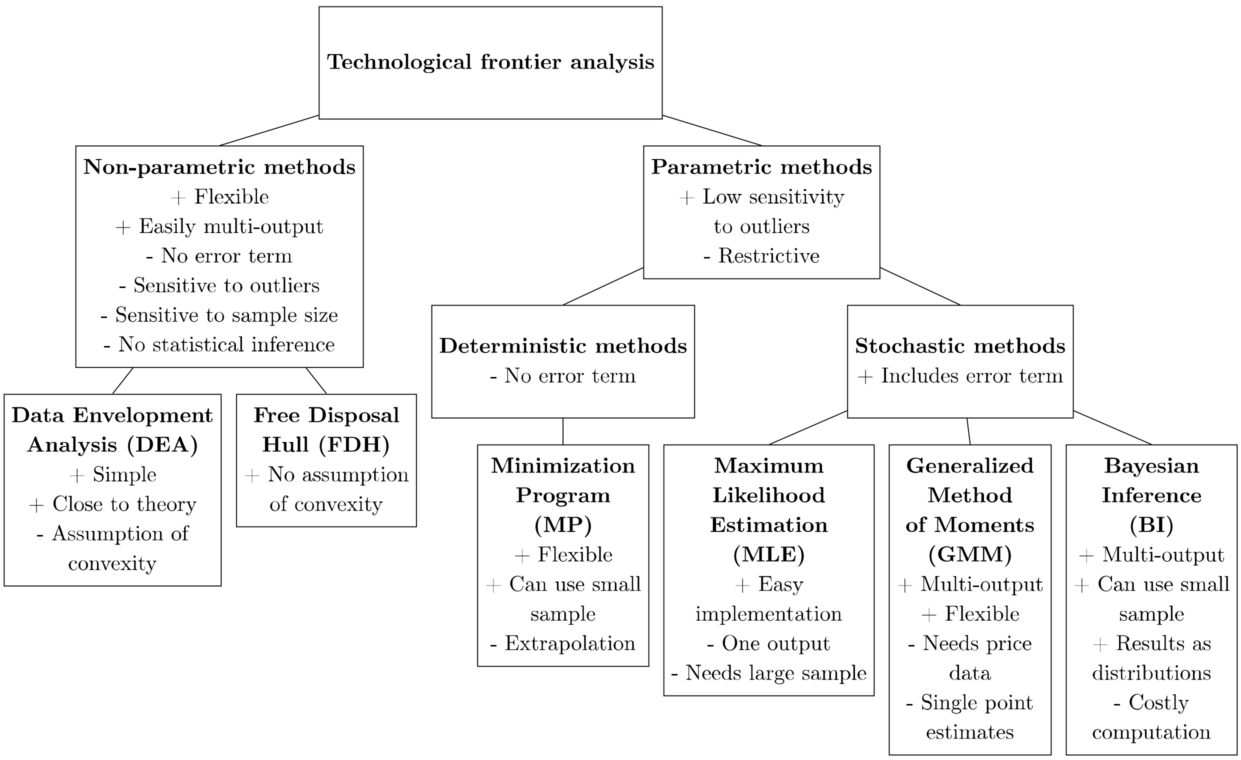
Final choice. Based on the above evaluation of available methodologies, this paper uses MP to perform TFA. This methodology fits well with the theoretical framework of one bad output and one good output and does not require many observations by sector, which corresponds well to our data. It is more flexible than a DEA and allows for a smoother representation of the frontier rather than a piece-by-piece linear approximation. It thus offers a mid-point between DEA and econometric approaches. To minimize the risk of outliers skewing our results, we ensure the quality of our data through the steps detailed in Section 4.2.1.

While it would be preferable to use a stochastic method to account for noise in the data, each of the possible methods are excluded for the following reasons:

- MLE is ill-suited to the multi-output framework, especially with one good output and one bad output.
- GMM requires data on the price of inputs and outputs, which is not available to us.
- BI has computational needs that go beyond the infrastructure available to us. This is nonetheless the most promising method for future research.

As a result, we opt for the MP methodology, which has the advantage of being highly flexible as it only makes assumptions about the functional form of the directional distance function. Additionally, it can be a first step towards a BI approach which requires values for priors to reduce computation needs.

Figure 6: Approaches to Technological Frontier Analysis



5.2 Step 1: TFA through linear-quadratic minimization programming

We apply a deterministic linear-quadratic minimization program for the TFA. Following Färe et al. (2005) and Baudry and Faure (forthcoming), we apply the following linear-quadratic program $\mathcal{P}$ to calibrate sector- and year-specific technological frontiers

$$\begin{aligned}
&\min \left[\sum_{i=1}^{N} \overrightarrow{D_{it}}(X_{it}, Y_{itg}, Y_{itb}; v) \right] \text{ such that} \\
&\text{(a) } \overrightarrow{D_{it}}(X_{it}, Y_{itg}, Y_{itb}; v) \geq 0 \,\forall\, i \\
&\text{(b) } \frac{\partial \overrightarrow{D_{it}}}{\partial Y_{itg}} \leq 0 \,\forall\, i \\
&\text{(c) } \frac{\partial \overrightarrow{D_{it}}}{\partial Y_{itb}} \geq 0 \,\forall\, i \\
&\text{(d) } \frac{\partial \overrightarrow{D_{it}}}{\partial X_{itq}} \geq 0 \,\forall\, q \text{ and } \forall\, i \\
&\text{(e) } \overrightarrow{D_{it}}(X_{it}, 0, 0; v) < 0 \,\forall\, i
\end{aligned}$$

where $\overrightarrow{D_{it}}(X_{it}, Y_{itg} Y_{itb}; v)$ is specified as a quadratic function to fulfill the constraints of the production technology model described in Section 3:

$$\begin{aligned}
\overrightarrow{D_{it}}(X_{it}, Y_{itg}, Y_{itb}; v_g, -v_b) = &\beta_{0t} + \sum_{q=1}^{3} \beta_{tq} X_{itq} + \sum_{o=1}^{2} \beta_{tp} Y_{ito} + \sum_{q=1}^{3} \sum_{q'=1}^{3} \beta_{tqq'} X_{itq} X_{itq'} \\
&+ \sum_{o=1}^{2} \sum_{o'=1}^{2} \beta_{to'} Y_{ito} Y_{ito'} + \sum_{q=1}^{3} \sum_{o=1}^{2} \beta_{tqp} X_{itq} Y_{ito}
\end{aligned} \tag{7}$$

The direction parameters v do not appear explicitly in Equation 7 because they are integrated in the constraints imposed on the β parameters.

Implicitly, $\hat{D}_{it}(X_{it}, Y_{itb}, Y_{itg}; v) = 0$ defines the technological frontier, since it defines a situation where a firm has no inefficiency. The program's constraints ensure the technological frontier takes on the appropriate shape, namely:

- (a) implies that firms are either on or below the technological frontier;
- (b) implies that a marginal increase in the good output increases a firm's efficiency;
- (c) implies that a marginal increase in the bad output decreases a firm's efficiency;
- (d) implies that a marginal increase in input use decreases a firm's efficiency;
- (e) implies that any use of inputs must be associated with some production;

- all the constraints allow for $Y_{itb} > 0$ even with a null production $Y_{itg} = 0$, which means $\mathcal{P}$ respects the assumption of weak disposability of good and bad outputs jointly, defined in Equation 4.

5.3 Step 2: Exploring technological progress

The purpose of our empirical analysis is to assess the effect of low-carbon patenting—measured here through patent families belonging to the CPC class Y02—on firms' technological progress—as defined through our frontier approach. We therefore estimate the following equation:

$$\begin{aligned}\text{TechProg}_{i,t} = \gamma_1 \log \text{GreenInv}_{i,t-1} + \gamma_2 \log \text{Inv}_{i,t-1} \\ + \sum_k \delta_k x^k_{i,t} + \mu_i + \mu_{ct} + \epsilon\end{aligned} \tag{8}$$

where:

- $\text{TechProg}_{i,t}$ is the dependent variable representing technical progress. It is either the continuous variable representing a firm's distance to the previous year's technological frontier (which takes a negative value when the firm is beyond the frontier, i.e., it contributed to technological change, and a positive value if it is below the frontier, i.e., it did not contribute to technological change) or the binary variable indicating if a firm displaced the previous year's technological frontier or not;
- $\text{GreenInv}_{i,t-1}$ and $\text{Inv}_{i,t-1}$ are respectively the count of low-carbon or "green" patent families (measured either as a flow or a stock) and the count of non-low-carbon or "brown" patent families (measured either as a flow or a stock) of firm i in time $t-1$;
- x^k_{it} is the set of firm-level control variables;
- μ_i are firm fixed effects;
- μ_{ct} are country-year fixed effects;
- ϵ is the error term.

We run two different specifications of this equation. The first is an OLS regression in which the dependent variable is firm's distance to the previous year's technological frontier. In this specification, we use the stock patent family count variables because distance is a continuous variable and it is likely that a firm's accumulation of knowledge rather than its knowledge at a specific time explains its relative efficiency within its sector. The second specification is a logit regression in which the dependent variable is the binary variable indicating whether a firm has displaced the frontier in a specific year. In this specification, we instead use the flow patent family count variables because the dependent variable is meant to capture a "jump" in a firm's knowledge and therefore is more likely explained by its patenting behavior in the year preceding the jump.

To mitigate potential reverse causality whereby proximity to the frontier may itself affect invention decisions (firms that are more efficient are those that are more likely to innovate), we lag both invention variables by one period. This lag also reflects the delay in the realization of productivity benefits from inventions.

In our baseline specification, we include a set of control variables designed to isolate the impact of low-carbon patented inventions and non-low-carbon patented inventions on firms' distances to the previous year's technological frontier. These controls account for observable heterogeneity which may affect a firm's invention patterns and its relative technological position, thereby mitigating omitted variable bias.

First, we include two dummy variables indicating organizational changes, namely, whether a firm has opened or closed an installation during the period under consideration. It takes the value of 1 the year that an installation is opened or closed and 0 otherwise. These indicators allow us to account for major internal restructuring events that may affect a firm's technological performance independently of its patenting activity. The opening of a new facility may reflect strategic expansion or investment in new capabilities, while a closure may signal downsizing or internal reallocation of resources, both of which can alter a firm's innovation dynamics and hence distance to the technological frontier (Cameron & Garrone, 2024).

We also account for firm-level environmental stringency, as measured by the proportion of its GHG emissions for which the firm must purchase allowances. This variable captures the extent of the regulatory pressure firms face under the emissions trading scheme (Borghesi et al., 2015) since heavy industry firms still received free allowances throughout all of Phase 3 of the EU ETS. Reverse causality may arise when examining the relationship between environmental regulatory stringency and firm-level efficiency (Rubashkina et al., 2015). Specifically, improvements in productivity or technological innovation may lead to reductions in emissions or lower abatement costs, thereby influencing the very measure intended to capture regulatory stringency. To address this concern, we lag the measure of environmental regulation to ensure that the policy variable is temporally prior to observed outcomes (Franco & Marin, 2017).

Another factor of endogeneity that could bias our results is measurement error. In our case, the dependent variable may be subject to this bias. If the measurement error is neither correlated with the error term nor the regressors, our estimates will remain unbiased, but the standard deviations will increase. This bias works against finding a significant effect.

To capture the possible correlation in errors arising from the fact that distances are computed relative to sector-year technological frontiers, errors are clustered at the sector-year level. If a frontier is biased for a specific sector-year, all the distances that are computed relative to it will inherit the same bias. This level of clustering thus allows us to avoid overemphasizing the importance of these types of errors.

A key concern in our framework arises from the dynamic nature of both innovation and technological distance, each of which reflects accumulated activity. The stock of low-carbon patented inventions and the firm's proximity to the technological frontier are inherently time dependent variables and potentially subject to hysteresis, shaped by intertemporal investment and learning dynamics. Consequently , current measures of technological distance may reflect prior innovation that is itself a function of past regulatory environments and firm specific factors. This time dependence introduces a risk of reverse causality. In our empirical strategy we account for this endogeneity threat by including firm fixed effects to control for time-invariant unobserved heterogeneity across firms—such as managerial quality, historical R&D capacity, or long-term strategic orientation. Furthermore, we use a short panel (up to seven year for firm) which helps isolate within-firm variation over time of our main regressors without worrying about confounding factors. We also test whether some specific firm-level controls (firm size and a firm's initial stock of patent families) can explain firms' distance to the frontier in a specification that excludes firm fixed effects. Lastly, we include country-year fixed effects in our preferred specification to control for policy shifts at the country level, including macroeconomic trends or regulatory stringency variations, which might simultaneously affect innovation incentives and the evolution of the technological frontier.

6 Results

6.1 Trends in firm-level distance to the frontier

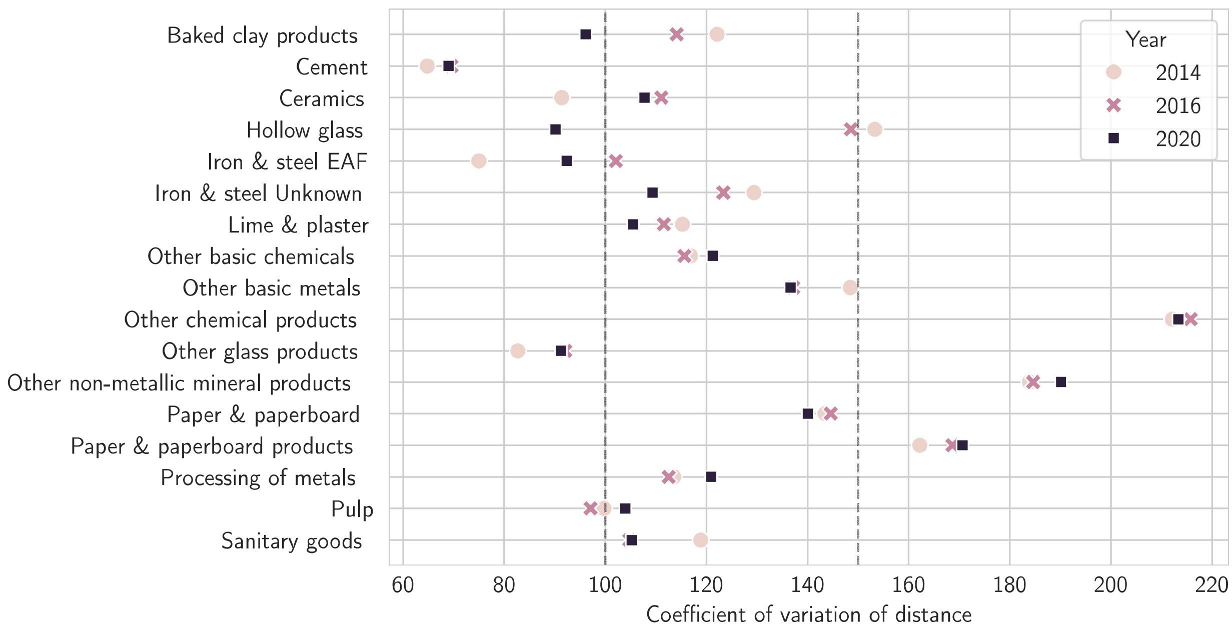
An interesting result from our analysis lies in the within-sector dispersion of firms' distances to the technological frontier. While the level values of distances are not comparable across sectors due to the within-sector calibration of the frontier, dispersion metrics (e.g., coefficient of variation) can reveal meaningful intra- and inter-sector dynamics. High dispersion signals significant heterogeneity in firm efficiency, whereas low dispersion reflects homogeneity—i.e., firms are clustered tightly around the sectoral mean efficiency. These patterns are not static; they evolve over time, offering insights into convergence or divergence of efficiency at the sector level (Figure 7).

The sectors in our analysis can be split into three groups based on the dispersion of their efficiency values. The first group comprises sectors with low levels of dispersion (coefficient of variation (CV) below 100%, meaning that the standard deviation is smaller than the mean). This group includes Cement and Other glass products for all years of the analysis, as well as Baked clay products, Hollow glass, and EAF Iron and steel in the most recent year of data (2020). The second group holds the most sectors. It is composed of sectors with middling dispersions, displaying a CV between 100 and 150%. This includes Iron and steel from an unknown technology, Lime and plaster, Other basic chemicals, Other basic metals, Paper and paperboard, Processing of metals, and Sanitary goods.

Pulp and Ceramics are also in this category in 2020. Finally, the last group is composed of sectors that have high levels of dispersion (CV above 150%, meaning the standard deviation is more than 1.5 times the mean). In this category, Other chemical products has the highest CV, followed by Other non-metallic mineral products, then Paper and paperboard products.

The evolution of dispersion also varies across sectors. The Hollow glass sector stands out as having the largest absolute change in dispersion between 2014 and 2020 (-63 percentage points), indicating a shrinking heterogeneity among firms. Baked clay products and Iron and steel from an unknown technology also became more homogeneous over this period (-26 and - 20 percentage points, respectively). On the other hand, Ceramics and EAF Iron and steel display a widening heterogeneity, increasing their CV by 16 and 17 percentage points, respectively. Some sectors' dispersion remained relatively stable over the entire period, with a difference in CV of less than 5 percentage points in absolute terms. This includes Other basic chemicals, Pulp, Cement, Other chemical products, and Paper and paperboard.

Figure 7: Coefficient of variation of distance to frontier

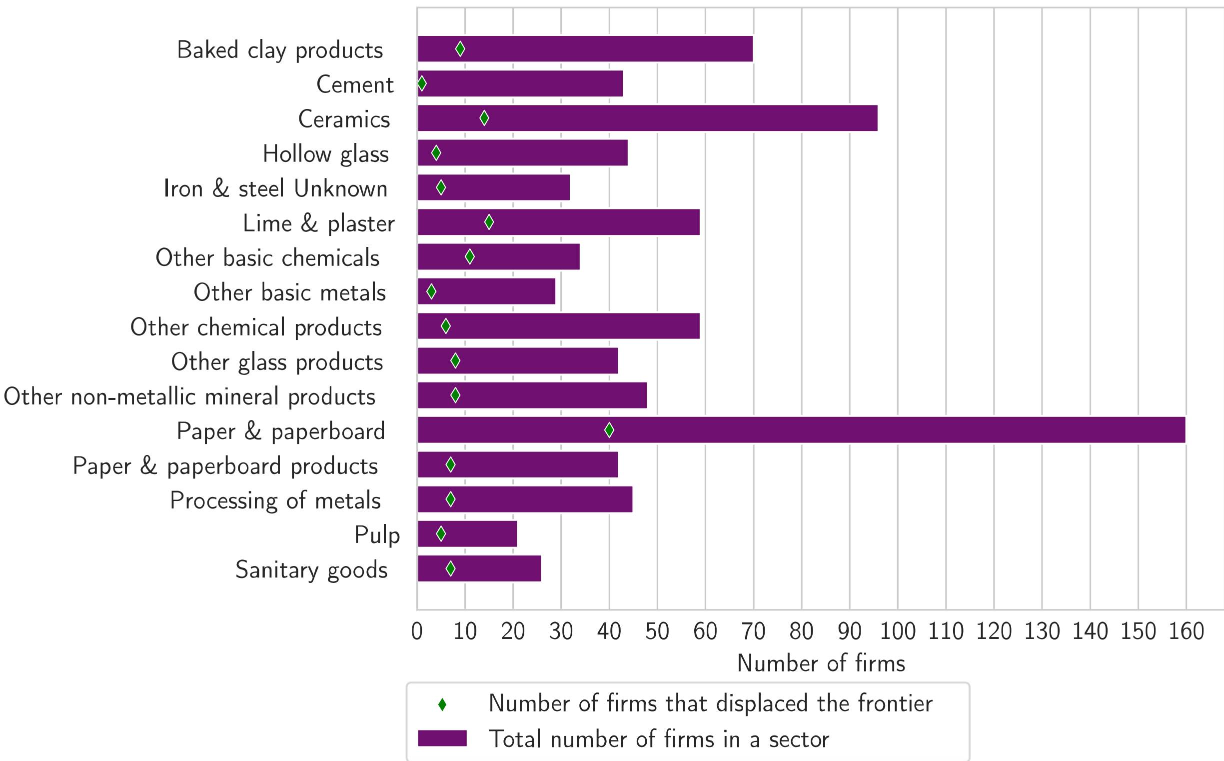


Source: Authors.
Note: The coefficient of variation is computed as the ratio of a sector's standard deviation and its mean, multiplied by 100.

Another key finding that is relevant to the second part of our empirical analysis concerns the trends in frontier displacement. Which firms are driving these shifts? Are the same firms consistently responsible for shifts in the frontier?

In all sectors except Pulp and paperboard, 15 or fewer firms displace the frontier at least once in our sample.[13] Some sectors exhibit particularly low numbers: Cement has only 1 firm (2% of the total), Other basic metals has 3 (10%), Hollow glass has 4 (9%), while Iron & steel (unknown technology) and Pulp have 5 each (15% and 24%, respectively). These results suggest that technological progress is concentrated in a small subset of firms within each sector (Figure 8).

Figure 8: Number of firms that displace the frontier

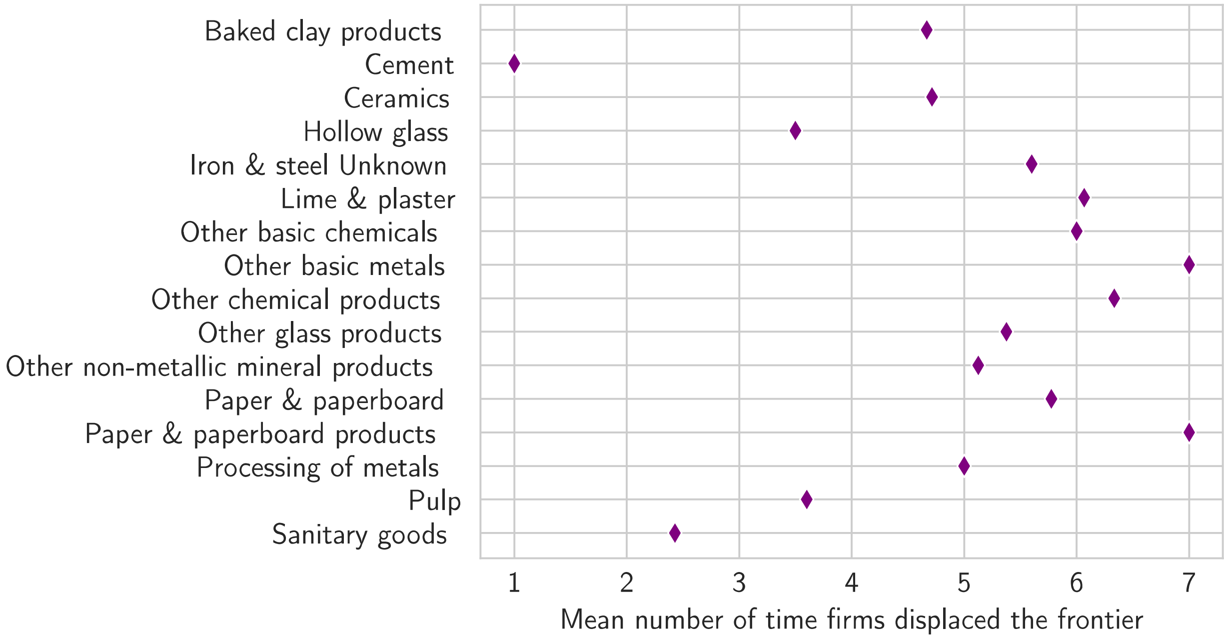


Source: Authors.

There are also differences regarding the frequency with which firms displace the frontier in each sector—i.e., whether the same firms consistently displace the frontier every year or if the firms displacing the frontier change over time. In some sectors, frontier displacement is rare and sporadic. The Cement firm that displaced the frontier did so only once in our sample. Firms in the Sanitary goods sector displaced the frontier 2–3 times on average, and Pulp and Hollow glass firms did so 3–4 times on average. In contrast, sectors like Paper and paperboard products and Other basic metals exhibit consistent displacement, with the same firms driving progress every year (Figure 8).

[13] Pulp and paperboard is an exception, though this sector also contains significantly more firms than the others.

Figure 9: Average frequency of frontier displacements



Source: Authors.

6.2 Do patents explain technological progress?

We now turn to the second stage of our analysis. Here, we present the results of the estimations that study the effect of patenting on firms' distances to the previous year's frontier, our proxy for technological progress.

Initial specification. Table 2 begins by showing the results from our simplest specification, a flexible version of Equation 8 where we replace country-year fixed effects by year fixed effects and use a within-firm estimator. These results show the impact of both the stock of low-carbon and of non-low-carbon patented inventions on a firm's distance to the previous year's technological frontier. Column 1 shows that the coefficient for the stock of low-carbon patented inventions is positive and significant at the 5% level. This indicates that, on average, an increase in low-carbon patented inventions between 2013 and 2020 increased a firm's distance to the previous year's technological frontier. In other words, it decreased its propensity to displace the technological frontier.

This is robust to the inclusion of the lagged variable for firm-level EU ETS stringency and both variables controlling for firms' internal restructuring (column 3).[14] Among the control variables, only the variable measuring whether a firm closed an installation in a specific year is significant. This coefficient is negative, indicating that firms that close an installation become relatively more

[14]Estimating the model without using a lag on the stringency variable produces the same results.

efficient (i.e., decrease their distance to the technological frontier). This is fairly intuitive as the installations that get closed are likely those that have the worst performance.

In column 5, the stock of brown patented inventions is added to ensure that the estimated effect in columns 1 and 3 is not a global effect of the stock of patented inventions due to correlation between the stock of green and brown inventions, but rather a specific effect of the stock of low-carbon patented inventions. The coefficient for the stock of low-carbon patented inventions remains constant in magnitude and significance. Perhaps surprisingly, the stock of non-low-carbon patented inventions has no significant effect by itself (column 2) or when combined with the other variables (column 4 and 5).

Table 2: Initial OLS specification results

	Dependent variable: Distance_t				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
log $\text{StockGreenInv}_{t\text{-}1}$	0.322**		0.323**		0.334**
	(0.128)		(0.128)		(0.132)
log $\text{StockBrownInv}_{t\text{-}1}$		0.0325		0.0332	-0.0113
		(0.0243)		(0.0243)	(0.0233)
Stringency $_{t\text{-}1}$			0.309	0.694	0.354
			(5.331)	(5.308)	(5.332)
Installation Closed $_t$			-0.121**	-0.121**	-0.121**
			(0.0570)	(0.0573)	(0.0571)
Installation Opened $_t$			-0.0225	-0.0188	-0.0219
			(0.0174)	(0.0175)	(0.0172)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	No	No	No	No	No
Adjusted R^2	0.945	0.944	0.945	0.944	0.945
F-statistic	6.330	1.787	2.949	1.883	2.380
Observations	6104	6104	6104	6104	6104

The dependent variable is a continuous variable representing a firm's distance to the previous year's technological frontier. Heteroskedasticity-robust standard errors are reported in parentheses. Errors are corrected for clustering at the sector-year level. ***, ** and * indicate significance at the one, five and ten percent levels respectively.

Preferred specification. Next, Table 3 presents the results for our preferred specification. The difference with the previous specification is that year fixed effects are dropped and replaced with country-year fixed effects. Combined with the inclusion of firm fixed effects as in the previous specification, this change significantly reduces the potential for bias. With these fixed effects, we control for time-invariant firm heterogeneity and country-specific temporal shocks, such as environmental policy changes or macroeconomic conditions.

A key finding emerging from the analysis is that the effect of low-carbon patented inventions on firms' distance to the previous year's technological frontier is positive and statistically significant. Across all specifications where it is included (columns 1, 3, and 5), the coefficient for this variable remains remarkably stable in magnitude—ranging from 0.337 to 0.340—and is consistently significant at the 1% level. This result is robust to the inclusion of additional controls, suggesting a stable relationship. In this log-level specification, the coefficient can be interpreted as a semi-elasticity. These results thus imply that a 1% increase in the stock of low-carbon patented inventions is associated with a 0.34 unit increase in a firm's distance to the previous year's technological frontier, on average and all else being equal.

Thus, the core result from Table 2 holds in both significance and magnitude, reinforcing the argument that the observed effect is not confounded by macro-level policy shifts. The only notable difference is observed in columns 2 and 4, where the coefficient on the stock of brown patented inventions becomes positive and significant at the 10% level. However, this effect turns negative and is no longer significant when we include all controls and both green and brown patented inventions stocks.

Exploring firm characteristics. We aim to investigate which firm-level characteristics might help explain the between variation in firms' distances to the previous year's frontier. To do this, we replace firm fixed effects with observable firm characteristics. If the coefficients on the patented invention variables remain stable and the included firm characteristics are found to be significant, this would suggest that the firm fixed effects were primarily capturing those characteristics. Conversely, if the results change, it would imply that the fixed effects are accounting for other, unobserved firm-level traits.

In our analysis, we focus on two specific firm-level characteristics: the initial stock of green and brown patented inventions at the beginning of our study period— measured on the basis of patent applications that were filed during the decade before our start date (2013). The initial stock variables are designed to capture a firm's innovative capacity prior to 2013, to test the hypothesis that inherently inventive firms are more likely to continue driving technological change. However, only the initial stock of green patented inventions is significant, and only in two model specifications without control variables, suggesting limited robustness.

When we include the second firm-level characteristic we are interested in, firm size—as measured by total sales—its coefficient emerges as positive and statistically significant at the 1% level. This

Table 3: Preferred OLS specification results

	Dependent variable: Distance_t				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
log $\text{StockGreenInv}_{t\text{-}1}$	0.337***		0.338***		0.340***
	(0.122)		(0.122)		(0.127)
log $\text{StockBownInv}_{t\text{-}1}$		0.0406*		0.0415*	-0.00222
		(0.0225)		(0.0226)	(0.0229)
Stringency $_{t\text{-}1}$			1.626	1.975	1.636
			(5.302)	(5.277)	(5.316)
Installation Closed $_t$			-0.119*	-0.119*	-0.118*
			(0.0604)	(0.0614)	(0.0605)
Installation Opened $_t$			-0.0272	-0.0237	-0.0271
			(0.0179)	(0.0177)	(0.0177)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.945	0.945	0.945	0.945	0.945
F-statistic	7.661	3.253	2.863	1.963	2.310
Observations	6104	6104	6104	6104	6104

The dependent variable is a continuous variable representing a firm's distance to the previous year's technological frontier. Heteroskedasticity-robust standard errors are reported in parentheses. Errors are corrected for clustering at the sector-year level. ***, ** and * indicate significance at the one, five and ten percent levels respectively.

suggests that, all else equal, larger firms tend to be further from the previous year's frontier, implying they contribute less to technological progress. This result aligns with the idea that smaller firms may be more agile and better positioned to adopt and implement new technologies. Overall, our findings indicate that the firm fixed effects from earlier regressions likely capture more than just size and pre-existing inventiveness, as the flow patented invention variables lose significance once these firm characteristics are explicitly included.

Table 4: Removing firm fixed effects

	Dependent variable: Distance$_t$			
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
log InitialStockGreenInv$_{t0}$	0.0843	0.0487	0.0841	0.0487
	(0.0731)	(0.0709)	(0.0732)	(0.0709)
log InitialStockBrownInv$_{t0}$	0.0738**	-0.00124	0.0738**	-0.00124
	(0.0315)	(0.0308)	(0.0315)	(0.0308)
log GreenInv$_{t-1}$	-0.281	-0.214	-0.280	-0.214
	(0.204)	(0.200)	(0.204)	(0.200)
log Inv$_{t-1}$	0.0838	0.0698	0.0838	0.0698
	(0.0823)	(0.0809)	(0.0823)	(0.0809)
Stringency $_{t-1}$		-1.395		-1.397
		(9.726)		(9.738)
Installation Closed $_t$		-0.144		-0.148
		(0.282)		(0.283)
Installation Opened $_t$		-0.259		-0.263
		(0.251)		(0.251)
log Size$_t$		0.141***		0.141***
		(0.00749)		(0.00749)
Firm FE	No	No	No	No
Year FE	No	No	Yes	Yes
Country-Year FE	No	No	No	No
Adjusted R^2	0.0195	0.0823	0.0187	0.0815
F-statistic	9.756	49.03	4.396	30.21
Observations	5232	5232	5232	5232

The dependent variable is a continuous variable representing a firm's distance to the previous year's technological frontier. Heteroskedasticity-robust standards errors are reported in parentheses.***, ** and * indicate significance at the one, five and ten percent levels respectively.

Logit specification. Here, we investigate an alternative specification in which, rather than examining a firm's distance to the previous year's technological frontier, we assess the probability that a firm displaces this frontier—i.e., that at time t, it is beyond the frontier constructed for $t-1$. Our dependent variable is a binary variable that takes the value of 1 if the firm is beyond the $t-1$ frontier and 0 otherwise. This prompts a switch to a logit specification. As discussed in the empirical strategy section, flows of patent families are more appropriate for capturing discrete shifts—or "jumps"—in a firm's technological position. Table 5 presents the results of the logit regression. The sample size decreases substantially because the estimation can only be conducted for firms that have displaced the frontier at least once due to the inclusion of firm fixed effects.

Focusing on the results reported in column (5) of Table 5, which include the full set of controls, shows that the coefficient associated with the logarithm of the flow of low-carbon patent families is estimated at -1.6 and is statistically significant at the 10% confidence level. This result implies that an increase in low-carbon patenting activity is associated with a drop in the likelihood that a firm displaces the technological frontier. In contrast, the coefficients on the remaining covariates are not statistically significant, indicating that they do not contribute meaningfully to explaining variation in frontier displacement. This result aligns with our earlier findings.

To ensure the robustness of the results presented in Table 3, three additional tests are conducted. Their results are provided in Appendix 11.

Robustness – CPC weighting. As presented in the data section, the patented inventions stock variables are constructed by weighting patent families belonging to both the low-carbon and non-low-carbon patent categories. Consequently, patent families belonging to a single category are implicitly given twice the weight of their bi-category peers. To assess whether this weighting scheme introduces bias into our estimates, we re-estimate the baseline specification using unweighted patent family stock measures, treating all patent families equally regardless of category overlaps. The results are reported in Appendix 11, Table 8. All the results presented in Table 3 are robust to this new weighting of patent counts. The only difference is that the magnitude of the coefficient for the low-carbon stock of patented inventions is reduced from around 0.34 to 0.24.

The smaller coefficient for the stock of low-carbon patented inventions in the robustness test may reflect the different informational content of mono- versus dual-category patents. Patents classified exclusively as low-carbon or non-low-carbon are likely to be more thematically focused, potentially yielding a stronger and more targeted impact on firm-level efficiency outcomes. In contrast, dual-category patents may embody more general-purpose inventions, whose benefits are diffused across multiple dimensions and thus less potent in any single domain. Equal weighting might mitigate the bias introduced by over-weighting such dual-purpose inventions, potentially reducing measurement error and enhancing statistical precision.

Robustness – Patent depreciation. The patented inventions stock variables are defined as the cumulative sums of patent families over time. This construction entails two key features that may introduce bias in the estimation. First, the stock variable never decreases since it captures

Table 5: Logit specification results

	Dependent variable: P(Displacement)$_t$				
	(1)	(2)	(3)	(4)	(5)
	Logit	Logit	Logit	Logit	Logit
log GreenInv$_{\text{t-1}}$	-1.868**		-1.845**		-1.603*
	(0.913)		(0.917)		(0.943)
log Inv$_{\text{t-1}}$		-0.551		-0.552	-0.402
		(0.340)		(0.340)	(0.349)
Stringency $_{\text{t-1}}$			43.37	42.26	43.26
			(32.32)	(32.03)	(32.25)
Installation Closed $_{\text{t}}$			2.094	2.301	2.131
			(2.114)	(2.027)	(2.095)
Installation Opened $_{\text{t}}$			-0.501	-0.456	-0.474
			(0.839)	(0.838)	(0.839)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	No	No	No	No	No
Pseudo R^2	0.0277	0.0251	0.0319	0.0295	0.0338
Log likelihood	-353.6	-354.6	-352.1	-352.9	-351.4
Observations	917	917	917	917	917

The dependent variable is a continuous variable representing a firm's distance to the previous year's technological frontier. Heteroskedasticity-robust standards errors are reported in parentheses. Errors are corrected for clustering at the sector-year level.***, ** and * indicate significance at the one, five and ten percent levels respectively.

only positive increments in patent counts. Second, all patents are weighted equally, irrespective of their filing year. As a result, older patents—for instance, those filed in 2014—contribute equally to the stock in 2020 as more recent ones, filed in 2018, despite possible differences in their current relevance or technological value. These features highlight a limitation of the stock measure: it does not account for knowledge depreciation or the dynamic nature of the technological frontier, wherein past innovation does not necessarily translate into sustained technological leadership (de Rassenfosse & Jaffe, 2018). Following (Huang & Diewert, 2011) we construct stock variables as weighted depreciated sums of past flows, applying an exponential decay to account for temporal distance. Each year's contribution is weighted by $1/(1+\delta)^{\text{age}}$, where $\delta = 0.05$ and age reflects the number of years that have passed since a patent was filed.

Re-estimating the baseline specification using the "depreciated" version of the patent stock variables yields the results displayed in Appendix 11, Table 9. These results do not depart from the preferred specification, either in sign or significance. There is however a slight change in the magnitude of the coefficients—from 0.34 to 0.27—which is similar to the one observed in the previous robustness check with the unweighted version of the stock of patented inventions (Appendix 11, Table 8).

Robustness – Reduced sample. Finally, there is a possibility that our estimation is affected by the fact that many observations in our sample have a value of zero for the main variable of interest—green patented inventions counts. 82% of the firms we observe never filed a patent in the period covered by our data. This might cause some statistical issues due to zero inflation (Czado et al., 2007).

To test for this bias, we run the baseline specification on a subsample of firms that have filed at least one patent between 2013 and 2020. The results for this test are reported in Appendix 11, Table 10. This regression can be understood as studying the intensive effect of the stock of green patented inventions on firms' distance to the previous year's frontier. The magnitude of the coefficient for the stock of green patented inventions increases slightly in magnitude—from 0.34 to 0.37—and decreases in significance—from a 1% to a 5% confidence level.

7 Discussion

The results presented in the previous section can be summarized as two key insights: (1) there is a high level of heterogeneity in the dispersion of efficiency levels between sectors; (2) green patenting is inversely related to technical progress. This section discusses some possible explanations and policy implications for each of these results.

Heterogeneity of dispersion in efficiency. The dispersion of efficiency within a sector can be interpreted as an indicator of its potential for emission reductions. Greater dispersion suggests that the least efficient firms are significantly lagging behind the most efficient ones, implying a higher opportunity for efficiency gains and corresponding emission cuts. Using a back-of-the-envelope calculation of efficiency[15] and potential emission reductions[16], we can evaluate this potential at the sectoral level.

Figure 10 illustrates that there is considerable variation across sectors in both the mean efficiency score and the total potential for emission reductions. The cement sector stands out, with the highest estimated potential for emission reductions—approximately 9 $MtCO_2$—despite exhibiting a relatively high average efficiency of 83%. This is largely due to the sector's inherently high emission intensity. Lime and plaster, along with Chemicals, follow as the sectors with the next

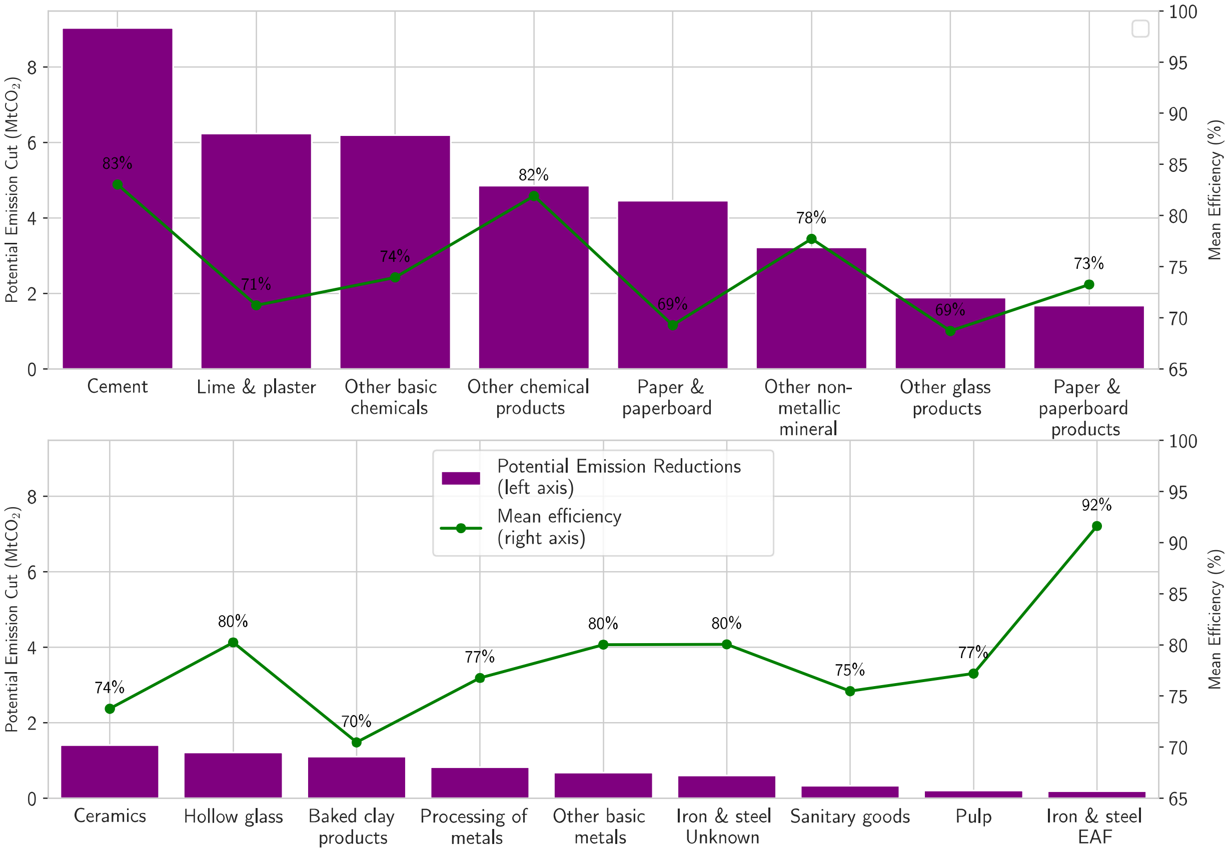
[15] Efficiency is computed as $1/(1 + \text{distance}_{it})$.

[16] Potential emission cuts within a sector are computed as $\sum_{i=1}^{N} \text{emissions}_{it} \cdot (1 - \text{efficiency}_{it})$.

highest reduction potential. In contrast, the EAF Iron and steel sector has the highest mean efficiency at 92%, but also the lowest potential for emission reductions, at just 0.2 $MtCO_2$, reflecting its significantly lower carbon intensity.

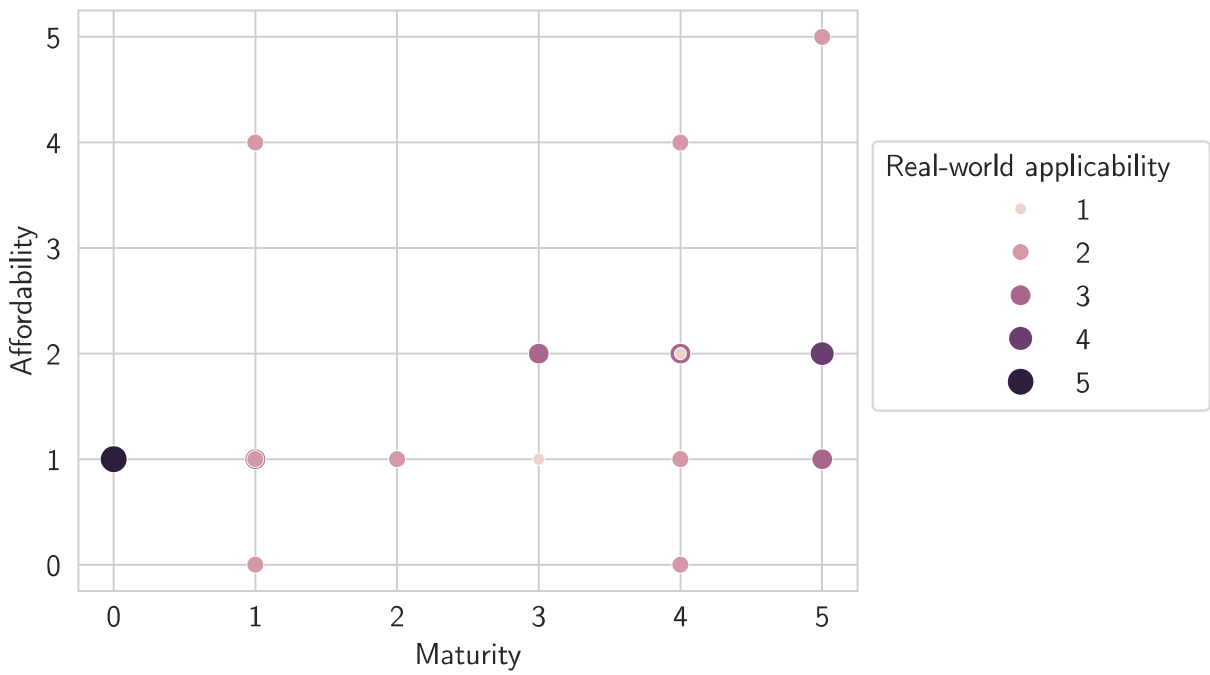
These findings offer valuable insights for policymakers regarding the emission reduction potential achievable through existing technologies. Overall, the analysis suggests that the scope for further reductions through efficiency improvements alone is limited. Even in the case of cement production—the sector with the greatest potential—the estimated reduction accounts for only about 10% of its total emissions. While this is not negligible, it highlights the critical need for technological innovation. To achieve climate targets, policy efforts should focus on transformative solutions that enable deep decarbonization beyond what incremental efficiency gains can deliver.

Figure 10: Mean efficiency and total potential emission reductions by sector (2020)



Green patenting and efficiency. At first glance, the finding that green patenting is associated with reduced firm-level efficiency may seem counterintuitive. However, we offer an explanation grounded in the broader economic and technological context, which—while supported by existing literature—warrants further empirical testing.

Figure 11: Viability of low-carbon heavy industry technologies



Source: Authors based on Diesing et al. (2025)

Our argument builds on the theory of carbon-intensive technology lock-in, as proposed by Acemoglu et al. (2012) and empirically supported by Aghion et al. (2016) and Janipour et al. (2020). Firms relying on brown technologies benefit from decades of accumulated knowledge, infrastructure, and learning-by-doing. In contrast, firms shifting toward green technologies face higher costs, technical uncertainty, and weaker performance relative to the established norm. As a result, green inventive firms may appear less efficient in relative terms, simply because their brown-technology peers are improving at a faster rate within the current paradigm.

This explanation is particularly relevant in the context of heavy industry, where green alternatives remain largely immature. Even where mature technologies exist, they tend to be costlier than conventional options or face practical constraints, limiting their adoption. A recent review by Diesing et al. (2025) finds that none of the available low-carbon technologies across major industrial sectors—Iron and steel, Cement, Chemicals, Glass, and Pulp and paper—score above 3 (on a 1–5 scale) across all three dimensions of maturity, affordability, and applicability (Figure 11). This suggests that, despite investment in green patenting, these technologies are not yet ready for widespread deployment. It also underscores that patents protect inventions which may take a long time before being profitable or even never succeed . Additionally, heavy industrial assets are long-lived, and are typically not retired before the end of their life cycle, which slows the pace at which cleaner technologies can be adopted.

There is also a methodological consideration related to how we define the technological frontier. Our directional distance function treats a 1% increase in output as equivalent to a 1% decrease in emissions. This implies that firms can improve efficiency by reducing emissions, increasing output, or both. In this context, green patenting might lead to better environmental performance while having no effect—or even a negative effect—on production-side efficiency. This interpretation aligns with findings from Xiang and Geng (2024), who also report mixed impacts of green patenting on firm efficiency in Chinese industry and it challenges the strong version of the Porter hypothesis (Porter & van der Linde, 1995).

Several macro-level studies offer similar insights, showing that green inventions alone may not reduce emissions unless accompanied by strong prior economic growth and complementary enabling factors (Du et al., 2019; Sahoo et al., 2022). A similar dynamic may be present in our data.

To test this hypothesis more directly, further studies could adjust the directional vector in the TFA to assign more weight either to emissions or to output. If green patenting shows a negative effect when output is prioritized, but a positive effect when emissions are prioritized, this would lend further support to the idea that green patented inventions boost environmental efficiency but not necessarily productive efficiency.

An alternative explanation is that our study period may simply be too short to capture the effects of green patenting. The transition from invention to commercialization is often slow and incremental, especially in capital-intensive sectors. As such, the benefits of green patenting might not yet be fully observable. A longer time horizon or the use of a model that explicitly captures delayed effects, such as a Nonlinear Autoregressive Distributed Lag model could help uncover these lagged relationships and better account for the cumulative impact of green patented inventions over time.

8 Conclusion

This paper has examined the relationship between firm-level efficiency, green patenting, technological progress, and the potential for emission reductions in the context of heavy industry sectors regulated by the EU ETS. Our findings highlight several key insights with important implications for both research and policy.

First, we observe substantial heterogeneity in the dispersion of efficiency scores across firms within sectors. This variation translates into differing levels of emission reductions that can be achieved solely through improvements in inefficiency. However, the overall picture suggests that incremental efficiency gains alone are insufficient. Most sectors will require more profound shifts in production technologies to achieve the deep decarbonization necessary to meet climate targets.

Second, our analysis shows that technological progress is driven by a small number of firms within each sector. This suggests the presence of a strong leader–laggard dynamic. From a policy perspective, this raises two distinct and potentially complementary strategic options: policymakers can either support the sectoral "champions" that are already innovating and leading in technical change, or they can adopt a broader approach that promotes technological diffusion by supporting a wider base of firms to stimulate more inclusive and competitive innovation.

Finally, our findings indicate that green patenting does not directly imply improvements in firm-level efficiency, even when the measure of efficiency includes both emission and output in its measure. This challenges the interpretation of earlier studies such as Calel and Dechezleprêtre (2014) and Calel (2020), which primarily measure the effect of the EU ETS on green patenting activity. Our results suggest that green patents do not necessarily translate into effective or implemented decarbonization technologies—at least in the short run that is analyzed in this paper. Consequently, policymakers should be cautious in using patent-based indicators to evaluate the success of climate policy. Greater emphasis should instead be placed on direct measures of technological change and real-world emission reductions at the firm level.

Future research can extend and refine the conclusions found in this paper. Other methodologies could be applied to measure firm-level efficiencies, namely Bayesian modeling which this paper has identified as the most promising and flexible methodology available, despite its heavy computational needs. Additionally, to further understand the effect of green patenting on firm-level efficiency outcomes, it could be useful to study innovation in sectors that are either upstream or downstream of the regulated heavy industry sectors. It could be that the green patenting that really matters to reduce emissions comes from these sectors instead of directly from the regulated sector.

Ultimately, achieving deep decarbonization in heavy industries will require a dual focus on accelerating technological breakthroughs among sectoral leaders while ensuring broader diffusion of innovations and process changes across lagging firms. Policymakers must also look beyond patent-based metrics and prioritize direct evidence of emission reductions when evaluating the effectiveness of climate regulations.

References

Abrell, J. (2022). Database for the European Union Transaction Log.

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The Environment and Directed Technical Change. *American Economic Review*, *102*(1), 131–166. Retrieved March 9, 2021, from https://www.aeaweb.org/articles?id=10.1257/aer.102.1.131

Acemoglu, D., & Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings*. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics* (pp. 1043–1171, Vol. 4). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Van Reenen, J. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry [Publisher: The University of Chicago Press]. *Journal of Political Economy*, *124*(1), 1–51. https://doi.org/10.1086/684581

Angelucci, S., Hurtado-Albir, F. J., & Volpe, A. (2018). Supporting global initiatives on climate change: The EPO's "Y02-Y04S" tagging scheme. *World Patent Information*, *54*, S85–S92. https://doi.org/10.1016/j.wpi.2017.04.006

Assaf, A. G., & Josiassen, A. (2016). Frontier Analysis: A State-of-the-Art Review and Meta-Analysis [Publisher: SAGE Publications Inc]. *Journal of Travel Research*, *55*(5), 612–627. https://doi.org/10.1177/0047287515569776

Atkinson, S. E., & Tsionas, M. G. (2018). Shadow directional distance functions with bads: GMM estimation of optimal directions and efficiencies. *Empirical Economics*, *54*(1), 207–230. https://doi.org/10.1007/s00181-017-1233-6

Bataille, C., Åhman, M., Neuhoff, K., Nilsson, L. J., Fischedick, M., Lechtenböhmer, S., Solano-Rodriquez, B., Denis-Ryan, A., Stiebert, S., Waisman, H., Sartor, O., & Rahbar, S. (2018). A review of technology and policy deep decarbonization pathway options for making energy-intensive industry production consistent with the Paris Agreement. *Journal of Cleaner Production*, *187*, 960–973. https://doi.org/10.1016/j.jclepro.2018.03.107

Baudry, M., & Faure, A. (N.d.). Decarbonization of EU-ETS firms: Myth or reality?

Bellocchi, A., Travaglini, G., & Vitali, B. (2023). How capital intensity affects technical progress: An empirical analysis for 17 advanced economies. *Metroeconomica*, *74*(3), 606–631. https://doi.org/10.1111/meca.12421

Bogetoft, P., & Otto, L. (2011). *Benchmarking with DEA, SFA, and R* (Vol. 157). Springer New York. https://doi.org/10.1007/978-1-4419-7961-2

Borghesi, S., Cainelli, G., & Mazzanti, M. (2015). Linking emission trading to environmental innovation: Evidence from the Italian manufacturing industry. *Research Policy*, *44*(3), 669–683. https://doi.org/10.1016/j.respol.2014.10.014

Bostian, M., Färe, R., Grosskopf, S., Lundgren, T., & Weber, W. L. (2018). Time substitution for environmental performance: The case of Swedish manufacturing. *Empirical Economics*, *54*(1), 129–152. https://doi.org/10.1007/s00181-016-1180-7

Calel, R. (2020). Adopt or Innovate: Understanding Technological Responses to Cap-and-Trade. *American Economic Journal: Economic Policy*, *12*(3), 170–201. https://doi.org/10.1257/pol.20180135

Calel, R., & Dechezleprêtre, A. (2014). Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. *The Review of Economics and Statistics*, *98*(1), 173–191. https://doi.org/10.1162/REST_a_00470

Cameron, A. (2025). Mind the Market: A Novel Measure of Carbon Leakage Risk. *Climate Economics Chair*. https://www.chaireeconomieduclimat.org/en/publications-en/20341/

Cameron, A., & Garrone, M. (2024). Carbon Intensity and Corporate Performance: A Micro-Level Study of EU ETS Industrial Firms. *Single Market Economics Conference Papers*, *[Working Paper]*. https://doi.org/10.2873/188206

Cameron, A., & Ho, V. (2024). *Matching the EU Transaction Log and ORBIS: A Natural Language Processing approach. Working paper.* (tech. rep.). European Commission, DG GROW, Chief Economist Team. Brussels.

Chambers, R. G., Chung, Y., & Färe, R. (1998). Profit, Directional Distance Functions, and Nerlovian Efficiency. *Journal of Optimization Theory and Applications*, *98*(2), 351–364. https://doi.org/10.1023/A:1022637501082

Curzi, D., Garrone, M., & Olper, A. (2021). Import Competition and Firm Markups in the Food Industry. *American Journal of Agricultural Economics*, *103*(4), 1433–1453. https://doi.org/10.1111/ajae.12175

Czado, C., Erhardt, V., Min, A., & Wagner, S. (2007). Zero-inflated generalized Poisson models with regression effects on the mean, dispersion and zero-inflation level applied to patent outsourcing rates [Publisher: SAGE Publications India]. *Statistical Modelling*, *7*(2), 125–153. https://doi.org/10.1177/1471082X0700700202

Dakpo, K. H., Jeanneaux, P., & Latruffe, L. (2016). Modelling pollution-generating technologies in performance benchmarking: Recent developments, limits and future prospects in the nonparametric framework. *European Journal of Operational Research*, *250*(2), 347–359. https://doi.org/10.1016/j.ejor.2015.07.024

de Rassenfosse, G., & Jaffe, A. B. (2018). Econometric evidence on the depreciation of innovations. *European Economic Review*, *101*, 625–642. https://doi.org/10.1016/j.euroecorev.2017.11.005

Diesing, P., Lopez, G., Blechinger, P., & Breyer, C. (2025). From knowledge gaps to technological maturity: A comparative review of pathways to deep emission reduction for energy-intensive industries. *Renewable and Sustainable Energy Reviews*, *208*, 115023. https://doi.org/10.1016/j.rser.2024.115023

Du, K., Li, P., & Yan, Z. (2019). Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. *Technological Forecasting and Social Change*, *146*, 297–303. https://doi.org/10.1016/j.techfore.2019.06.010

Dzemydaitė, G., & Naruševičius, L. (2023). Exploring efficiency growth of advanced technology-generating sectors in the European Union: A stochastic frontier analysis [Number: 6]. *Journal of Business Economics and Management*, *24*(6), 976–995. https://doi.org/10.3846/jbem.2023.20688

European Commission. (2023). Commission Delegated Regulation (EU) 2019/856 of 26 February 2019 supplementing Directive 2003/87/EC of the European Parliament and of the Council with regard to the operation of the Innovation Fund. Retrieved March 26, 2025, from http://data.europa.eu/eli/reg_del/2019/856/2023-11-21/eng

European Commission. (2025a). The Clean Industrial Deal: A joint roadmap for competitiveness and decarbonisation.

European Commission. (2025b). A Competitiveness Compass for the EU.

European Parliament and Council. (2003). Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a scheme for greenhouse gas emission allowance trading within the Community and amending Council Directive 96/61/EC (Text with EEA relevance). Retrieved September 15, 2023, from http://data.europa.eu/eli/dir/2003/87/oj/eng

European Parliament and Council. (2024). Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a scheme for greenhouse gas emission allowance trading within the Community and amending Council Directive 96/61/EC (Text with EEA relevance). Retrieved March 26, 2025, from http://data.europa.eu/eli/dir/2003/87/oj/eng

European Securities and Markets Authority. (2022). *Final Report: Emission allowances and associated derivatives* (tech. rep. No. ESMA70-445-38). ESMA. Paris.

Färe, R., Grosskopf, S., Noh, D.-W., & Weber, W. (2005). Characteristics of a polluting technology: Theory and practice. *Journal of Econometrics*, *126*(2), 469–492. https://doi.org/10.1016/j.jeconom.2004.05.010

Fernández, C., Koop, G., & Steel, M. (2000). A Bayesian analysis of multiple-output production frontiers. *Journal of Econometrics*, *98*(1), 47–79. https://doi.org/10.1016/S0304-4076(99)00074-3

Franco, C., & Marin, G. (2017). The Effect of Within-Sector, Upstream and Downstream Environmental Taxes on Innovation and Productivity [Publisher: Springer]. *Environmental & Resource Economics*, *66*(2), 261–291. https://doi.org/10.1007/s10640-015-9948-3

Gal, P. N. (2013). *Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS* (tech. rep.). OECD. Paris. https://doi.org/10.1787/5k46dsb25ls6-en

Global Energy Monitor. (2024). Global Steel Plant Tracker. https://globalenergymonitor.org/projects/global-steel-plant-tracker/

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L., & Villegas-Sanchez, C. (2017). Capital Allocation and Productivity in South Europe. *The Quarterly Journal of Economics*, *132*(4), 1915–1967. https://doi.org/10.1093/qje/qjx024

Hicks, J., R. (1932). *The Theory of Wages* (First edition). Macmillan.

Huang, N., & Diewert, E. (2011). Estimation of R&D depreciation rates: A suggested methodology and preliminary application. *Canadian Journal of Economics/Revue canadienne d'économique*, *44*(2), 387–412. https://doi.org/10.1111/j.1540-5982.2011.01638.x

International Energy Agency. (2024). *World Energy Outlook 2024* (tech. rep.). International Energy Agency. Paris.

IPCC. (2023). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (tech. rep.) ([Core Writing Team, H. Lee and J. Romero (eds.)].). IPCC. Geneva. Retrieved March 16, 2025, from https://www.ipcc.ch/report/ar6/syr/

Janipour, Z., de Nooij, R., Scholten, P., Huijbregts, M. A. J., & de Coninck, H. (2020). What are sources of carbon lock-in in energy-intensive industry? A case study into Dutch chemicals production. *Energy Research & Social Science*, *60*, 101320. https://doi.org/10.1016/j.erss.2019.101320

Kaldor, N. (1957). A Model of Economic Growth. *The Economic Journal*, *67*(268), 591–624. https://doi.org/10.2307/2227704

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., & Yesiltas, S. (2015). *How to Construct Nationally Representative Firm Level Data from the Orbis Global Database: New Facts and Aggregate Implications* (tech. rep.). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w21558

Liu, G. (2020). Data quality problems troubling business and financial researchers: A literature review and synthetic analysis. *Journal of Business & Finance Librarianship*, *25*(3-4), 315–371. https://doi.org/10.1080/08963568.2020.1847555

Löschel, A., Lutz, B. J., & Managi, S. (2019). The impacts of the EU ETS on efficiency and economic performance – An empirical analyses for German manufacturing firms. *Resource and Energy Economics*, *56*, 71–95. https://doi.org/10.1016/j.reseneeco.2018.03.001

Lundgren, T., Marklund, P.-O., Samakovlis, E., & Zhou, W. (2015). Carbon prices and incentives for technological development. *Journal of Environmental Management*, *150*, 393–403. https://doi.org/10.1016/j.jenvman.2014.12.015

Martinez, C. (2010). *Insight into Different Types of Patent Families* (OECD Science, Technology and Industry Working Papers No. 2010/02) (Series: OECD Science, Technology and Industry Working Papers Volume: 2010/02). OECD. Paris. https://doi.org/10.1787/5kml97dr6ptl-en

Morfeldt, J., & Silveira, S. (2014). Capturing energy efficiency in European iron and steel production—comparing specific energy consumption and Malmquist productivity index. *Energy Efficiency*, *7*(6), 955–972. https://doi.org/10.1007/s12053-014-9264-8

OECD. (2024). Towards more accurate, timely, and granular product-level carbon intensity metrics. *OECD Publishing, Inclusive Forum on Carbon Mitigation Approaches Papers*. https://doi.org/https://doi.org/10.1787/4de3422f-en

Oggioni, G., Riccardi, R., & Toninelli, R. (2011). Eco-efficiency of the world cement industry: A data envelopment analysis. *Energy Policy*, *39*(5), 2842–2854. https://doi.org/10.1016/j.enpol.2011.02.057

Porter, M. E., & van der Linde, C. (1995). Toward a New Conception of the Environment - Competitiveness Relationship. *Journal of Economic Perspectives*, *9*(4), 97–118. https://doi.org/10.1257/jep.9.4.97

Rekker, L., Kesina, M., & Mulder, M. (2023). Carbon abatement in the European chemical industry: Assessing the feasibility of abatement technologies by estimating firm-level marginal abatement costs. *Energy Economics*, *126*, 106889. https://doi.org/10.1016/j.eneco.2023.106889

Rigby, D. L., & Essletzbichler, J. (1997). Evolution, Process Variety, and Regional Trajectories of Technological Change in U.S. Manufacturing. *Economic Geography*, *73*(3), 269–284. https://doi.org/10.1111/j.1944-8287.1997.tb00089.x

Robaina-Alves, M., Moutinho, V., & Macedo, P. (2015). A new frontier approach to model the eco-efficiency in European countries. *Journal of Cleaner Production*, *103*, 562–573. https://doi.org/10.1016/j.jclepro.2015.01.038

Rubashkina, Y., Galeotti, M., & Verdolini, E. (2015). Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors. *Energy Policy*, *83*, 288–300. https://doi.org/10.1016/j.enpol.2015.02.014

Sahoo, B., Behera, D. K., & Rahut, D. (2022). Decarbonization: Examining the role of environmental innovation versus renewable energy use. *Environmental Science and Pollution Research*, *29*(32), 48704–48719. https://doi.org/10.1007/s11356-022-18686-1

Shephard, R. W., & Färe, R. (1974). The Law of Diminishing Returns [Publisher: Springer]. *Zeitschrift für Nationalökonomie / Journal of Economics*, *34*(1/2), 69–90. Retrieved February 18, 2025, from https://www.jstor.org/stable/41797657

Shephard, R. W. (1970). *Theory of Cost and Production Functions*. Princeton University Press.

Skevas, I. (2025). Technical and environmental inefficiency measurement in agriculture using a flexible by-production stochastic frontier model. *Journal of Agricultural Economics*, *76*(1), 164–181. https://doi.org/10.1111/1477-9552.12619

Walheer, B. (2024). Meta-frontier: Literature review and toolkit. *Operational Research*, *24*(2), 20. https://doi.org/10.1007/s12351-024-00830-z

Xiang, X., & Geng, Y. (2024). Assessing the impact of green patents on pollution reduction: A micro-level study of Chinese industrial firms. *Journal of Environmental Management*, *368*, 122193. https://doi.org/10.1016/j.jenvman.2024.122193

Zurano-Cervelló, P., Pozo, C., Mateo-Sanz, J. M., Jiménez, L., & Guillén-Gosálbez, G. (2018). Eco-efficiency assessment of EU manufacturing sectors combining input-output tables and data envelopment analysis following production and consumption-based accounting approaches. *Journal of Cleaner Production*, *174*, 1161–1189. https://doi.org/10.1016/j.jclepro.2017.10.178

Appendix

9 Sector-NACE correspondence table

Table 6: Aggregated Manufacturing Descriptions and Associated Codes

Aggregated sector code	N° firms	4-digit NACE code	N° firms
Manufacture of articles of paper and paperboard	42	Manufacture of veneer sheets and wood-based panels	3
		Wholesale of wood, construction materials and sanitary equipment	7
		Manufacture of paper stationery	1
		Manufacture of other articles of paper and paperboard	5
		Manufacture of articles of paper and paperboard	4
		Manufacture of paper and paper products	1
		Manufacture of corrugated paper and paperboard and of containers of paper and paperboard	18
		Manufacture of wallpaper	1
		Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials	1
		Silviculture and other forestry activities	1
Manufacture of basic iron and steel and of ferro-alloys	60	Manufacture of basic iron and steel and of ferro-alloys	60
Manufacture of bricks, tiles and construction products, in baked clay	70	Manufacture of bricks, tiles and construction products, in baked clay	70
Manufacture of cement	43	Manufacture of cement	43
Manufacture of ceramic tiles and flags	96	Manufacture of ceramic tiles and flags	96

Table 6: Aggregated Manufacturing Descriptions and Associated Codes

Aggregated sector code	N° firms	4-digit NACE code	N° firms
Manufacture of hollow glass	45	Manufacture of hollow glass	45
Manufacture of household and sanitary goods	26	Manufacture of household and sanitary goods and of toilet requisites	26
Manufacture of lime and plaster	59	Manufacture of plaster products for construction purposes	7
		Quarrying of ornamental and building stone, limestone, gypsum, chalk and slate	8
		Manufacture of lime and plaster	44
Manufacture of other basic chemicals	34	Manufacture of fertilisers and nitrogen compounds	10
		Manufacture of other inorganic basic chemicals	12
		Manufacture of other organic basic chemicals	12
Manufacture of other basic metals	29	Manufacture of basic precious and other non-ferrous metals	1
		Lead, zinc and tin production	6
		Manufacture of basic metals	1
		Mining of other non-ferrous metal ores	2
		Wholesale of metals and metal ores	1
		Copper production	8
		Aluminium production	10
Manufacture of other chemical products n.e.c.	59	Manufacture of dyes and pigments	2
		Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms	2
		Manufacture of plastics in primary forms	17

Table 6: Aggregated Manufacturing Descriptions and Associated Codes

Aggregated sector code	N° firms	4-digit NACE code	N° firms
		Wholesale of chemical products	3
		Manufacture of chemicals and chemical products	3
		Manufacture of industrial gases	4
		Manufacture of paints, varnishes and similar coatings, printing ink and mastics	14
		Manufacture of basic pharmaceutical products	1
		Manufacture of synthetic rubber in primary forms	1
		Manufacture of other chemical products n.e.c.	10
		Manufacture of glues	2
Manufacture of other glass products	42	Manufacture of glass and glass products	7
		Shaping and processing of flat glass	2
		Manufacture of flat glass	14
		Manufacture and processing of other glass, including technical glassware	6
		Manufacture of glass fibres	13
Manufacture of other non-metallic mineral products n.e.c.	48	Cutting, shaping and finishing of stone	1
		Manufacture of other articles of concrete, plaster and cement	2
		Manufacture of other ceramic products	4
		Manufacture of other non-metallic mineral products n.e.c.	19
		Manufacture of refractory products	10
		Manufacture of concrete products for construction purposes	5

Table 6: Aggregated Manufacturing Descriptions and Associated Codes

Aggregated sector code	N° firms	4-digit NACE code	N° firms
		Manufacture of ceramic sanitary fixtures	7
Manufacture of paper and paperboard	160	Manufacture of paper and paperboard	156
		Manufacture of pulp, paper and paperboard	4
Manufacture of pulp	21	Manufacture of pulp	21
Processing of metals	45	Other non-ferrous metal production	1
		Manufacture of wire products, chain and springs	1
		Forging, pressing, stamping and roll-forming of metal; powder metallurgy	12
		Manufacture of railway locomotives and rolling stock	1
		Casting of iron	7
		Manufacture of other taps and valves	1
		Cold drawing of wire	2
		Manufacture of fabricated metal products, except machinery and equipment	1
		Casting of steel	4
		Treatment and coating of metals	1
		Manufacture of other fabricated metal products n.e.c.	4
		Cold forming or folding	1
		Casting of metals	1
		Casting of light metals	1
		Casting of other non-ferrous metals	2
		Manufacture of tubes, pipes, hollow profiles and related fittings, of steel	2

Table 6: Aggregated Manufacturing Descriptions and Associated Codes

Aggregated sector code	N° firms	4-digit NACE code	N° firms
		Manufacture of metal structures and parts of structures	2
		Manufacture of other products of first processing of steel	1

10 Summary of TFA literature on European heavy industry sectors

Table 7: Literature applying TFA to European heavy industry sectors

Paper	# DMU	Geographical Coverage	Observation Level	Sectoral Coverage	Time Coverage	Method	Main Results
Löschel et al. (2019)	473	Germany	Firm	4 manuf.	2003-2012	SFA	Median distance to production function decreased during early 2000s then increased in median firm efficiency, driven by technological progress.
Baudry and Faure (forthcoming)	249	EU	Firm	9 manuf.	2012-2021	LP	No low-carbon technological change.
Morfeldt and Silveira (2014)	15	EU	Country	Iron and steel	1992-2010	DEA	Improvements in energy efficiency 1992-1995, then slowdown until 2000. Acceleration until 2008, then crash in 2009 and recovery in 2010.
Bostian et al. (2018)	46	Sweden	Firm	Pulp and paper	2002-2008	DEA	Overall productivity decline when considering both emissions and output objectives, due primarily to technological decline.

Note: DMU stands for Decision-Making Unit.

Table 7: Literature applying TFA to European heavy industry sectors

Paper	# DMU	Geographical Coverage	Observation Level	Sectoral Coverage	Time Coverage	Method	Main Results
Lundgren et al. (2015)	90	Sweden	Firm	Pulp and paper	1998-2002	DEA	Modest impact of climate policy on technological change in pulp and paper industry; fossil fuel prices significantly incentivized technological change.
Oggioni et al. (2011)	21	Global	Country	Cement	2005-2008	DEA	European countries under EU-ETS maintained a nearly constant efficiency level.
Dzemydaitė and Naruševičius (2023)	22	EU	Country	Chemicals	2000-2019	SFA	The chemicals sector exhibited a high technical progress, more than five times higher than the overall sample.
Rekker et al. (2023)	24	EU	Firm	Chemicals	2015-2020	Deterministic LP	Chemicals carbon intensity could be reduced by 3.96 to 10.61% if all firms operated efficiently.
Zurano-Cervelló et al. (2018)	14	EU	EU	14 manufacturing sectors	2009	DEA	Pulp and paper production and wood product sectors were found to be entirely efficient compared to other sectors.

Note: DMU stands for Decision-Making Unit.

11 Econometric robustness checks

Table 8: Unweighted CPC class

	Dependent variable: Distance_t				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
log $\text{unweightStockGreenInv}_{\text{t-1}}$	0.240***		0.241***		0.243***
	(0.0777)		(0.0778)		(0.0822)
log $\text{unweightBrownStockInv}_{\text{t-1}}$		0.0434*		0.0443*	-0.00265
		(0.0224)		(0.0224)	(0.0230)
Stringency $_{\text{t-1}}$			0.177	0.195	0.179
			(0.529)	(0.528)	(0.530)
Installation Closed $_{\text{t}}$			-0.119*	-0.120*	-0.119*
			(0.0605)	(0.0614)	(0.0607)
Installation Opened $_{\text{t}}$			-0.0265	-0.0240	-0.0263
			(0.0177)	(0.0177)	(0.0175)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.945	0.945	0.945	0.945	0.945
F-statistic	9.535	3.767	3.275	2.081	2.624
Observations	6104	6104	6104	6104	6104

The dependent variable is a continuous variable representing a firm's distance to the previous year's technological frontier. Heteroskedasticity-robust standards errors are reported in parentheses. Errors are corrected for clustering at the sector-year level.***, ** and * indicate significance at the one, five and ten percent levels respectively.

Table 9: Patent stock variables with depreciation

	Dependent variable: Distance$_t$				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
log DeprecStockGreenInv$_{t\text{-}1}$	0.269***		0.270***		0.270***
	(0.0798)		(0.0798)		(0.0833)
log DeprecBrownStockInv$_{t\text{-}1}$		0.0461**		0.0470**	-0.0000499
		(0.0228)		(0.0229)	(0.0237)
Stringency $_{t\text{-}1}$			0.184	0.196	0.184
			(0.529)	(0.529)	(0.530)
Installation Closed $_t$			-0.118*	-0.119*	-0.118*
			(0.0605)	(0.0613)	(0.0607)
Installation Opened $_t$			-0.0266	-0.0238	-0.0266
			(0.0176)	(0.0177)	(0.0175)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.945	0.945	0.945	0.945	0.945
F-statistic	11.34	4.077	3.675	2.168	2.943
Observations	6104	6104	6104	6104	6104

The dependent variable is a continuous variable representing a firm's distance to the previous year's technological frontier. Heteroskedasticity-robust standards errors are reported in parentheses. Errors are corrected for clustering at the sector-year level.***, ** and * indicate significance at the one, five and ten percent levels respectively.

Table 10: Reduced Sample

	Dependent variable: $Distance_t$				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
log $StockGreenInv_{t-1}$	0.374**		0.367**		0.355**
	(0.145)		(0.145)		(0.145)
log $StockBrownInv_{t-1}$		0.0525*		0.0569*	0.0349
		(0.0312)		(0.0308)	(0.0313)
Stringency $_{t-1}$			4.540**	4.769**	4.576**
			(2.248)	(2.203)	(2.249)
Installation Closed $_t$			-0.182	-0.204	-0.194
			(0.200)	(0.196)	(0.199)
Installation Opened $_t$			-0.109	-0.0916	-0.112
			(0.0896)	(0.0931)	(0.0899)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.931	0.930	0.931	0.930	0.931
F-statistic	6.625	2.833	2.350	2.440	2.142
Observations	1092	1092	1092	1092	1092

The dependent variable is a continuous variable representing a firm's distance to the previous year's technological frontier. Heteroskedasticity-robust standards errors are reported in parentheses. Errors are corrected for clustering at the sector-year level.***, ** and * indicate significance at the one, five and ten percent levels respectively.

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