Mind the Emission Gap: Policy Stringency Matters for Emission Reductions in the EU ETS*

Leonardo Bortolan[1] Lorenzo Prosperi[1,2] Luca Taschini[1,3] Luca Zanin[2]

[1] *University of Edinburgh Business School*
Centre for Business, Climate Change, and Sustainability

[2] *Prometeia*

[3] *London School of Economics*
Grantham Research Institute

Abstract

We document that firm-level emission reductions under the EU ETS program are strongly influenced by climate policy stringency. We define this stringency as the firm-specific expected compliance gap over time, which in turn is defined as the difference between projected allowances and emissions, adjusted by the allowance price and scaled by sales. By capturing both immediate regulatory pressure and firms' expectations about future compliance obligations, our stringency measure emerges as a key determinant of firms' decisions to reduce emissions. Sectoral analyses confirm that policy stringency remains influential across diverse industries, irrespective of financial constraints or technological barriers. We use the sectoral model to assess progress toward the EU's emission goals by 2030. While the phased reduction of free allowances associated with the Carbon Border Adjustment Mechanism (CBAM) drives emissions reductions in covered sectors, it is insufficient to drive the economy-wide reduction required to meet this goal. Meeting the required regulatory pressure across the economy would entail an immediate carbon price of around €125 per tonne.

Keywords: Carbon pricing; Climate policy; Low-carbon transition; Policy-stringency.

JEL Classification: C58, E58, G32, Q51, Q56, Q58

*The authors' email addresses are Leonardo.Bortolan@eniplenitude.com, Lorenzo.Prosperi@prometeia.com, Luca.Taschini@ed.ac.uk, luca.zanin@studio.unibo.it. Bortolan, Prosperi and Taschini are affiliated to the Centre for Business, Climate Change, and Sustainability at the University of Edinburgh Business School.

1 Introduction

In recent decades, cap-and-trade programs like the European Union Emissions Trading System (EU ETS), the Western Climate Initiative in California and Quebec, and the Regional Greenhouse Gas Initiative in the northeastern United States have emerged as a preferred approach to controlling air pollution and reducing greenhouse gas emissions (Pryor et al., 2023; World Bank Group, 2024). Under such policies, companies receive an allocation of free emission permits, which represent their share of the overall emissions cap set by the regulator. Firms can comply with the policy either by reducing emissions through abatement, or by purchasing additional allowances on the market. The difference between a firm's emissions and its allocated permits reflects the degree of regulatory pressure each firm faces. Greater regulatory pressure implies a stronger need for action – either cutting emissions or acquiring permits – making it a central factor in shaping firm-level abatement decisions. However, despite the widespread adoption of market-based climate policies, recent studies often find only a modest relationship between existing measures of *regulatory pressure* and observed emission reductions. While firm-specific heterogeneity is to be expected, given the market-based nature of the EU ETS mechanism, this has led some to conclude that financial constraints, technological limitations, and firm-specific characteristics may outweigh regulatory incentives in driving emissions outcomes (Bartram et al., 2022; Carradori et al., 2023; Haas et al., 2025).[1] We argue, however, that the conventional approach of measuring regulatory pressure focusing primarily on the *current-year compliance obligation*, overlooks the inherently forward-looking nature of firms' compliance decisions under market-based regulations and, specifically, cap-and-trade programs. Our first contribution is a theoretically grounded definition of firm-specific regulatory pressure, which we term *policy stringency*, that explicitly incorporates both current and expected future compliance obligations. These are collectively captured by what we define as the *compliance gap*: the difference between a firm's current and projected emissions and its corresponding current and expected allowance allocations over a given planning horizon. By adjusting this gap for expected permit prices, normalized by firm size (measured by sales), our

[1] While emissions reductions under cap-and-trade systems are progressing, the pace remains slow (Allcott and Greenstone, 2012; Calel, 2020). Several structural and organizational barriers have been identified as contributing factors. Technological constraints pose a major hurdle, particularly in industries like steel or cement, where operational processes are highly emissions-intensive and capital assets have long depreciation cycles. Transitioning to cleaner technologies often entails prohibitively high upfront costs (Calel, 2020; Pinkse et al., 2024) and may lock firms into irreversible and costly long-term investments (Chao and Wilson, 1993; Taschini, 2021). Financial constraints also play a role, as firms with limited access to external capital are less likely to invest in emissions-reducing technologies (Bartram et al., 2022; Carradori et al., 2023; Haas et al., 2025). In addition, organizational factors such as management quality can influence a firm's capacity to adopt abatement strategies. Evidence shows substantial heterogeneity in green management practices across firms, which can impact their ability to respond effectively to environmental regulation (Bloom et al., 2010; Martin et al., 2012; Haas et al., 2025). We account for these firm-level financial and organizational characteristics in the empirical analysis to isolate the specific effect of regulatory pressure on emissions outcomes.

policy stringency measure serves as an improved firm-level indicator of the economic and operational pressure under cap-and-trade programs. Applying our measure to firm-level data from Phase III of the EU ETS (2013–2021), we show that regulatory pressure is indeed a more central factor shaping firms' emission reductions than previously suggested. This enhanced measurement places regulatory incentives back at the center of the emissions reduction narrative, helping reconcile discrepancies in earlier findings and highlighting the essential role of forward-looking expectations in firms' emission reduction strategies.

Our definition of policy stringency re-examines the approach of most existing studies, which measure regulatory pressure using a static, year-by-year comparison between current free allowances and verified emissions (European Central Bank, 2022; Carradori et al., 2023). While this approach offers a useful snapshot of regulatory exposure, it overlooks the forward-looking nature of carbon pricing regulations and the compliance decisions firms must make now, based on both current and expected future requirements (Rubin, 1996; Schennach, 2000). To address this limitation, we frame compliance as an intertemporal decision-making problem and link it to the concept of the *expected* compliance gap. This accounts for both present and future regulatory constraints by integrating *current* free allowances and emissions alongside *expected* future free allowances and emissions. Firms seek to close the expected compliance gap either by reducing emissions or by purchasing additional allowances on the market. In equilibrium, the per-unit cost of compliance – whether through abatement or trading – is the permit price. As a result, the firm's total expected compliance cost is the product of the compliance gap and the permit price. To assess the relative burden of this cost across firms of different sizes and sectors, we express the expected compliance cost as a share of expected revenue. This normalization yields our *policy stringency* measure, which we argue provides a more accurate representation of the firm-specific financial salience of regulatory pressure.

We then empirically examine how policy stringency affects changes in carbon emissions by specifying a regression that accounts for both cross-sectional and time-series variations in firm-specific characteristics (such as total assets, fixed assets, number of installations, sales, firm age, sector, and country), and potential financial constraints (leverage, cash holdings, return-on-asset, listed status). This forms our second and most substantive contribution: demonstrating that policy stringency is indeed a central factor shaping firms' emission reductions decisions. While changes in emissions are shaped by a range of factors – including financial conditions, technological constraints, and other firm-specific characteristics – our findings show that policy stringency and firm size are the most decisive drivers of firms' emissions reduction decisions, thus re-centering the role of regulatory pressure.[2] Policy stringency remains a key driver of emission reductions across

[2]Sales influence emissions because firms with higher revenues typically operate at larger production scales, resulting in increased emissions (Zhang, 2023). This relationship also motivates our decision to normalize policy

the Manufacturing, Construction, Utilities, Mining, and Transportation sectors. Despite substantial sectoral differences in terms of financial constraints and technological limitations, regulatory pressure plays a decisive role in shaping firms' emissions reduction decisions.

Our definition of policy stringency captures both immediate regulatory pressure (the current compliance gap as in European Central Bank (2022); Carradori et al. (2023)) and firms' expectations about future compliance obligations. To better understand the contribution of each component to overall policy stringency, we deconstruct the measure and assess each part separately. This analysis highlights two important insights. First, future compliance obligations exert a stronger influence on firms' emissions reduction decisions than current regulatory pressure. As a result, measures that exclude forward-looking elements are likely to underestimate the true effect of policy stringency, potentially leading to the mistaken conclusion that regulation plays only a limited role in driving emissions reductions. Second, when policy stringency is expressed as a unified, size-adjusted, and price-sensitive metric, it emerges as a key determinant of firm-level compliance decisions under market-based regulations.

We explore the robustness of our results and find that they are robust across alternative definitions of policy stringency based on different assumptions for the length of the planning horizon used in computing expected compliance gaps, projecting future allowances, emissions, and permit prices. While the specific level of policy stringency varies with different planning horizons and the assumptions used to project allowances, emissions, and prices, the overall pattern remains clear: incorporating forward-looking expectations consistently strengthens the relevance of policy stringency in explaining firms' emissions reduction decisions.

Our third contribution is the application of the sectoral model to assess whether the regulatory pressure embedded in current and proposed EU ETS policies is sufficient to meet the annual linear reduction rate of the EU's Fit for 55. First, we simulate individual firms' emission trajectories under the anticipated increase in policy stringency resulting from the phased reduction of free allowances associated with the EU Carbon Border Adjustment Mechanism (CBAM). We find that while policy stringency increases for CBAM-exposed sectors, CBAM alone is insufficient to achieve the economy-wide emissions reductions needed to meet the Fit for 55 target, as reflected in the projected annual reduction rate through 2030. We then conduct a "what-if" analysis to identify the carbon price level, starting in 2022, that would generate the regulatory pressure needed to meet these targets. Our results indicate that achieving the necessary economy-wide reductions would require an immediate carbon price of approximately €125 per tonne of carbon dioxide equivalent.[3]

stringency by sales, ensuring that the measure reflects regulatory pressure relative to firm size and operational scale.

[3] This is consistent with the OECD's assessment of the carbon price needed to achieve the EU's 2030 climate goals.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents key stylized facts on emissions and free-allowance allocation during Phase III of the EU ETS, and introduces the foundational model underlying the concept of expected compliance costs and the definition of policy stringency. Section 4 outlines the empirical analysis and results, including the deconstruction of the definition of policy stringency, robustness analysis, and counterfactual simulations. Section 5 concludes.

2 Data

The analysis combines three data sources: (i) the European Union Transaction Log (EUTL), which provides installation-level information on allocated allowances, verified emissions and compliance,[4] (ii) company-level financial data from the Orbis database by Bureau van Dijk, and (iii) the EU ETS carbon allowance prices are sourced from the London Stock Exchange Group (LSEG).

We map installations to their owners using national identification and trade registry numbers. This enables us to aggregate verified emissions and received free allowances at the parent-company level. We then match the EUTL data to the Orbis data using company registration numbers. We include only regulated stationary installations and their respective companies. We focus our analysis on firms operating in the majority of emitting sectors, specifically Mining (NACE B), Manufacturing (NACE C), Electricity, gas, etc. (NACE D), Water supply and waste management (NACE E), Construction (NACE F), and Transportation (NACE H). In subsequent analyses, due to sample size we combine firms classified under Manufacturing (NACE C) and Construction (NACE F) into a single consolidated group referred to as *Manufacturing and Construction* or, for short, *Industrials*. Plants that have ceased operations are typically not linked to a parent company and are therefore excluded from the final dataset. We also exclude firms in Agriculture (NACE A) and Wholesale and retail trade (NACE G) due to insufficient sample size. This yields a dataset covering 6,273 firms in the EUTL, which together accounted for approximately 73% of emissions recorded in the database in 2021. Of these, we successfully matched 3,913 firms to the Orbis database, yielding a final sample that accounts for roughly 50% of EUTL emissions. While this reduces overall coverage, the sample remains representative of the largest and most emission-intensive firms in the EU ETS, offering a comprehensive basis for robust empirical analysis. We use the Orbis database to map a range of variables capturing company-level characteristics and financial performance over the sample period. Drawing on standard practice in literature (Bolton

[4] The EUTL, maintained by the European Commission, serves as the EU ETS's central reporting and monitoring platform. The data is available here. Each year, the Commission publishes allocation and emissions data (Scope 1) in the EUTL. The EUTL also includes a descriptive dataset providing qualitative information on the installations and their ownership. For a detailed description of the EUTL, see Letout (2022).

and Kacperczyk, 2021; Alam et al., 2022; Apergis et al., 2013; Ishikawa and Okubo, 2017; Colmer et al., 2024; Zanin, 2025), we compile data on each parent company's asset structure, profitability, leverage, number of affiliated installations, age, geographic headquarter, and NACE two-digit sector classification. The variables are described in Table 6 in Appendix A.

Our analysis focuses on the period from 2013 to 2021, which corresponds with Phase III of the EU ETS. We focus on this phase because it is characterized by more stringent regulations than Phase II, allowing for a clearer examination of the impacts of policy stringency on emission reductions (Kalantzis et al., 2024).[5]

2.1 Firm-level emissions and allowances

This section defines and describes the main variables of interest in the analysis.

Annual free allowance allocation: We aggregate the free allowances allocated to each installation j owned by parent company i in year t:

$$a_{i,t} = \sum_{j=1}^{N_{j,i,t}} a_{j,i,t}$$

Annual verified emissions: For each parent company i in year t, verified carbon emissions (hereafter emissions) are calculated as the sum of emissions from all its installations j in that year:

$$e_{i,t} = \sum_{j=1}^{N_{j,i,t}} e_{j,i,t}$$

This is calculated based on the number of installations $N_{j,i,t}$ owned by parent company i at the end of year t, capturing the total EU ETS-regulated emissions for each parent company in a given year. Our variable of interest is the (logarithm of) annual change in emissions for firm i:

$$\Delta\log(e)_{i,t} = \log(e)_{i,t} - \log(e)_{i,t-1} \tag{1}$$

We focus on the year-on-year change because firms periodically adjust their emission reduction decisions in response to evolving expectations about future emissions obligations and allowance

[5] Significant reforms were introduced to strengthen the EU ETS during this phase. The emissions cap was set at the EU level, rather than as a sum of national caps, with an annual linear reduction factor of 1.74% of the amount of allowances in 2010. In July 2015, a linear reduction factor of 2.2% was proposed to take effect from 2021 onward, but in December 2022, it was set to 4.3% per year from 2024 to 2027, and 4.4% from 2028 to 2030. Free allowances were allocated based on emission intensity benchmarks rather than grandfathering, and the scheme was expanded to include additional sectors. These changes made Phase III the first truly constraining phase of the EU ETS for regulated firms.

allocations — as outlined in the model in Section 3.2.

2.2 Control variables

A description and some key summary statistics for the control variables used in the empirical analyses are presented in Tables 6 and 7, respectively, in Appendix A. Firm size is assessed as the value of total assets, which is about 785 million euros on average. We also consider the value of fixed assets as a measure of the firm's production capacity and operational footprint (e.g., Ferrell et al., 2016; Bolton and Kacperczyk, 2021; Zanin, 2025). On average, about 60% of firms' assets in the sample consist of properties, plants, and equipment. Return on assets (ROA) is a short-term indicator of how efficiently a firm generates profit from its assets, providing insight into management performance (Trinks et al., 2020; Alam et al., 2022). The average ROA for firms in the sample is 2.9%. A firm's ability to comply with emissions regulations also depends on its access to capital for financing pollution control technologies. This includes internal liquidity, loans and, where applicable, access to financial markets (for listed firms). We capture these factors by noting whether the firm is publicly listed, introducing an indicator of cash holdings for measuring internal liquidity, and calculating the debt-to-asset ratio (or leverage) as a measure of external sources from the banking system (Carradori et al., 2023; Haas et al., 2025; Zanin, 2025). On average, firms in the sample hold 6.7% of their assets as cash (liquidity), have a debt-to-asset ratio of 16.6%, and only 2% are publicly listed. Firm age is also considered, as it can influence a company's ability to comply with emissions regulations. On average, firms participating in the EU ETS monitoring plan have been in operation for over 30 years. Older firms are more likely to rely on outdated, less emission-efficient technologies and may face higher costs for retrofitting emission control equipment, which can significantly strain parent company resources (Ren et al., 2019). The acquisition, sale, and closure of production plants and installations can also influence a firm's ability to comply with emissions regulations by affecting production capacity and operational efficiency. To capture these dynamics, we track changes in the number of installations per firm over time. Geographical location and sector of operation also play a crucial role in compliance, as external political and regulatory factors can shape the timeline and effort required for a low-carbon transition (Dechezleprêtre et al., 2022; Ortiz et al., 2020).

Figure 1 illustrates the geographic concentration of companies in the EU ETS, based on the number of firms headquartered in each country. France, Germany, Italy, Poland, and Spain have the highest concentrations. The right figure shows the distribution of companies by their NACE one-digit sector of operation, with the highest representation in the combined Manufacturing and Construction sector, followed by Mining, Transportation, and Utilities. All these variables serve as controls for firm-specific financial performance, identifying potential constraints at the parent-

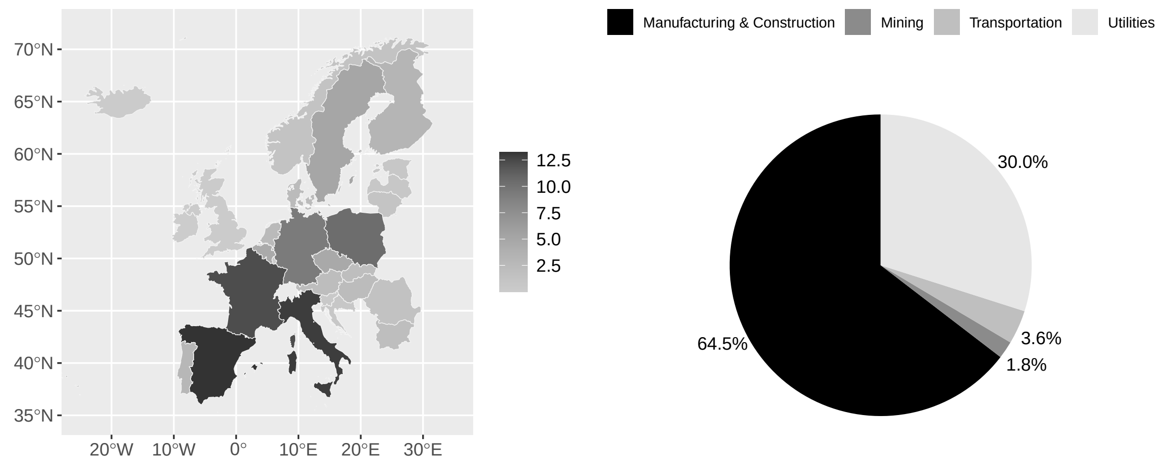

Figure 1: The left plot illustrates the geographic concentration of companies (in %) within the EU ETS framework, highlighting the primary locations where companies are headquartered. The right plot displays the distribution of companies (in %) according to their NACE one-digit sector of operation. Manufacturing and Construction are combined.

company level, as well as firm-specific characteristics indicative of the scale of operations. They capture key aspects of the firm's activities and capabilities.

3 What drives firms' emissions reduction in Europe

We begin by presenting key stylized facts on emissions reductions and the allocation of free allowances during Phase III of the EU ETS. We then present a simple model of firm compliance under a cap-and-trade system, which forms the basis for our definition of expected compliance costs and policy stringency, linking compliance efforts with changes in firms' emissions reduction decisions.

3.1 Stylized facts on emissions and allowance allocation in Phase III

Since its launch in 2005, the EU ETS has covered approximately 40% of Europe's greenhouse gas emissions, see EU ETS portal. Over 18 years, it has provided a valuable empirical case for tracking emissions from more than 11,500 installations across electricity and heat generation, and various energy-intensive industries.[6] Historically, Phase III of the EU ETS (beginning in 2013) has experienced lower reductions in emissions across major sectors compared to previous phases (Bijnens and Swartenbroek, 2022; Colmer et al., 2024), despite a decline in free allocations

[6]These sectors include oil refineries, steelworks, and the production of iron, aluminum, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids, and bulk organic chemicals.

compared to previous phases. This raises a broader concern increasingly echoed by stakeholders and researchers alike: is regulatory pressure (or policy stringency) a relevant determinant of firm-level emissions reductions?

One potential explanation for these weaker-than-expected emissions reductions lies in firm-level production processes. While total program-wide emissions have consistently remained below the cap, the bulk of the reductions have come from the electricity generation sector, which has significantly cut its emissions, as shown in Bijnens and Swartenbroek (2022) and Kalantzis et al. (2024). This is further confirmed by Figure 2, which illustrates annual changes in emissions relative to baseline emissions in 2013. The decline in aggregate emissions is predominantly driven by the Utilities sector, while emissions from Manufacturing and construction, Mining, and Transportation remained relatively stable until 2019, with a drop in the two subsequent years.

Indeed, cross-sectoral differences in emission reductions stem largely from the distinction between combustion-related emissions – predominant in electricity generation – and process-related emissions from industrial activities.[7] Combustion-related emissions have notably declined since Phase II of the EU ETS, not only in the Utility sector but also across various other industries (Bijnens and Swartenbroek, 2022; Pinkse et al., 2024). This reduction is primarily due to fuel-switching – shifting to less carbon-intensive fossil fuels – which lowers the emissions per unit of energy. In contrast, process-related emissions have remained relatively stable due to the technical complexity and high costs associated with reducing emissions in certain industrial processes. Unlike combustion-related emissions, which can be mitigated through improved energy efficiency or renewable energy adoption, the abatement of process-related emissions often requires substantial investment in advanced technologies and significant commitments to technological innovation.

Figure 2 displays the decline in free allocations and change in emissions, both aggregated to the sectoral level. Comparing these two panels provides no clear link between regulatory pressure and emission reduction decisions, but also masks underlying intra-sectoral heterogeneity. As shown in Figure 3, firm-level changes in emissions reveal significant variation within sectors. This firm-level heterogeneity is consistent with the design of the EU ETS, which allows regulated firms to optimize their emissions reduction strategies based on firm- and sector-specific circumstances. Nevertheless, it suggests that there is more to be said about the role of regulatory pressure. The question, therefore, is not whether an increase in regulatory pressure translates directly into a commensurate decrease in emissions, but whether firm-level emissions reduction decisions respond to regulatory pressure once other confounding factors are taken into account.[8]

[7]For example, the steel industry relies on coke in blast furnaces to reduce iron ore, while the petrochemical and fertilizer sectors use oil or natural gas as critical inputs in their production processes. Similarly, the conversion of limestone into cement or lime inherently releases carbon dioxide equivalent emissions, not just from the heat required but as an unavoidable byproduct of the chemical reactions involved.

[8]Intra-sectoral variability may stem from a range of factors that can obscure the effect of regulatory pressure,

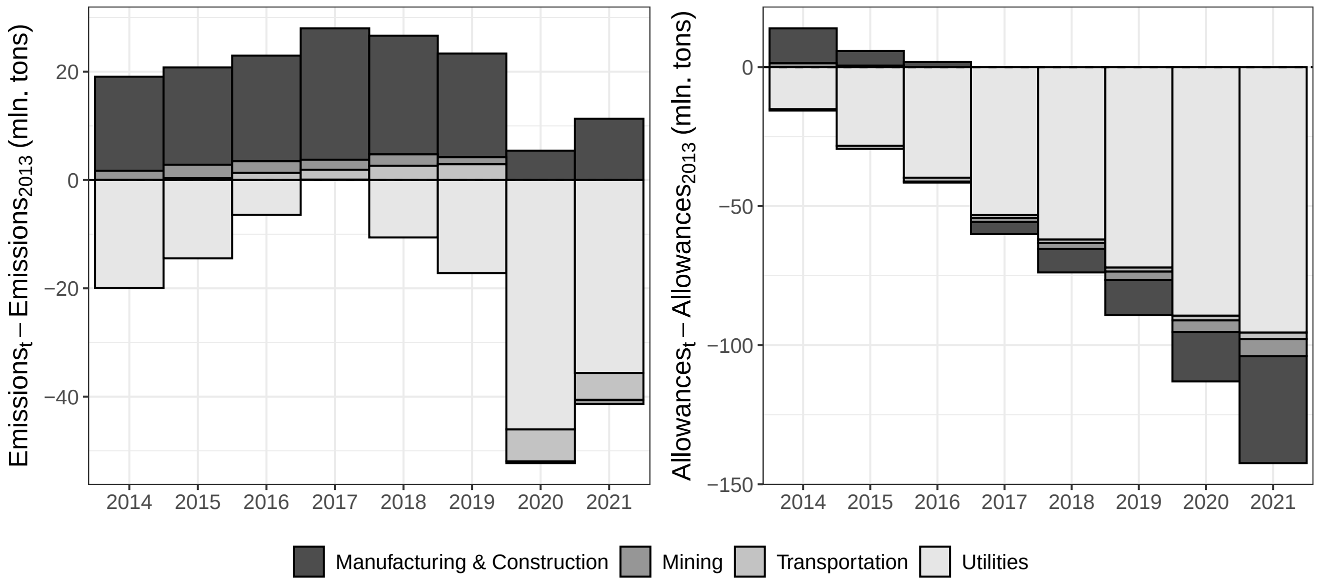

Figure 2: Left plot: change in emissions compared to 2013 across major sectors (Manufacturing and construction, Mining, Transportation, and Utilities) during Phase III of the EU ETS for a panel-balanced sample. Right plot: change in free allowance allocations compared to 2013 over the same period. The sample comprises data from 2013/01/01 to 2021/12/31 in yearly frequency. The panel-balanced sample includes 64.4% (2,520 of 3,913) of the firms from the full database.

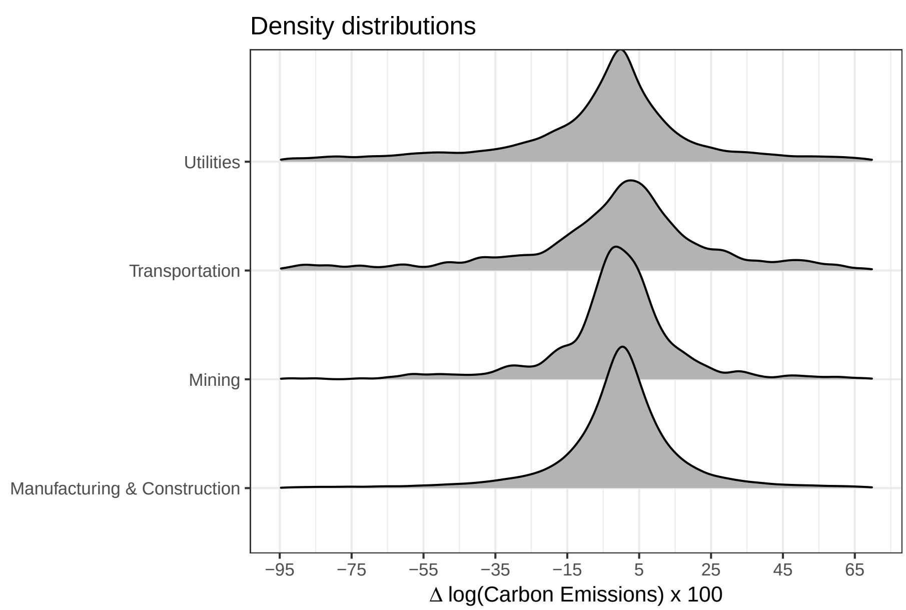

Figure 3: Distribution of change in emissions within sectors during Phase III of the EU ETS. The sample comprises data from 2013/01/01 to 2021/12/31 in yearly frequency.

3.2 Policy stringency model: mind the compliance gap

To provide the theoretical foundation for our definition of policy stringency, and to illustrate the relationship between the compliance gap and firms' emissions reduction decisions, we use a highly stylized model. We consider a single representative firm operating under a regulatory framework that requires it to hold sufficient emissions allowances to cover its emission output. The firm can dynamically adjust its compliance strategy, choosing whether to abate emissions internally or acquire allowances in a market. In this model, the compliance gap captures the firm's projected shortfall or surplus of allowances relative to its planned production and, consequently, emissions prior to any additional abatement activities or trades.[9] Intuitively, if the firm anticipates a large positive compliance gap – meaning its projected emissions exceed the total of its current allowances and those it expects to receive – it must exert substantial compliance effort, either by undertaking costly abatement measures or by purchasing additional permits.[10] In contrast, if the compliance gap is small or negative, the firm faces less regulatory pressure and can comply with the policy at a lower or no cost. This crucial determinant of perceived policy stringency (defined later) prompts firms to periodically reassess the compliance gap and adjust their strategies accordingly throughout the regulatory period. The firm's compliance problem can be described as follows:

$$\min_{\alpha,\beta} \mathbb{E}\left[\sum_{t=0}^{T} C(\bar{e}_t - e_t(p_t,\bar{e}_t)) + p_t \cdot \beta_t\right] \tag{2}$$

$$\text{s.t. } E_T - A_T = \sum_{t=0}^{T} \alpha_t + \sum_{t=0}^{T} \beta_t$$

including firm-specific characteristics, financial constraints, and differences in technological capabilities. In the econometric analysis that follows, we address these potential confounders by controlling for a rich set of firm-level financial and structural variables, a granular sector classification, and including both time and country fixed effects.

[9] Although the actual compliance decision is inherently complex, the use of a simple model allows us to escape from many real-world complexities and focus on the core conceptual link between the firm's compliance gap and their decisions to reduce emissions.

[10] Provided that a series of conditions are met, cap-and-trade programs ensure a (total) efficient allocation of abatement activity among regulated firms, regardless of the initial distribution of allowances – a concept known as Coase independence (Coase (1960)). However, if free allowance allocations influence individual firms' emissions and abatement decisions, the *aggregate* compliance gap should reflect the role of allowance distribution. Empirical studies suggest that Coase independence may not always hold due to market frictions and behavioral factors, including transaction costs (Gangadharan (2000); Baudry et al. (2021)), managerial preferences for staying within allocated limits (Sandoff and Schaad (2009); Martin et al. (2015)), regulatory uncertainty (Montero et al. (2002)), the endowment effect (Murphy and Stranlund (2007); Yoon et al. (2024)), and loss aversion (Kreutzer (2006)). In our model, however, individual firm decisions depend directly on their specific allowance allocation, which determines their net permit position, that is whether they face a surplus or a shortfall of allowances, as shown in the model.

where $C(\cdot)$ is the cost of abating emissions, $\bar{e}_t$ and $e_t(\cdot)$ are business-as-usual and verified emissions respectively, $\alpha_t = (\bar{e}_t - e_t(p_t,\bar{e}_t))$ represents the quantity of emissions that the firm decides to abate at time t, and β_t is the number of allowances the firm decides to acquire at the allowance permit price p_t at time t. Here, T represents the length of the planning horizon.[11] Abatement and the purchase of allowances are interchangeable actions for achieving compliance.[12] These strategies depend on the total expected free allowances over the planning horizon, $A_T = \sum_{t=0}^{T} a_t$, and the total projected emissions before abatement, $E_T = \sum_{t=0}^{T} e_t$.[13] The constraint $E_T - A_T$ captures the firm's total compliance gap over the planning horizon, which it must control by either abating emissions or purchasing additional allowances. As time progresses, firms periodically revise their compliance strategies based on updated expectations of current and future emissions and allowances over their planning horizon. As a result, annual *changes in verified emissions* $\Delta(e)_{i,t}$ reflect firms' dynamic response to evolving perceptions of policy stringency – this provides the rationale for using year-on-year changes in emissions as our main variable of interest. Unlike approaches focusing on year-by-year differences between current free allowances and verified emissions, such as the European Central Bank (2022)'s "allowance-to-emission gap" measure, or those that consider the cumulative balance of free allowances net of total emissions, such as Carradori et al. (2023), our framework treats compliance as a forward-looking problem. By accounting for current allowances and emissions alongside future allowances and projected emissions, the compliance gap captures a firm's long-term exposure to regulatory pressure.

Solving the compliance control problem and deriving the standard first-order conditions, one finds the well-established result that in equilibrium, the marginal cost of abatement equals the permit price, $C'(\alpha_t) = p_t$. Thus, the *per-unit* compliance cost is always p_t, whether the firm abates emissions at cost $C'(\alpha_t)$ or purchases allowances at price p_t. From the perspective of year $t = 0$, the *individual total expected compliance cost* is:

$$\sum_{t=0}^{T} \Big(\alpha_t + \beta_t\Big) \cdot p_t = \sum_{t=0}^{T} (e_t - a_t) \cdot p_t$$

thereby representing the expected cost implications of the policy's stringency for an individual firm. For simplicity, we omit the expectation operator in this summation, but it should be understood

[11] Quemin and Trotignon (2021) identify ten years as the average planning horizon for firms under the EU cap-and-trade program, which we adopt later in the empirical analysis.

[12] The firm chooses its mix of abatement and trading by comparing their respective costs $C(\cdot)$ and p_t. If abatement is cheaper, it reduces emissions by abating; if purchasing allowances is cheaper, it opts to trade. In equilibrium, the two costs are equal.

[13] A_T incorporates adjustments in future allowance allocations and related policy changes, such as the progressive reduction in free allowances under the CBAM. Any existing allowance stockpile (bank of allowances) is also included in A_T.

that each term reflects an individual expected value.

We now introduce our definition of policy stringency using the expression of the individual total expected compliance cost. To make the definition more concrete, we impose a set of simplifying assumptions – later relaxed in Section 4.4 – regarding the regulatory horizon, future allocations, emissions, and permit prices. First, we assume the firm looks ahead over a ten-year period ($T = 10$) to evaluate its total expected compliance cost.[14] We also assume the firm has perfect knowledge of how many free allowances $a_{i,t+k}$ it will receive in each future year $t+k$. In the previous expression, $\mathbb{E}_t\left[a_{i,t+k}\right] = a_{i,t+k}$. This simplification lets us focus on the role of policy design – how the cap and allocation schedule evolve – without introducing forecast errors about future allocations. We then assume that, under a no-abatement scenario, the firm's emissions remain at their current level. In the previous expression, $\mathbb{E}_t\left[e_{i,t+k}\right] = e_{i,t}$. This reflects a baseline in which the firm does not foresee changes in its production process. Any adjustments in actual (verified) emissions would instead stem from abatement efforts (e.g., installing cleaner technologies or improving energy efficiency) or other compliance strategies (e.g., purchasing additional allowances), rather than from changes in business-as-usual production. Finally, we assume that the carbon price changes are purely random $\mathbb{E}_t\left[P_{t+k}\right] = P_t$. This assumption aligns with the empirical finding that allowance prices in cap-and-trade markets exhibit martingale properties (Back, 2010; Cantillon and Slechten, 2018), meaning that the best estimate of a future permit price is simply the current price.[15] Additionally, we assume that the firm is small enough relative to the market that its own compliance gap does not influence the market price. Formally, $\mathbb{E}_t\left[(a_{i,t+k} - e_{i,t+k}) \times P_{t+k}\right] = \mathbb{E}_t\left[(a_{i,t+k} - e_{i,t+k})\right] \times \mathbb{E}_t\left[P_{t+k}\right].$ To ensure comparability across firms of different sizes, we normalize the expected compliance gap cost by each firm's annual sales. This yields a standardized measure of regulatory burden, capturing the monetary salience of our definition of policy stringency. By expressing expected compliance costs relative to expected revenue, this definition reflects the financial significance of regulatory pressure on a firm's operations, highlighting the extent to which regulation-related costs impact firms with different revenue scales. Formally, we define policy stringency as:

$$PS_{i,t} = \mathbb{E}_t\left(\frac{1}{T}\sum_{k=1}^{T}\left[\frac{1}{\text{Sales}_t}(a_{i,t+k} - e_{i,t+k}) \times P_{t+k}\right]\right) = \frac{1}{10}\sum_{k=1}^{10}\left[\frac{(a_{i,t+k} - e_{i,t}) \times P_t}{\text{Sales}_{i,t}}\right] \tag{3}$$

This normalized value of the compliance gap (multiplied by the allowance price and divided by

[14] As already mentioned, we select a ten-year horizon based on Quemin and Trotignon (2021). Although the relevant time horizon may vary across sectors depending on specific investment cycles and regulatory expectations, the robustness analysis in Section 4.4 confirms that our results remain directionally robust, rather than overly sensitive to specific horizon choices.

[15] Assuming an increasing price path à la Hotelling would reinforce the effect of policy stringency, as confirmed in the robustness checks in Section 4.4.

sales) can be interpreted as the firm's *annual expected compliance cost* as a fraction of its current sales. It reflects the monetary salience of the total expected compliance cost.

To illustrate the expected policy stringency numerically, we use our dataset to calculate each firm's compliance gap from 2013 to 2021 and then project it forward to 2031 ($T = 10$ years). For each year, we determine the annual difference between free allowances (a) and verified emissions (e), where a negative value indicates insufficient allowances, requiring either emission reductions or the purchase of additional allowances. This difference is multiplied by the corresponding average yearly permit price (P_t) and divided by yearly sales ($Sale_t$), which yields the sales-adjusted annual compliance cost. For 2013–2021, we rely on historical data on free allowances, verified emissions, yearly average permit prices, and sales data, ensuring our calculations reflect *observed* compliance costs. Beyond 2021, we project compliance costs to 2031 under the assumptions described above (later relaxed in robustness checks): (i) a 4.3% reduction in free allowances each year until 2028, followed by a 4.4% annual reduction from 2029 to 2031 (as mandated by the EU ETS Directive); (ii) emissions remain constant at 2021 levels; (iii) constant allowance prices at their 2021 values; and (iv) sales remain constant at their 2021 levels. Dividing the total 10-year compliance cost by 10 gives the average annual compliance cost, adjusted for sales.

Figure 4 presents the evolution of the policy stringency measure from 2013 through 2021, reflecting the intra-sector variability observed in Figure 3. It illustrates how policy stringency has evolved over time and differs substantially across firms, even within the same sector. For example, at the beginning of the sample period, the expected compliance cost for the Utilities sector accounted for nearly 0.5% of sales for the median utility firm. This reflects the fact that, starting that year, power plants ceased receiving free allowances and were required to purchase all permits either at auction or on the secondary market. This sharply increased their compliance gap. By contrast, other sectors continued to benefit from substantial free allowances. From 2018 onward, all sectors experienced a rise in policy stringency, largely driven by the sharp increase in allowance prices following structural reforms to the EU ETS, including the introduction of the Market Stability Reserve in 2019.[16] In particular, average compliance cost as a fraction of revenues increased from 0.7% to almost 2% from 2017 to 2020. By 2021, the median firm across all sectors faced a negative compliance gap, meaning projected emissions exceeded the expected allocation of free allowances. Within a single sector, firms can differ markedly in how they experience policy stringency. While part of this variation may stem from underlying differences among firms operating in different sub-sectors within the same industry,[17] the key point remains: differences

[16]The Market Stability Reserve is a mechanism introduced to the EU ETS to improve its resilience to supply–demand imbalances. It adjusts the supply of allowances by placing market-wide surplus allowances into the reserve and releasing them as needed, thereby increasing the scarcity of permits.

[17]A common limitation of sector classifications is that, even with the most granular classification, they cannot fully capture firm-level heterogeneity in industry factors or technological differences.

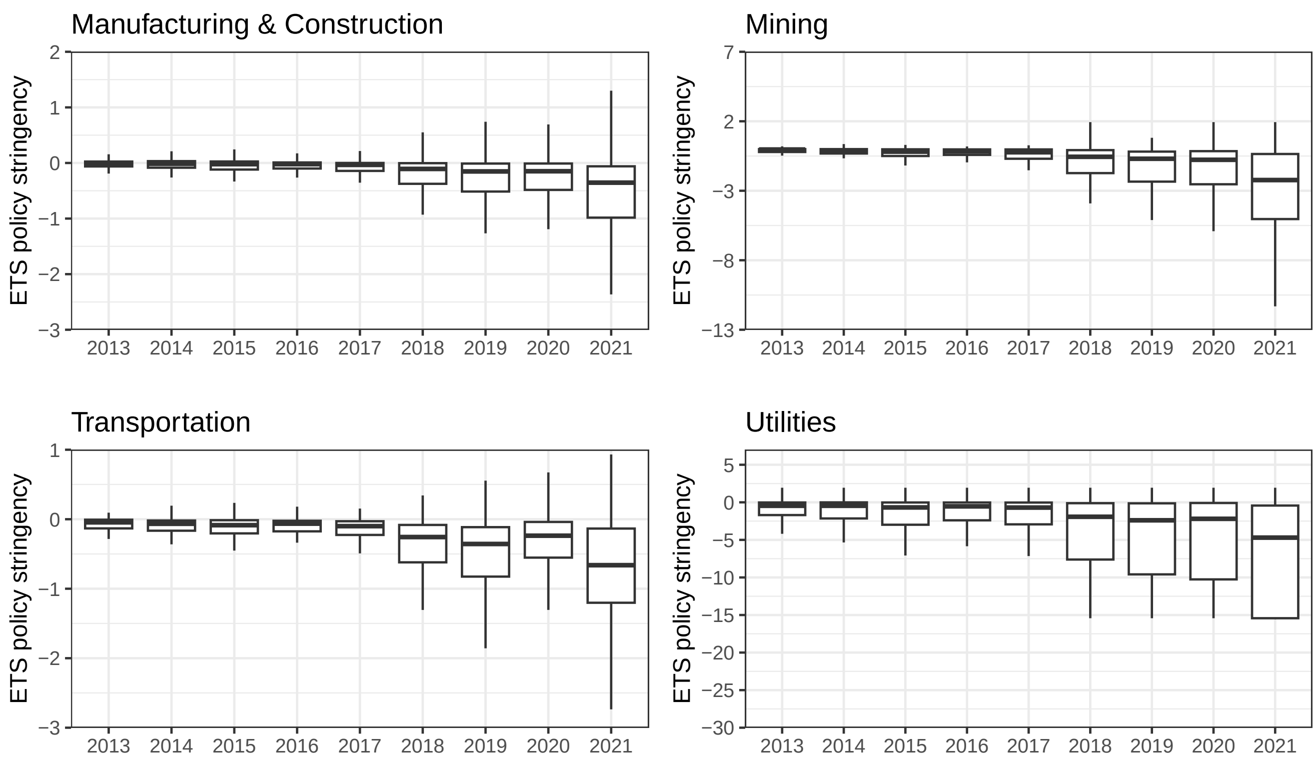

Figure 4: Evolution of our policy stringency measure from 2013 through 2031. Policy stringency, calculated as the expected compliance gap (allowances minus emissions) over 10 years, multiplied by the corresponding yearly allowance price and normalized by firm-level sales, provides a monetary gauge of each firm's regulatory burden. Historical data (2013–2021) rely on observed free allowances, verified emissions, average allowance prices, and sales. Projected data (2022–2031) assume declining free allowances but stable emissions, allowance prices, and sales at 2021 levels.

in the ratio of the compliance gap to sales, scaled by permit prices, result in some firms facing compliance costs that are several times higher than others in the same sector.

4 Empirical analyses

To examine how policy stringency affects changes in carbon emission, we specify a regression that controls for both cross-sectional and time-series variation in a firm's asset structure, potential financial constraints, and other firm-specific characteristics.[18] The regression is specified as follows:

$$\Delta\log(e)_{i,t} = \quad \beta_1' X_{1i,t-1} + \boldsymbol{\beta_2}'\boldsymbol{X}_{2i,t-1} + \boldsymbol{\beta_3}'\boldsymbol{X}_{3i,t} + \mu_t + \gamma_s + \zeta_c + \gamma_s \times \mu_t + \varepsilon_{i,t} \tag{4}$$

where $i = 1, \ldots, n$ indexes firms, and $t = 1, \ldots, T$ indexes time. Our primary variable of interest is:

$$X_{1i,t-1} = \left(\text{ Policy stringency } \right)$$

$\boldsymbol{X}_{2i,t-1}$ is a six-dimensional vector containing firm-specific financial variables, lagged by one year to account for the time it takes for financial decisions to impact emissions:

$$\boldsymbol{X}_{2i,t-1} = \begin{pmatrix} \text{Leverage} \\ \text{Leverage}^2 \\ \log(\text{Fixed assets}) \\ \text{Cash holding} \\ \text{ROA} \\ \text{ROA}^2 \end{pmatrix}$$

We account for possible non-linear effects by including the square term in the leverage (ratio of debt to total assets) and profitability (measured by ROA) performance indicators. The assumption is that a firm's profitability or leverage only affects emission reductions after reaching certain thresholds (Carradori et al., 2023; Zanin, 2025).

$\boldsymbol{X}_{3it}$ is a five-dimensional vector containing firm-specific characteristics measuring the scale of operations. These variables represent, for example, the firm's activities, capturing both output

[18] We use $\Delta\log(e)$ to capture firms' dynamic compliance responses. As outlined in the theoretical model in Section 3.2, firms periodically adjust their emissions reduction decisions in response to evolving expectations about future emissions obligations and allowance allocations. This measure reflects how firms revise their compliance strategies as regulatory expectations shift over time. Moreover, expressing emissions in log-differences facilitates comparisons of emissions reduction outcomes across firms with different baseline emission levels.

and input scales:

$$\boldsymbol{X}_{3it} = \begin{pmatrix} \Delta\log(\text{Sales}) \\ \log(\text{Total assets}) \\ \Delta \text{ N. installations of the firm} \\ \log(\text{Age of firm}) \\ \text{Dummy listed firm (Yes)} \end{pmatrix}$$

The coefficients β_1, $\boldsymbol{\beta_2} = (\beta_{21}, \beta_{22}, ..., \beta_{26})'$ and $\boldsymbol{\beta_3} = (\beta_{31}, \beta_{32}, ..., \beta_{35})'$ are the parameters to be estimated; μ_t and ζ_c represent time and country fixed effects, respectively; γ_s represents NACE two-digit sector fixed effects[19] and $\gamma_s \times \mu_t$ represent NACE two-digit sector–time interaction fixed effects.[20] ε_{it} is the error term and it is assumed to be standard normal i.i.d. with $\mathbb{E}(\varepsilon_{it}) = 0$ and $\mathbb{V}(\varepsilon_{it}) = \sigma^2$. The regression's coefficients of expression (4) are estimated by applying a pooled OLS estimation (Wooldridge, 2010).[21]

The selected set of controls and fixed effects are similar to the controls used in Carradori et al. (2023) and helps reduce the risk of omitting important factors that could bias our results. By using the first difference of emissions, we focus on year-to-year changes rather than absolute levels, which removes any influence from time-invariant firm characteristics. This approach also aligns with our theoretical model, where annual changes in emissions reflect firms' dynamic responses to expected policy stringency. We also lag the independent variables to address the possibility that changes in emissions are affecting policy stringency, rather than the other way around (Leszczensky and Wolbring, 2019).

4.1 Full sample estimates

Table 1 reports the estimates for all outcomes of interest, distinguishing between regressions excluding policy stringency (Columns 1 and 3) and regressions including policy stringency (Columns 2 and 4). Regressions 3 and 4 present standardized estimated parameters, allowing us to compare the relative importance of different drivers in explaining changes in carbon emissions. In what follows, we discuss the results based on the estimates with standardized independent variables (Regressions 3 and 4).

Policy stringency emerges as a key factor in explaining changes in carbon emissions. A more negative policy stringency – indicating a larger compliance gap, with fewer emissions covered by

[19] We use two-digit sector granularity to capture heterogeneity that may be obscured in broader sectoral groupings (e.g., NACE one-digit or aggregated multi-sector classifications; (see also Prosperi and Zanin, 2024)), as discussed in Section 3.1.

[20] The interaction term captures sector-specific shocks over time, such as changes in regulations, subsidies, environmental policies, and other sectoral initiatives.

[21] The regression is estimated using the *feols()* function of the R-package *fixest*, which adopts an efficient maximum likelihood estimator in a panel data setting with multiple fixed effects (Bergé, 2018).

free allowances and higher permit prices – gives firms stronger incentives to reduce their carbon emissions. Table 1 indicates that for a 1% *decrease* in policy stringency, carbon emissions increase by 0.62% (Column 2).[22] Like Carradori et al. (2023), who analyzed the effect of the instantaneous imbalance between emissions and allowances – a concept that closely resembles our policy stringency but focuses solely on the current year's compliance gap – we find that policy stringency plays a critical role in driving emissions reductions. Stricter regulations exert pressure on firms to adopt emission reduction strategies, making policy stringency a key factor in explaining carbon mitigation efforts.

Sales also significantly influence emissions, reflecting the scale of output. Firms with higher sales typically operate at greater production levels and thus have higher emissions (Zhang, 2023).[23] We acknowledge that sales (levels) are also embedded in the policy stringency measure, as they normalize the compliance gap and permit price, and therefore simultaneously moderate the stringency value. For example, two firms with the same negative compliance gap, but different sales, will face different regulatory pressure: the firm with higher sales will perceive a lower policy stringency, as its gap is spread over larger revenue. As a result, it may feel less compelled to reduce emissions. This scaling effect highlights both the rationale for normalizing by sales and the dual role played by sales in shaping emissions and the financial weight of the compliance gap.

To put the relative importance of policy stringency and sales into context, a one-standard-deviation increase in sales results in a 5.48% rise in emissions – approximately twice the emissions reduction driven by an equivalent increase in policy stringency. Notably, even a substantial increase in sales (e.g., a 10% expansion in sales, yielding about a 3% increase in emissions) could be fully offset by a comparatively smaller rise in expected compliance costs (approximately 5%). This simple calculation underscores the potential of regulatory pressure to counterbalance emission growth induced by higher production levels.

As reported in Table 1, all other control variables have lower relevance. The number of installations is positively associated with emissions, reflecting the scale of a firm's operations. More installations typically indicate higher production capacity, which directly correlates with increased emissions (Abrell et al., 2022; Carradori et al., 2023). Similarly, fixed assets – representing a firm's production capacity and operational footprint – influence emissions by reflecting the scale of its infrastructure (Ferrell et al., 2016; Bolton and Kacperczyk, 2021; Zanin, 2025). Larger fixed assets typically reflect more extensive machinery, facilities, and equipment, and are therefore associated

[22]Conversely, a one-standard-deviation increase in the policy stringency variable decreases carbon emissions by 2.19% (Column 4).

[23]As documented in Zhang (2023), sales provide a clear snapshot of the economic activity driving both operational and energy-related emissions. In terms of economic magnitude, Zhang (2023) reports that sales explain as much as 71% of the variation in U.S. emissions and 66% of the variation in global emissions. As such, sales are the most important determinant of emissions.

with higher emissions. Focusing on profitability – expressed as ROA – and emissions, we observe a non-linear relationship where higher ROA initially leads to an increase in emissions, but this effect diminishes and eventually reverses as ROA rises further. More profitable firms often have lower incentives to reduce emissions, as the costs associated with the compliance gap are less financially impactful for them (Alam et al., 2022). Initially, when profitability is low, firms find it more cost-effective to purchase additional allowances rather than invest in emission-reduction technologies, as their weaker financial position restricts their capacity to absorb the upfront costs. As their profitability grows, these firms increasingly invest in abatement measures, reducing both their reliance on purchased allowances and their overall emissions. At moderate leverage levels, emissions tend to increase as firms have sufficient financial capacity to purchase additional allowances and remain compliant without making significant changes to their emission levels. However, as leverage reaches higher still, financial pressures intensify, necessitating stricter cost controls.[24] In such scenarios, the rising cost of compliance associated with purchasing allowances compels firms to actively reduce emissions, often through more efficient operations or investment in abatement measures (Zanin, 2025). Firms with greater access to internal cash resources tend to exhibit higher emissions. This relationship highlights the role of liquidity in enabling short-term compliance strategies, such as purchasing allowances to cover temporary compliance gaps rather than undertaking structural emission reductions. The availability of internal cash reserves provides firms with financial flexibility, allowing them to address compliance gaps without immediately investing in potentially costly abatement technologies or operational changes. Although not statistically significant, listed firms tend to show greater reductions in emissions, reflecting their increased exposure to environmental and climate performance scrutiny. Publicly traded companies face pressure from investors, regulators, and stakeholders to align with climate goals, as poor carbon performance can lead to reputational damage and reduced investor confidence (Khalid et al., 2023). Investors often penalize listed firms with low carbon performance by divesting or applying downward pressure on stock valuations (Prosperi and Zanin, 2024). This might incentivize listed firms to prioritize abatement as part of their broader environmental strategies (Zanin, 2025). While these reductions may not yet translate into significant statistical effects in our analysis, the negative sign highlights the growing importance of investor expectations in driving down emissions (Benkraiem et al., 2022; Bissoondoyal-Bheenick et al., 2023; Zanin, 2023). These findings are consistent after controlling for sectoral NACE two-digit classification, year of reference, the interaction between sector and year, the country of the headquarters, and time fixed effects.

A growing body of literature examines the factors influencing changes, or lack thereof, in

[24]Carradori et al. (2023) identified a non-linear relationship between emission levels and financial leverage. However, our analysis, which examines changes in emissions as the dependent variable, suggests a different relationship.

Variables	Dependent variable: $\Delta\log(e)\times 100$ Model 1	Model 2	Model 3	Model 4
Policy stringency				
ETS Policy stringency		0.62^{***}		2.20^{***}
		(0.08)		(0.27)
Financial variables				
Leverage_{t-1}	0.04^{*}	0.03	1.10^{*}	0.90
	(0.02)	(0.02)	(0.60)	(0.60)
Leverage^2_{t-1}	-0.00^{**}	-0.00^{**}	-0.63^{**}	-0.62^{**}
	(0.00)	(0.00)	(0.27)	(0.27)
Cash holdings_{t-1}	0.03^{**}	0.04^{**}	0.42^{**}	0.44^{**}
	(0.02)	(0.02)	(0.20)	(0.20)
Listed firm (Yes)	-0.96	-0.92	-0.15	-0.14
	(1.10)	(1.11)	(0.17)	(0.17)
ROA_{t-1}	0.07^{***}	0.06^{***}	0.64^{***}	0.54^{***}
	(0.02)	(0.02)	(0.20)	(0.20)
ROA^2_{t-1}	-0.00^{***}	-0.00^{**}	-0.24^{***}	-0.22^{**}
	(0.00)	(0.00)	(0.09)	(0.09)
Company-level characteristic				
$\log(\text{Fixed Assets})_{t-1}$	0.34^{***}	0.34^{***}	0.34^{***}	0.34^{***}
	(0.09)	(0.09)	(0.09)	(0.09)
$\Delta\log(\text{Sales})\times 100$	0.29^{***}	0.30^{***}	5.42^{***}	5.49^{***}
	(0.01)	(0.01)	(0.27)	(0.27)
log(Age of firm)	0.03	-0.03	0.03	-0.03
	(0.16)	(0.16)	(0.16)	(0.16)
ΔN. Installations	4.93^{***}	4.97^{***}	1.87^{***}	1.88^{***}
	(1.81)	(1.82)	(0.69)	(0.69)
Fixed effects				
Country	Y	Y	Y	Y
NACE two-digits	Y	Y	Y	Y
Year	Y	Y	Y	Y
NACE two-digits $\times Year$	Y	Y	Y	Y
Num. obs.	27,177	27,177	27,177	27,177
R^2	0.11	0.12	0.11	0.12
AIC	259,019.75	258,946.25	259,019.75	258,946.25
BIC	262,361.27	262,295.98	262,361.27	262,295.98
Log Lik.	-129,102.88	-129,065.12	-129,102.88	-129,065.12

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 1: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions ($\Delta\log(e)\times 100$). The explanatory variables include: debt-to-total-assets ratio (leverage), fixed assets, cash holdings, return on assets (ROA), firm age, a dummy variable for listed companies, total assets, change in the number of installations, growth of sales, and policy stringency. The variables are lagged by one year to account for potential endogeneity. Standard errors are clustered at the firm level and reported in parentheses. Models 3 and 4 are estimated using the standardized independent variables.

emissions within carbon-regulated economies. As described in Carradori et al. (2023), Pinkse et al. (2024), and Haas et al. (2025), these factors range from economic conditions and technological barriers to financial constraints. Our analysis confirms that changes in emissions are driven by a combination of scale and production factors, financial characteristics, technological constraints and, crucially, policy stringency. To understand which factors matter most in explaining firms' emissions reductions, we test how the model's fit changes when we remove certain variables or groups of variables — such as those related to financial conditions, technology, or policy stringency. We use standard statistical measures (AIC, BIC, and log-likelihood) to assess this. If removing a variable worsens the model fit, it means that factor plays an important role in explaining emissions changes. This approach helps us identify which drivers are most influential.

Table 2 presents the analysis results. Compared to the full regression (shown in the last column), we observed a greater decrease in goodness-of-fit indicated by an increase in the selection criteria when policy stringency was removed (in Column 2), than when financial variables were excluded (in Column 1). This indicates that policy stringency is a more influential factor than financial constraints are in driving emission reductions. Excluding sectoral fixed effects (Column 3) further reduces the goodness-of-fit indicators, particularly the AIC and the log-likelihood. However, the BIC shows an improvement. This occurs because the AIC is less sensitive to the number of parameters in the regression (in our case, the fixed effects of different sectors and the interaction between the year and the sectors). This analysis suggests that technological factors play the most significant role in driving changes in emissions within our sample, followed in importance by policy stringency, while financial constraints have the least impact, confirming Pinkse et al. (2024), and Haas et al. (2025). However, it is important to note that certain regulatory aspects of the EU ETS, such as sector-specific differences in allowance allocation, are inherently tied to individual sectors, and hence some effects of policy stringency may be partially absorbed by sector-specific fixed effects.

4.2 Sectorial analysis

The previous regression examined the effect of policy stringency on the full sample of firms, abstracting away from the sector-specific differences in regulatory pressure. But this approach overlooks the fact that the incremental effect of the compliance gap, which underpins policy stringency, can vary across sectors. Some sectors, such as Utilities, receive little to no free allowance allocations, while others benefit from more generous allocations. To address this, we re-estimate the regression by splitting the firm–year observations into the main sectors: Manufacturing and Construction (hereafter "Industrial"), Mining, Utilities, and Transportation. This allows us to explore the potential heterogeneous effect of policy stringency across different sectors.

	Dependent variable: Δlog(e)$\times$100			
	Excl. Financials	Excl. Stringency	Excl. Sectors	Full model
Policy stringency				
ETS Policy stringency	2.21***		2.30***	2.20***
	(0.27)		(0.22)	(0.27)
Financial variables				
Leverage$_{t-1}$		1.10*	0.89	0.90
		(0.60)	(0.60)	(0.60)
Leverage$^2{}_{t-1}$		-0.63**	-0.65**	-0.62**
		(0.27)	(0.27)	(0.27)
Cash holdings$_{t-1}$		0.42**	0.37*	0.44**
		(0.20)	(0.20)	(0.20)
Listed firm (Yes)		-0.15	-0.18	-0.14
		(0.17)	(0.17)	(0.17)
ROA$_{t-1}$		0.64***	0.50**	0.54***
		(0.20)	(0.20)	(0.20)
ROA$^2_{t-1}$		-0.24***	-0.19**	-0.22**
		(0.09)	(0.09)	(0.09)
Company-level characteristic				
log(Fixed Assets)$_{t-1}$	0.28***	0.34***	0.23***	0.34***
	(0.08)	(0.09)	(0.08)	(0.09)
Δlog(Sales)$\times$100	5.48***	5.42***	5.86***	5.49***
	(0.27)	(0.27)	(0.27)	(0.27)
log(Age of firm)	0.11	0.03	0.15	-0.03
	(0.16)	(0.16)	(0.16)	(0.16)
ΔN. Installations	1.88***	1.87***	2.08***	1.88***
	(0.69)	(0.69)	(0.71)	(0.69)
Fixed effects				
Country	Y	Y	Y	Y
NACE two-digits	Y	Y	N	Y
Year	Y	Y	Y	Y
NACE two-digits$\times Year$	Y	Y	N	Y
Num. obs.	27,177	27,177	27,177	27,177
R^2	0.12	0.11	0.08	0.12
AIC	258,971.51	259,019.75	259,284.79	258,946.25
BIC	262,271.98	262,361.27	259,670.67	262,295.98
Log Lik.	-129,083.76	-129,102.88	-129,595.40	-129,065.12

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 2: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions (Δlog(e)$\times$100). The explanatory variables excluded in each model are, repressively, Leverage, Cash holding, the dummy for listed firms and ROA from 'No Financial' model (column 1), ETS policy stringency from 'No Stringency' model (column 2), and NACE-2 related fixed effects from 'No Sector' model (column 3). Financial variables are lagged by one year to account for potential endogeneity. Standard errors are clustered at the firm level and reported in parentheses. All independent variables are standardised for comparability across coefficients. Independent variables standardized.

Variables	Full sample	Mining (B)	Industry (C + F)	Utilities (D+E)	Transportation (H)
	Dependent variable: Δlog(e)$\times$100				
Policy stringency					
ETS Policy stringency	2.20***	5.70***	5.60***	1.97***	4.88*
	(0.27)	(1.66)	(0.82)	(0.33)	(2.51)
Financial variables					
Leverage$_{t-1}$	0.90	-5.02	0.32	1.31	5.18
	(0.60)	(4.77)	(0.64)	(1.30)	(4.67)
Leverage$^2_{t-1}$	-0.62**	2.28	-0.15	-1.02**	-1.79
	(0.27)	(2.65)	(0.31)	(0.51)	(1.62)
Cash holding$_{t-1}$	0.44**	2.97**	0.20	1.12**	1.34
	(0.20)	(1.34)	(0.22)	(0.45)	(1.12)
Listed firm (Yes)	-0.14	1.43**	-0.22	-0.49	0.95
	(0.17)	(0.64)	(0.18)	(0.64)	(1.03)
ROA$_{t-1}$	0.54***	0.40	0.62***	0.67	1.10
	(0.20)	(1.50)	(0.22)	(0.49)	(1.04)
ROA$^2_{t-1}$	-0.22**	0.23	-0.28***	-0.23	-0.21
	(0.09)	(0.55)	(0.09)	(0.23)	(0.37)
Company-level characteristic					
log(Fixed Assets)$_{t-1}$	0.34***	0.03	0.32***	0.52***	-0.27
	(0.09)	(0.62)	(0.10)	(0.18)	(0.55)
Δlog(Sales)$\times$100	5.49***	4.74***	5.01***	6.20***	8.18***
	(0.27)	(1.62)	(0.29)	(0.61)	(1.53)
log(Age of firm)	-0.03	-0.08	-0.08	0.10	-2.66**
	(0.16)	(1.89)	(0.18)	(0.40)	(1.28)
ΔN. Installations	1.88***	2.67***	1.76*	2.29***	0.88
	(0.69)	(0.65)	(0.92)	(0.55)	(1.19)
Fixed effects					
Country	Y	Y	Y	Y	Y
NACE two-digits	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
NACE two-digits $\times Year$	Y	Y	Y	Y	Y
Num. obs.	27,177	495	17,539	8,302	841
R^2	0.12	0.27	0.11	0.10	0.34
AIC	258,946.25	4,467.72	159,084.33	83,711.90	8,362.36
BIC	262,295.98	4,812.50	161,268.32	84,323.01	8,726.92
Log Lik.	-129,065.12	-2,151.86	-79,261.17	-41,768.95	-4,104.18

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 3: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions (Δlog(e)$\times$100). The explanatory variables include: debt-to-total-assets ratio (leverage), fixed assets, cash holdings, return on assets (ROA), firm age, a dummy variable for listed companies, total assets, change in the number of installations, growth of sales, and policy stringency. The variables are lagged by one year to account for potential endogeneity. Standard errors are clustered at the firm level and reported in parentheses. All independent variables are standardised for comparability across coefficients.

Table 3 presents the estimated standardized coefficients, enabling a direct comparison of variables across sectors. Focusing on the two primary variables of interest identified in the previous analysis – policy stringency and annual growth in sales – both are consistently relevant across all sectors. The statistical significance of the remaining variables varies by sector, indicating specific drivers of emission dynamics within each sector. For example, changes in the number of installations significantly impact emissions in all sectors except Transportation. An increase in the number of installations, through acquisition or merging of production plants, may represent a significant constraint in reducing carbon emissions. This is particularly important for the most emission intensive firms in the Mining and Utilities sectors, where expanding operations can result in increased emissions. Total assets emerge as a crucial factor in the Industrial sector, where their influence is four times greater than either growth in sales or policy stringency. Total assets, an indicator of a firm's operational scale, are particularly critical for the Industrial sector due to the capital-intensive nature of operations, such as manufacturing processes and heavy machinery, which directly drive emissions. The significant influence of total assets highlights how operational infrastructure and production capabilities underpin emission levels in this sector. While ROA is only significant for the Industrial sector, cash holdings are relevant for Mining and Utilities. Firm age is significant for the Transportation sector, and being listed is only a significant factor in the Mining sector.

Returning to the two key variables of interest – growth in sales and policy stringency – the latter demonstrates substantial variation in its magnitude across sectors. Compared to the full sample, policy stringency is over 2.5 times more influential in the Mining and Industrial sectors and twice as relevant in the Transportation sector.[25] This implies that a similar change in policy stringency, such as halving the program-wide total amount of freely available allowances while maintaining the historical distribution across sectors, would have the most pronounced impact on emissions in the Mining sector, followed by the Industrial sector, the Transportation sector, and lastly, the Utilities sector.[26] The varying degrees of sensitivity to policy stringency across different sectors can be attributed to several factors, from the technological availability of solutions to the existing regulatory framework. For instance, the Transportation sector has fewer technological options available for reducing emissions, making it more of a challenge to comply with stringent policies (Ovaere and Proost, 2022). In contrast, the Utilities sector benefits from a wider range

[25] We have calculated the 95% confidence intervals associated with the estimated parameter of policy stringency for each sub-sample. Specifically, the estimated coefficient of policy stringency for the full sample is 2.19 (with a confidence interval from 1.66 to 2.72). For the Mining sector, the coefficient is 5.77 (2.36 to 9.18); for the Industrial sector, it is 5.65 (4.04 to 7.26); for Utilities, it is 1.99 (1.32 to 2.66); and for Transportation, it is 4.71 (-0.41 to 9.83). The estimated confidence intervals of the full sample do not overlap with those estimated for the Industrial sector, suggesting a statistically significant difference in magnitude.

[26] This is also confirmed by regression results using non-standardized variables. These estimation outputs are available from the authors upon request.

of technological abatement alternatives, such as renewable energy sources, which can be more readily integrated into their operations (Patala et al., 2021). Additionally, Utilities can often pass a portion of the policy stringency costs onto consumers through adjustments in pricing, thereby mitigating the financial impact on the firms themselves (Huisman and Kiliç, 2015; Cludius et al., 2020). This ability to transfer costs, coupled with greater access to emission reduction technologies, makes the Utilities sector less sensitive than the Transportation sector to policy stringency.

4.3 Deconstructing the definition of policy stringency

Our proposed definition of policy stringency integrates both current and future compliance gaps, capturing not only the current imbalance between allowances and emissions but also firms' expectations about potential future imbalances. To show how we develop our measure of policy stringency, we break it down and analyze each component's contribution separately. This allows us to identify whether firms respond more strongly to current compliance imbalances or to their monetized value, and assess the influence of forward-looking regulatory expectations. This exercise also clarifies the importance of incorporating future compliance considerations into regulatory analysis. To that end, we rewrite the policy stringency definition from expression (3) as:

$$\frac{1}{10}\sum_{k=0}^{9}\left[\frac{(a_{i,t+k}-e_{i,t})\times P_t}{\text{Sales}_{i,}}\right]=\frac{P_t}{\text{Sales}_{i,t}}\Bigg(\underbrace{(a_{i,t}-e_{i,t})}_{\substack{\text{current allowance}\\ \text{to emission gap}}}+\underbrace{\frac{1}{9}\sum_{k=1}^{9}(a_{i,t+k}-e_{i,t})}_{\substack{\text{forward looking}\\ \text{allowance to emission gap}}}\Bigg) \tag{5}$$

where we assume a constant allowance price (P_t) and sales level (Sales_t) over the period $t = 2, \ldots, 10$ as described in Section 3.2. The first component considers only the present balance of allowances and emissions, excluding any forward-looking expectations, analogously to studies by European Central Bank (2022), Carradori et al. (2023), and Huij et al. (2024). Using this decomposition, we also test alternative definitions of policy stringency, evaluate them separately in the empirical analysis, and assess their individual contributions to firm-level emissions reductions. The decomposition begins with the simplest component and progressively builds up to the full definition of policy stringency:

1. Current allowance-to-emission gap (CA2E) $(a_{i,t} - e_{i.t})$: this definition considers only the present compliance gap (European Central Bank, 2022; Carradori et al., 2023; Huij et al., 2024).[27]

[27] This definition is consistent with the non-cumulative version of the allowances balance metric used in Carradori et al. (2023). In contrast, their cumulative version accounts for banking by tracking the year-by-year difference between allocated allowances and verified emissions over time.

2. Cost of current allowance-to-emission gap (Cost CA2E) $P_t(a_{i,t} - e_{i,t})$: this version evaluates the contemporaneous compliance gap in monetary terms by considering the prevailing average permit price.[28]

3. Current policy stringency (Current PS) $\frac{P_t}{\text{Sales}_{i,t}}[(a_{i,t} - e_{i,t})]$: this definition of policy stringency is contemporaneous only, reflecting current policy stringency while neglecting any forward-looking considerations.[29]

Re-estimating regression (4) by introducing each alternative definition of policy stringency individually allows us to isolate the specific contribution of each component embedded in our original definition (3). Table 4 reports the estimated standardized coefficients for $\Delta \log(e)$ across these alternative definitions. Focusing on the key variables of interest, we observe that a one-standard-deviation increase in the current allowance-to-emission gap (CA2E) – a measure that ignores both sales adjustments and future expectations – reduces carbon emissions by 0.63%. When expressed in monetary terms, a one-standard-deviation increase in the contemporaneous compliance gap (Cost CA2E) is associated with a 0.70% reduction in $\Delta \log(e)$. Incorporating the current compliance gap into a sales-normalized framework, represented by current policy stringency (Current PS), doubles this effect. This suggests that adjusting for firm size and allowance prices significantly strengthens the relationship between regulatory pressure and emissions reductions. Finally, when forward-looking components are also incorporated, yielding our full policy stringency measure (3), the impact intensifies further, nearly quadrupling the effect observed for the CA2E component. This provides further evidence that firms respond not only to current compliance imbalances (European Central Bank, 2022; Carradori et al., 2023; Huij et al., 2024), but also incorporate expectations of future regulatory constraints into their emissions reduction decisions. The stronger effect observed under our complete definition of policy stringency underscores the importance of forward-looking compliance considerations in shaping firm behavior under cap-and-trade regulations.

4.4 Robustness analysis

To ensure the robustness of our findings on policy stringency, we conduct three additional checks. First, we consider potential endogeneity concerns arising from unobserved omitted variables. Sec-

[28]We also evaluate a Sales-adjusted current allowance-to-emission gap (Sale-adj CA2E) $\frac{(a_{i,t} - e_{i,t})}{\text{Sales}_{i,t}}$: This metric normalizes the current compliance gap by the firm's sales, offering a size-adjusted perspective on regulatory pressure. The results are available upon request and substantially confirm the importance of including a scale measure in a policy stringency metric.

[29]This formulation also ignores the role of banked allowances, which we incorporate later in the robustness analysis in the next section.

	Dependent variable: Δlog(e)×100			
	Current A2E	Cost CA2E	Current PS	Policy stringency
Policy stringency				
CA2E	0.65^{***}			
	(0.18)			
Cost CA2E		0.73^{***}		
		(0.19)		
Current PS			0.87^{***}	
			(0.19)	
ETS Policy stringency				2.20^{***}
				(0.27)
Financial variables				
Leverage_{t-1}	1.04^{*}	1.03^{*}	1.01^{*}	0.90
	(0.60)	(0.60)	(0.60)	(0.60)
Leverage^2_{t-1}	-0.63^{**}	-0.62^{**}	-0.62^{**}	-0.62^{**}
	(0.27)	(0.27)	(0.27)	(0.27)
$\text{Cash holdings}_{t-1}$	0.45^{**}	0.45^{**}	0.45^{**}	0.44^{**}
	(0.19)	(0.19)	(0.20)	(0.20)
Listed firm (Yes)	−0.13	−0.13	−0.12	−0.14
	(0.17)	(0.17)	(0.17)	(0.17)
ROA_{t-1}	0.63^{***}	0.62^{***}	0.61^{***}	0.54^{***}
	(0.20)	(0.20)	(0.20)	(0.20)
ROA^2_{t-1}	-0.23^{***}	-0.23^{***}	-0.23^{**}	-0.22^{**}
	(0.09)	(0.09)	(0.09)	(0.09)
Company-level characteristic				
$\log(\text{Fixed Assets})_{t-1}$	0.45^{***}	0.45^{***}	0.47^{***}	0.34^{***}
	(0.09)	(0.09)	(0.09)	(0.09)
Δlog(Sales)×100	5.42^{***}	5.42^{***}	5.42^{***}	5.49^{***}
	(0.27)	(0.27)	(0.27)	(0.27)
log(Age of firm)	0.02	0.02	0.01	−0.03
	(0.16)	(0.16)	(0.16)	(0.16)
ΔN. Installations	1.87^{***}	1.87^{***}	1.86^{***}	1.88^{***}
	(0.68)	(0.68)	(0.68)	(0.69)
Fixed effects				
Country	*Y*	*Y*	*Y*	*Y*
NACE two-digits	*Y*	*Y*	*Y*	*Y*
Year	*Y*	*Y*	*Y*	*Y*
NACE two-digits $\times Year$	*Y*	*Y*	*Y*	*Y*
Num. obs.	27,177	27,177	27,177	27,177
R^2	0.12	0.12	0.12	0.12
AIC	259,012.08	259,011.77	259,006.77	258,946.25
BIC	262,361.81	262,361.50	262,356.50	262,295.98
Log Lik.	−129,098.04	−129,097.88	−129,095.38	−129,065.12

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 4: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions (Δlog(e)×100). This table compares the effects of different policy stringency specifications. The policy stringency specifications analysed include current allowance-to-emission gap (CA2E), sales-adjusted current allowance-to-emission gap (Sale-adj CA2E), cost of current allowance-to-emission gap (Cost CA2E), current policy stringency (Current PS), and non-sale-adjusted policy stringency (Non-sale PS). Independent variables standardized.

ond, we re-estimate the model using two alternative specifications of policy stringency (one incorporating an alternative evolution of future permit prices and the other accounting for banked allowances). Third, we explore the sensitivity of our results to the assumed length of the planning horizon used in computing expected compliance gaps. Across all these robustness checks, the central finding – that policy stringency is a key driver of firm-level emissions reductions – remains consistent.

First, to address endogeneity, we estimate an instrumental variable model using Baltagi's transformation in panel data (Baltagi, 2021).[30] The coefficient on policy stringency remains positive and statistically significant ($\hat{\beta} = 0.48$; CI: 0.32,0.64) showing points of overlap in confidence intervals compared to the baseline estimate ($\hat{\beta} = 0.62$; CI: 0.46,0.78) from Model 2 in Table 1, lending support to the reliability of our main results.

Second, we re-estimate the regression using two alternative policy stringency specifications, calculating the average annual expected compliance cost using different assumptions for allowance prices from 2022 onward, and the initial amount of free allowances. In the previous analysis, we utilized a policy stringency definition in which the firm has information about future allocations of free allowances, but no expectations regarding future allowance prices or emissions. In that definition, the assumptions used to project future compliance costs at any given t are: (i) emissions are expected to remain constant (in the absence of any abatement decision) at their last observed levels at time t; (ii) allowance permit prices are expected to remain constant at current levels (martingale assumption); and (iii) the firm perfectly forecasts future allowances up to 2021, after which a reduction factor of 4.3% is applied to free allowances annually until 2028, followed by a 4.4% reduction factor from 2029 through 2031. We now consider two additional specifications: the first is a policy stringency pathway in line with the Network for Greening the Financial System (NGFS) where, in addition to knowing the evolution of future free allowance allocations, the firm also has information about the expected path of allowance prices; second, any surplus (banked) allowances are carried forward from one compliance period to the next, starting from the first period. By incorporating these banked allowances, we effectively increase the total available allowances A.

Network for Greening the Financial System (NGFS) policy stringency (NPS): Besides knowing the evolution of future free allowance allocations, firms also have information about the expected path of the allowance price, therefore departing from the original martingale assumption. We assume that up to 2021, firms observe realized prices, and beyond that point, they expect the allowance price to follow the NGFS carbon price trajectory aligned with the Fit for 55 targets

[30] Implemented via the `plm()` function in the `plm` R package (Croissant and Millo, 2008).

(Net Zero 2050 scenario).[31] Since the NGFS price path rises over time, this could be interpreted as an upper-bound estimate of policy stringency. Both emissions and sales are assumed to remain constant at their last observed values in 2021. The average annual expected compliance cost in this case is:

$$\text{NPS}_{i,t} = \frac{1}{10}\sum_{k=1}^{10}\left[\frac{(a_{i,t+k} - e_{i,t}) \times P_{t+k}}{\text{Sales}_{it}}\right] \tag{6}$$

Banking policy stringency (BPS): This measure includes banked allowances since 2005 in the total available allowances, easing immediate compliance pressures by enabling firms to draw from past surpluses. This could be interpreted as a lower-bound estimate of policy stringency. This definition is consistent with the cumulative allowances balance metric in Carradori et al. (2023), and also incorporates future compliance obligations, offering a more forward-looking perspective.

The estimated coefficients for the two alternative policy stringency specifications are presented in Table 5, covering the full sample of firms. All coefficients are standardized to facilitate direct comparison. The discussion focuses specifically on the estimates of the alternative policy stringency definitions. The estimated coefficients remain statistically significant across all specifications of policy stringency. The NPS appears to perform best, perhaps reflecting firms' anticipation of a progressively rising allowance price consistent with NGFS projections. As one would expect, the coefficient estimate for the BPS is approximately half of the baseline result. This outcome is attributed to the increased availability of banked allowances, which reduces regulatory pressure and provides firms with greater flexibility in meeting their emissions constraints. While the coefficient estimate for the BPS is approximately half of the baseline result, regulatory pressure remains a key driver of emissions reductions. Notably, this holds even when banked allowances reduce the compliance gap, alleviating regulatory pressure. However, data limitations, as highlighted by Abrell et al. (2022), prevent a full reconstruction of firm-level banking behavior. Consequently, while the BPS specification provides a conservative estimate of policy stringency, the precise impact of allowance banking on individual compliance gaps remains uncertain.

Based on AIC and BIC criteria, when including NPS in the regression, we note a marginally better fit than the alternatives. However, all regressions perform well, confirming the robustness of our results across various policy stringency definitions, consistently highlighting policy stringency as a significant factor in explaining changes in carbon emissions.

We then re-estimate the impact of policy stringency from a sectoral perspective. The findings, presented in Tables 8 and 9 in Appendix B, reinforce the evidence discussed in Section 4.2,

[31] Specifically, we considered the NGFS Phase 3 scenario and select the carbon price scenario generated by the REMIND-MAgPIE 3.0-4.4 IAM model for the European Union 2028. Under this scenario, the projected carbon prices (in 2010 US dollars per tonne of CO_2) are \$85 in 2025, \$114 in 2030, \$180 in 2035, and \$255 in 2040.

Variables	Dependent variable: Δlog(e)$\times$100 Policy stringency	NPS	BPS
Policy stringency			
ETS Policy stringency	2.20^{***}		
	(0.27)		
NPS		2.79^{***}	
		(0.26)	
BPS			1.42^{***}
			(0.26)
Financial variables			
Leverage_{t-1}	0.90	0.79	1.03^{*}
	(0.60)	(0.61)	(0.60)
Leverage^2_{t-1}	-0.62^{**}	-0.61^{**}	-0.64^{**}
	(0.27)	(0.27)	(0.27)
Cash holding_{t-1}	0.44^{**}	0.41^{**}	0.44^{**}
	(0.20)	(0.20)	(0.19)
Listed firm (Yes)	-0.14	-0.13	-0.15
	(0.17)	(0.17)	(0.17)
ROA_{t-1}	0.54^{***}	0.47^{**}	0.61^{***}
	(0.20)	(0.20)	(0.20)
ROA^2_{t-1}	-0.22^{**}	-0.22^{**}	-0.23^{***}
	(0.09)	(0.09)	(0.09)
Company-level characteristic			
log(Fixed $\text{Assets})_{t-1}$	0.34^{***}	0.28^{***}	0.38^{***}
	(0.09)	(0.09)	(0.09)
Δlog(Sales)$\times$100	5.49^{***}	5.51^{***}	5.43^{***}
	(0.27)	(0.27)	(0.27)
log(Age of firm)	-0.03	-0.07	0.00
	(0.16)	(0.16)	(0.16)
ΔN. Installations	1.88^{***}	1.88^{***}	1.88^{***}
	(0.69)	(0.69)	(0.69)
Fixed effects			
Country	Y	Y	Y
NACE two-digits	Y	Y	Y
Year	Y	Y	Y
NACE two-digits $\times Year$	Y	Y	Y
Num. obs.	27,177	27,177	27,177
R^2	0.12	0.12	0.12
AIC	258,946.25	258,885.76	258,982.93
BIC	262,295.98	262,235.49	262,332.67
Log Lik.	-129,065.12	-129,034.88	-129,083.47

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 5: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions (Δlog(e)$\times$100). This table presents standardized estimates for the full sample of firms using two alternative definitions of policy stringency: (i) NGFS policy stringency (NPS), which follows the projected carbon price trajectory under the NGFS Net Zero 2050 scenario – representing an upper-bound estimate of regulatory pressure, and (ii) Banking policy stringency (BPS), which accounts for the cumulative banking of allowances since 2005, representing a lower-bound estimate of regulatory pressure.

confirming that the relationship between policy stringency and emissions reductions holds across different sectors and specification choices.

Finally, we test the sensitivity of our results to the assumed length of the planning horizon used in calculating expected compliance gaps. This robustness check evaluates whether our findings are contingent on the specific choice of horizon length over which firms are assumed to plan their compliance strategies. We compare the estimated effects of policy stringency under alternative horizons of 1, 3, 5, and 7 compared to 10 years, as in our baseline definition.[32] The findings, presented in Table 10 in Appendix B show that as the horizon extends – from a static, one-year compliance gap to progressively longer forward-looking periods – the strength of the relationship between policy stringency and emissions reductions becomes more pronounced. This pattern confirms that incorporating forward-looking expectations strengthens the influence of our policy stringency measure on the emission reduction decision. The progressive improvement in the goodness-of-fit is also confirmed by the AIC and BIC model selection criteria.

4.5 Counterfactual analysis: Aligning with EU "Fit for 55" implied reduction rate

The EU Fit for 55 package aims to reduce the EU's greenhouse gas emissions by at least 55% by 2030 compared to 1990 levels. A central component of this effort is the gradual phase-out of free allowance allocations in the EU ETS.[33] In parallel, the EU has introduced a Carbon Border Adjustment Mechanism (CBAM) to mitigate carbon leakage and address competitiveness concerns previously managed through free allocations.[34] To assess the impact of the phased reduction in free allowances, we simulate projected firm-level emissions reductions using estimated elasticities and expected changes in policy stringency under both current and planned policies. Specifically, we evaluate how the planned phase-out of free allowances alters regulatory pressure across sectors. By incorporating these policy adjustments into our definition of policy stringency, we estimate the additional emission reductions this change in the allocation program is expected to incentivize and assess whether these are sufficient to meet emission reduction targets. We acknowledge that the EU ETS, and by extension the Fit for 55 package, does not impose explicit annual emissions

[32] We do not consider longer horizons, as empirical evidence suggests that firms' expectations tend to be anchored within a 10-year window, consistent with findings from Quemin and Trotignon (2021).

[33] As outlined in the EU ETS Directive, Article 10a(1a), a CBAM factor is applied to progressively reduce free allocations for covered goods. The CBAM factor remains at 100% until the end of 2025, then declines annually: 97.5% in 2026, 95% in 2027, 90% in 2028, 77.5% in 2029, 51.5% in 2030, 39% in 2031, 26.5% in 2032, and 14% in 2033. From 2034 onward, no free allocation will apply to these sectors.

[34] CBAM targets imports in carbon-intensive sectors to ensure that domestic and foreign products face comparable carbon costs, thereby maintaining a level playing field and mitigating carbon leakage. For further details, see Vidovic et al. (2023).

reduction targets on individual regulated firms. To assess how the policy adjustment compares with the overarching EU climate ambition, we translate the Fit for 55 target into an implied average annual reduction rate. Based on historical emissions trends, this corresponds to an annual decline of approximately 2% in aggregate emissions between 2021 and 2030.[35] By expressing the Fit for 55 goal in these terms, we can evaluate the extent to which projected firm-level emissions trajectories, under the simulated decline in free allocations, align with this benchmark.

4.5.1 The phased reduction of free allowances and CBAM

To assess the impact of the planned phase-out of free allowances connected to CBAM, culminating in their full removal by 2035, we identify which firms in our sample are likely to be affected by CBAM based on their primary sector of activity. To that end, we gather each firm's 3-digit Standard Industrial Classification (SIC) code and link it to CBAM-affected goods (classified under 6-digit CN or HS codes) following Meinerding et al. (2024) and the bridging table provided by Pierce and Schott (2012). For simplicity, we assume that any firm subject to the EU ETS and operating in these sectors is fully within the scope of the CBAM. Consequently, the free allowances allocated to these firms are assumed to decline at the rate stipulated by CBAM. This represents an upper-bound approximation, likely overestimating the projected emissions reductions resulting from this policy. Even under this optimistic scenario, likely overestimating the number of firms affected by the policy, these firms represent only 13% of all EU ETS participants, and their emissions account for just 27% of total EU ETS emissions.

We run two simulations under an assumed carbon price of €80, a figure close to the average allowance price in 2022. This assumption provides a conservative estimate of regulatory pressure in the baseline scenario. Considering a higher or increasing carbon price would amplify regulatory pressure on firms, potentially leading to greater reductions in emissions. We explore this possibility later in the analysis. In the baseline scenario, we assume all firms expect free allowances to decline at a uniform rate of 4.4%, as outlined in Section 3.2 on policy stringency. In the counterfactual scenario, we instead assume that CBAM-exposed firms anticipate a steeper reduction in allowances starting from 2022, following the phase-out schedule described in footnote 33. By comparing the projected emissions under these two scenarios, we estimate the additional reductions incentivized and assess whether they are sufficient to align with the Fit for 55 annual reduction. This enables us to quantify the extent to which the planned reduction in free allowances for CBAM-affected firms contributes to achieving broader emissions reduction targets. The projection analysis models each firm's emissions trajectory based on anticipated policy stringency over time, allowing us to estimate

[35] The 2% annual reduction rate is derived by calculating the *linear* annual rate needed for the EU to reach its Fit for 55 target — a 55% reduction in emissions by 2030 relative to 1990.

how firms adjust their emissions in response to evolving regulatory pressure under different policy scenarios.[36] Using annual iterations of the process described below, we project how firms adjust their emission path in response to the evolving compliance gap. To conduct the counterfactual analysis, we design the simulation by considering all active firms in 2021 – the most recent year for which data were available For each existing firm i, starting from year $t = 2021$, we proceed with the following steps for $t + 1$:

1. **Projecting emissions of firm i at $t + 1$:** we project the change in emissions for firm i, $\Delta\log(e)_{i,t+1}$, using the sector-specific regression defined in Equation (4) and estimated on unscaled variables.

2. **Computing the emissions at year $t + 1$:** We estimate the emissions for each firm at year $t + 1$ by assuming a constant sector-specific growth rate (g_s) in sales, which is equal to the historical average for that sector.

3. **Update policy stringency in $t + 1$:** With the newly calculated emissions e_{t+1}, we update the firm's policy stringency measure by incorporating the revised projected emission path, the allocation plan, and the projected permit prices.

Figure 5 illustrates the change in policy stringency for CBAM-exposed and CBAM-unexposed firms over time. For CBAM-exposed firms, the annual expected compliance cost as a percentage of sales increases from 1% in 2023 to 2.5% in 2030, driven by the phase-out of free allowances. By then, their regulatory pressure nearly matches that of unexposed firms, whose average stringency is 2.2%. The sharp increase from 1% to 2% in 2022 reflects the full update in firms' expectations that occurred in 2022, when information about the planned phase-out of free allowances under CBAM was incorporated into their compliance assessments, leading to a recalibrated and higher level of perceived policy stringency.

Figure 6 presents projected free allowance and emissions paths for CBAM-exposed and unexposed firms. Exposed firms reduce emissions by 2.45% annually on average, driven by the decline in free allowances, while unexposed firms see a much smaller reduction of 0.64%.

Considering the average annual reduction of approximately 2% in aggregate emissions assumed from the EU's Fit for 55, the combined effect of CBAM-induced reductions, while helpful, remains insufficient. This is primarily because CBAM-covered firms make up only a small share of all entities regulated under the EU ETS. The simulated reductions bring the system closer to the target, but additional policy measures are needed to achieve the required economy-wide abatement.

[36] The underlying logic is that firms' abatement and allowance purchase decisions are primarily driven by expected policy stringency. These decisions create a feedback loop, however, because they alter the balance between allowances and emissions, which in turn affects future stringency.

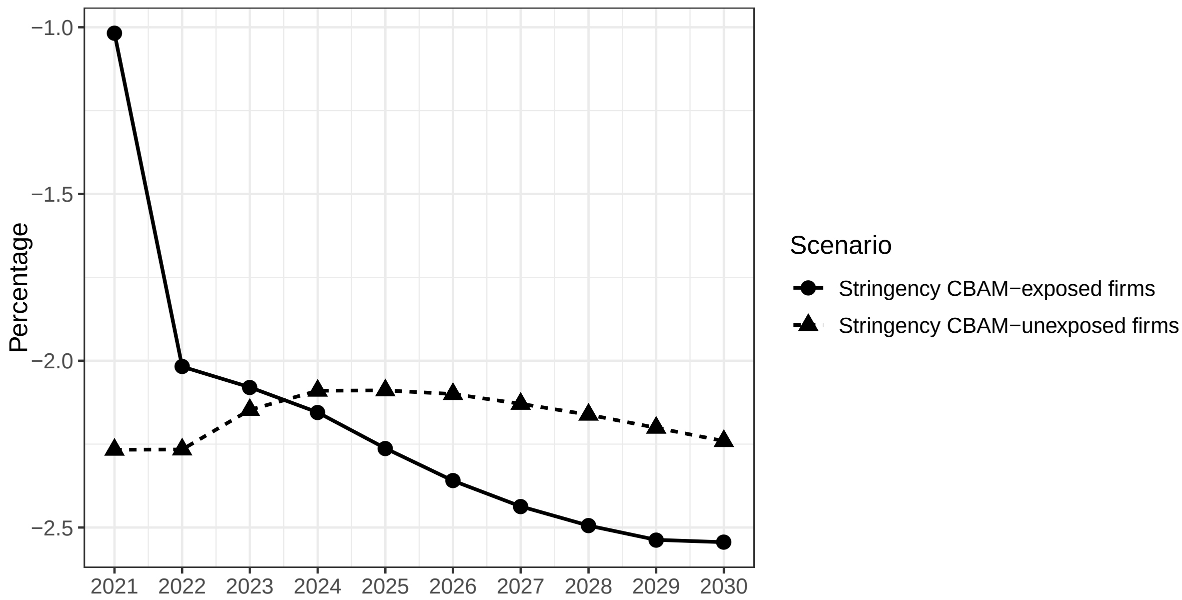

Figure 5: Evolution of policy stringency, expressed as the annual expected compliance cost as a percentage of sales, from 2021 to 2030, indexed to 2021 levels, under the CBAM scenario for CBAM-exposed and CBAM-unexposed firms.

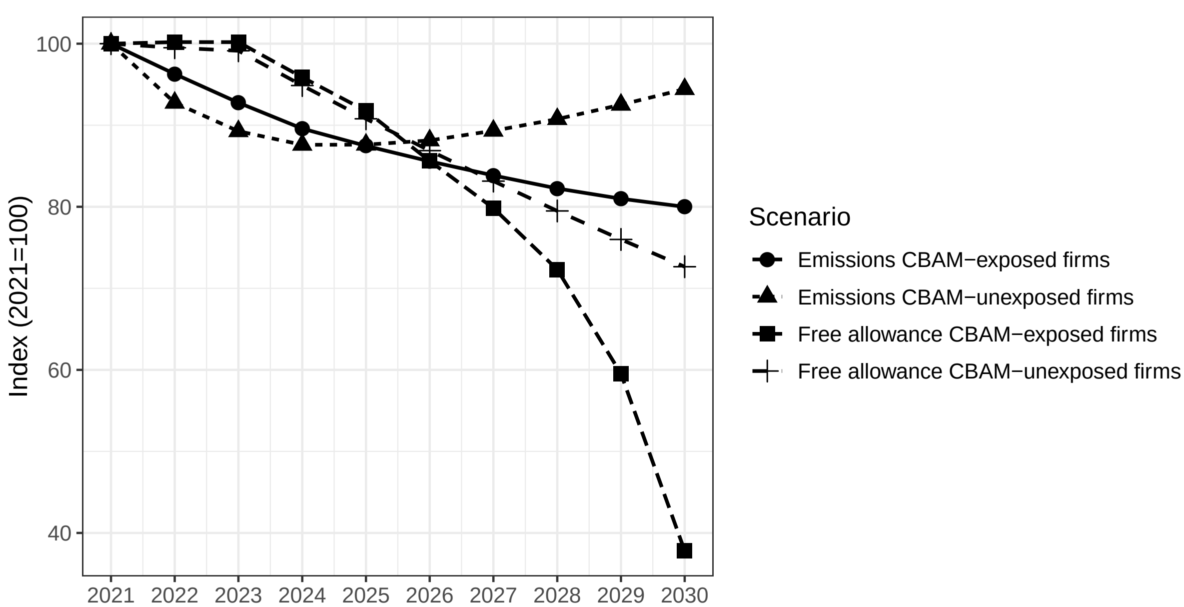

Figure 6: Simulated free allowance allocation paths and emissions trajectories for CBAM-exposed and CBAM-unexposed firms from 2021 to 2030, indexed to their 2021 levels.

4.5.2 Counterfactual analysis on allowance prices

As CBAM-driven reductions alone are insufficient to align with the assumed annual reduction rate of 2%, we extend our analysis by conducting a "what-if" experiment, simulating firm-level emissions under four allowance price scenarios starting in 2022: €80, €100, €125, and €150 per tonne of carbon dioxide equivalent.[37] Rather than modeling market clearing to identify an equilibrium carbon price, our simulation adopts a stylized iterative approach, akin to an ascending auction, in which the allowance price progressively increases until firms collectively reduce emissions in line with the annual rate of 2%. To clarify our simulation setup, in each scenario, the carbon price is assumed to reach its predetermined level in the first year (2022). As shown in Figure 7, the most significant update in firms' expectations occurs in 2022, when new information about the carbon price is incorporated into their compliance planning. This leads firms to reassess their anticipated compliance needs and adjust their emissions accordingly, resulting in the largest reduction taking place in 2022. After this initial adjustment, policy stringency begins to decline from 2023 onward, as the updated expectations have already been absorbed and firms progressively adapt to the new expected price levels.

For each price point, we estimate the projected firm-level regulatory pressure and assess whether the resulting aggregate emissions reductions align more closely with the annual reduction linear trend of the "Fit for 55" target. As allowance prices rise, compliance costs increase, sharpening firms' incentives to cut emissions.

At the lower price level of €80 per tonne, emissions reductions remain modest, as most firms can comply by drawing on allocated allowances without undertaking major operational changes. This yields an aggregate emissions reduction of just 0.61% by 2030 – well below the required 2% aggregate annual average. As the allowance price increases to €100 and €125, firms face stronger financial incentives to abate emissions, resulting in aggregate reductions of 1.60% and 2.59% respectively by 2030. At €125 per tonne, the average annual reduction not only meets but exceeds the percentage target of 2%. This result is broadly consistent with the OECD's estimated requirement of around €120 per tonne of carbon dioxide equivalent (OECD, 2023) to achieve the EU's 2030 climate targets. At the highest simulated price of €150, emissions reductions accelerate further, reaching an annual rate of 3.40% – well beyond the reduction trend line of the "Fit for 55", suggesting potential over-compliance or inefficiency if prices rise too steeply.

[37]These price levels are informed by forecasts from researchers at the Potsdam Institute for Climate Impact Research, the Centre for Climate and Energy Analyses, and specialized carbon price forecasting teams including Enerdata, Bloomberg New Energy Finance, Veyt, and Refinitiv (Reuters). Based on presentations at the Carbon Forward conference in London on October 16th, 2024 and reporting in Carbon Pulse, March 7, 2025.

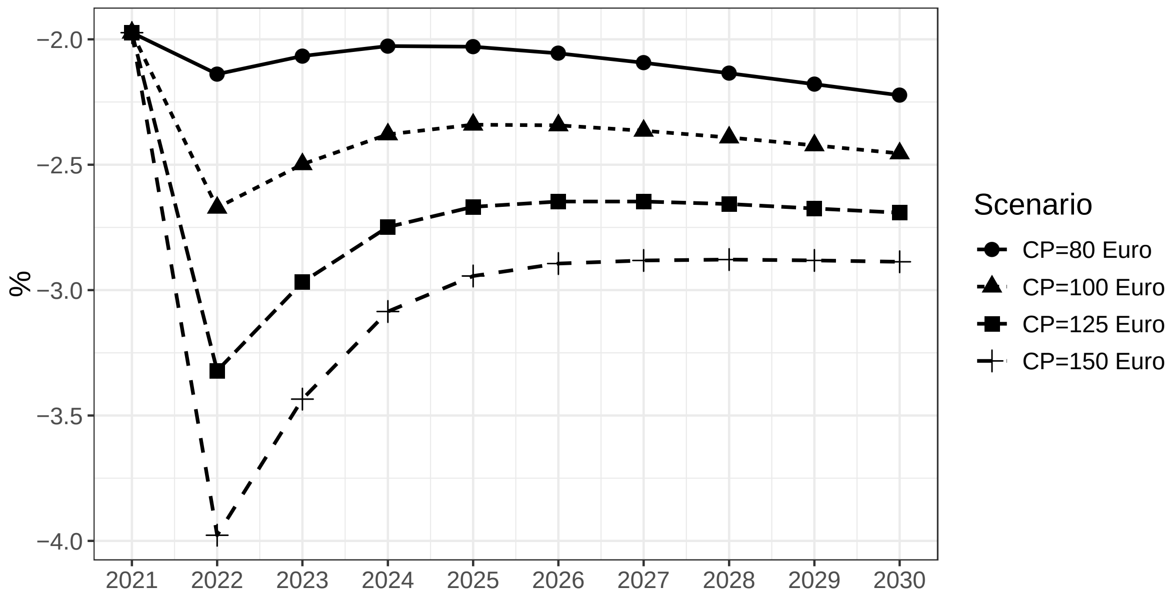

Figure 7: Evolution of policy stringency, expressed as the annual expected compliance cost as a percentage of sales, from 2021 to 2030 under four allowance price scenarios (€80, €100, €125, and €150).

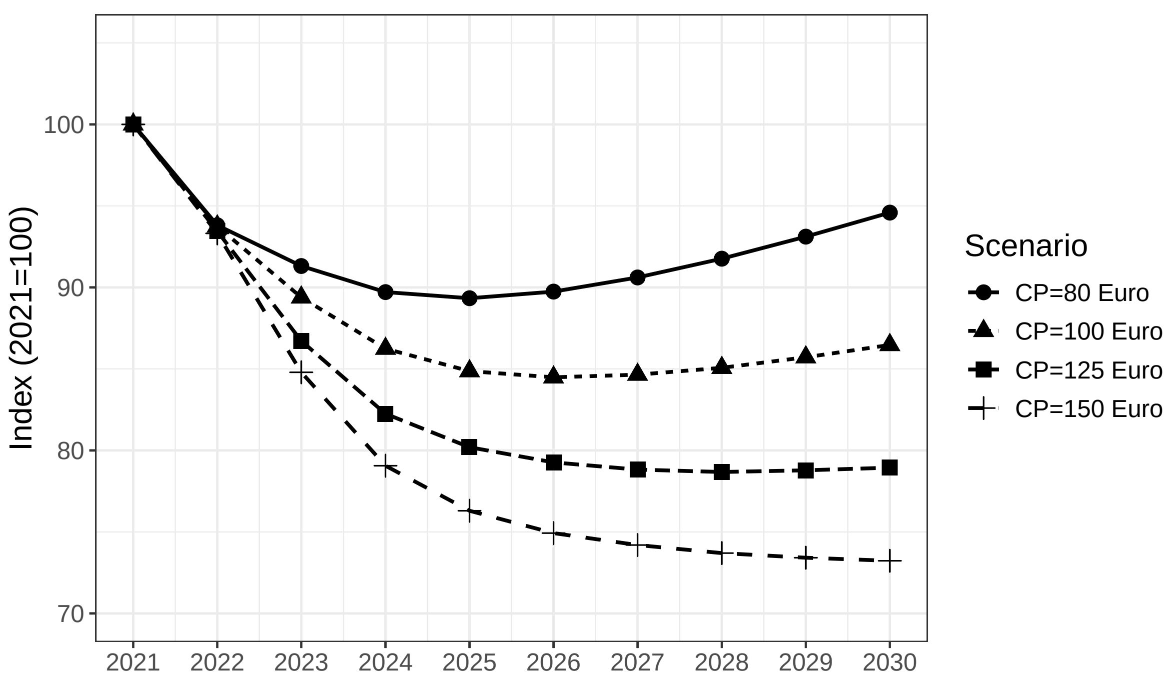

Figure 8: Simulation of economy-wide emissions from 2021 through 2030, indexed to their 2021 levels, under four allowance price scenarios (€80, €100, €125, and €150).

5 Conclusions

We re-examine the role of regulatory pressure in driving firm-level emissions reductions under the EU cap-and-trade system. Previous studies, which focus on the current allowance imbalance – typically calculated as the year-by-year difference between current (or cumulative) free allowances and verified emissions – have often found only limited effects of regulatory pressure. This has contributed to the prevailing view that financial constraints, technological barriers, and firm-specific characteristics play a more prominent role in shaping emissions outcomes. Building on a model of firm compliance under cap-and-trade, we argue that firms respond not just to current imbalances but to expected compliance gaps. This provides the theoretical foundation for our definition of policy stringency, which captures firms' expectations about both current and future obligations—based on anticipated allowances and emissions — and adjusts for permit prices and firm size.

We apply our policy stringency measure to firm-level data from Phase III of the EU ETS (2013–2021) and show that regulatory pressure is a key driver of firms' emissions reduction decisions, placing carbon regulation back at the center of the decarbonization narrative and helping to reconcile differences in the current empirical literature. Crucially, it is the forward-looking component of policy stringency – capturing firms' expectations about future allowance allocations, emissions, and carbon prices over a defined planning horizon – that proves most influential. A decomposition of the measure confirms that firms respond more strongly to anticipated future compliance obligations than to current regulatory conditions. Importantly, the explanatory power of policy stringency remains robust across alternative specifications. Whether we vary the length of the planning horizon or modify assumptions about the evolution of allowances, emissions, or permit prices, policy stringency consistently emerges as a key determinant of firm-level emission reductions.

We leverage our sectoral model to evaluate how the phase-out of free allowances reshapes regulatory pressure across sectors – a core element of the EU Fit for 55 package aimed at achieving a 55% reduction in greenhouse gas emissions by 2030 relative to 1990 levels. Our simulations show that the gradual elimination of free allowances, accompanied by the compensatory Carbon Border Adjustment Mechanism (CBAM), strengthens policy stringency and helps move the system closer to the Fit for 55 implied annual reduction rate. However, the resulting emissions reductions remain insufficient to fully meet the 2% annual decline in aggregate emissions implied by the Fit for 55 objective. We then simulate a series of counterfactual scenarios with higher carbon prices and find that raising the allowance price to €125 per tonne of carbon dioxide starting from 2022 provides the necessary regulatory pressure to close the gap. This price level aligns with the OECD's estimates of the effective carbon price needed to achieve the EU's 2030 climate goals.

Acknowledgements

We would like to thank Katia Colaneri, Margherita Giuzio, Christoph Meinerding, Michael Pahle, Simon Quemin, Ben Sila, Leonard Stimpfle, and Huacheng Zhang for their constructive suggestions. The paper was presented at seminars and conferences, including the 2024 Florence School of Regulation on Climate Annual Conference and the 2024 Sustainable Finance and Investment Conference organized by the University of Tor Vergata. We thank the participants at these events for their helpful comments and suggestions.

A Appendix A: Summary statistics

This appendix offers a description of the variables utilized to construct the EU ETS policy stringency measure and of those considered for the econometric analysis. Furthermore, we provide key descriptive statistics for these variables.

Variable	Description	Source
Firm balance sheet variables		
Assets (Euro)	Total assets of the firm	Orbis
Sales (Euro)	The sales from business operations	Orbis
Fixed assets (Euro)	Tangible fixed assets	Orbis/Constructed
Leverage (%)	Short and long-terms debts on total assets	Orbis/Constructed
ROA (%)	Net income on total assets	Orbis
Cash holding (%)	Liquidity on total assets	Orbis/Constructed
Other firm characteristics		
Age of firm (years)	The number of years from incorporation	Orbis
Sector	NACE two-digits classification	Orbis
Country	Country of the headquarter	Orbis
Listed	Dummy indicating if the firm is listed	Orbis
Installations	Number of EU ETS installations of the firm	EU ETS
Emissions and future on carbon price		
Future EU ETS prices (Euro)	Price for a tonne(t) of CO_2 emission	Refinitiv
Emission allocated (t)	ETS allowances allocated to each installation of the firm	EU ETS/Constructed
Emission verified (t)	ETS emissions verified for each installation of the firm	EU ETS/Constructed

Table 6: Variables description and data source

Variable	Min	Max	Mean	St.d	Percentiles				
					1%	25%	50%	75%	99%
Financial variables									
Leverage (%)	0.00	89.78	16.63	21.26	0.00	0.00	6.91	27.90	89.78
Cash holding (%)	-16.32	52.15	6.66	10.28	0.00	0.29	2.30	8.48	52.15
Listed firm (Yes)	0.00	1.00	0.02	0.15	0.00	0.00	0.00	0.00	1.00
ROA (%)	-34.07	31.67	2.88	9.04	-34.07	0.00	2.50	6.45	31.67
Firm characteristics									
Assets (mln/euro)	0.00	528,609.00	784.60	8929.91	0.44	21.31	75.38	246.41	11,623.06
Fixed assets (mln/euro)	0.00	328,262.00	488.30	5567.18	0.09	9.88	37.21	138.32	7,532.53
Sales (mln/euro)	0.53	86,19.34	346.69	1086.86	0.66	16.16	64.02	203.61	8,619.34
Age of firm	1.00	139.00	31.53	27.27	1.00	14.00	24.00	41.00	139.00
N. Installations	1.00	54.00	1.76	2.17	1.00	1.00	1.00	2.00	11.00
Policy stringency									
Future EU ETS prices	4.49	53.46	16.66	14.82	4.49	6.19	7.48	25.18	53.46
ETS Policy stringency	-15.43	1.94	-1.28	3.30	-15.43	-0.88	-0.12	0.00	1.94
NPS	-51.27	4.00	-5.49	11.68	-51.27	-4.42	-0.78	-0.11	4.00
BPS	-14.67	7.29	-0.76	3.51	-14.67	-0.63	-0.05	0.09	7.29

Table 7: This table presents summary statistics of relevant company characteristics for the sample period from 2013 to 2021. The sample comprises 28,402 firm-year observations. All variables are winsorized at the 1st and 99th percentiles.

B Appendix B: Robustness

This appendix presents additional robustness checks to validate the core findings of our analysis. We examine the sensitivity of our results to alternative definitions of policy stringency and varying assumptions regarding the length of the planning horizon. These checks are designed to confirm that our conclusions hold under different model specifications and are not driven by specific parameter choices.

Variables	Full sample	Mining (B)	Industry (C + F)	Utilities (D+E)	Transportation (H)
	Dependent variable: Δlog(e)$\times$100				
Policy stringency					
NPS	2.79***	4.98***	7.19***	2.38***	4.57**
	(0.26)	(1.72)	(0.75)	(0.33)	(2.26)
Financial variables					
Leverage$_{t-1}$	0.79	-4.59	0.08	1.23	5.13
	(0.61)	(4.78)	(0.64)	(1.31)	(4.68)
Leverage$^2_{t-1}$	-0.61**	2.15	-0.10	-1.01**	-1.77
	(0.27)	(2.65)	(0.31)	(0.51)	(1.63)
Cash holding$_{t-1}$	0.41**	2.87**	0.17	1.12**	1.31
	(0.20)	(1.33)	(0.22)	(0.45)	(1.11)
Listed firm (Yes)	-0.13	1.33**	-0.13	-0.55	0.96
	(0.17)	(0.63)	(0.18)	(0.63)	(1.04)
ROA$_{t-1}$	0.47**	0.36	0.50**	0.66	1.07
	(0.20)	(1.50)	(0.22)	(0.49)	(1.04)
ROA$^2_{t-1}$	-0.22**	0.21	-0.29***	-0.22	-0.22
	(0.09)	(0.53)	(0.09)	(0.22)	(0.37)
Company-level characteristic					
log(Fixed Assets)$_{t-1}$	0.28***	0.03	0.19**	0.50***	-0.30
	(0.09)	(0.65)	(0.10)	(0.19)	(0.55)
Δlog(Sales)$\times$100	5.51***	4.44***	5.02***	6.27***	8.15***
	(0.27)	(1.62)	(0.29)	(0.61)	(1.53)
log(Age of firm)	-0.07	0.11	-0.21	0.01	-2.65**
	(0.16)	(1.98)	(0.17)	(0.41)	(1.28)
ΔN. Installations	1.88***	2.64***	1.74*	2.28***	0.88
	(0.69)	(0.64)	(0.91)	(0.55)	(1.18)
Fixed effects					
Country	Y	Y	Y	Y	Y
NACE two-digits	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
NACE two-digits$\times Year$	Y	Y	Y	Y	Y
Num. obs.	27,177	495	17,539	8,302	841
R^2	0.12	0.27	0.11	0.11	0.34
AIC	258,885.76	4,470.42	158,930.97	83,701.10	8,363.13
BIC	262,235.49	4,815.19	161,114.95	84,312.21	8,727.69
Log Lik.	-129,034.88	-2,153.21	-79,184.49	-41,763.55	-4,104.56

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 8: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions (Δlog(e)$\times$100). The explanatory variables include: debt-to-total-assets ratio (leverage), fixed assets, cash holdings, return on assets (ROA), firm age, a dummy variable for listed companies, total assets, change in the number of installations, growth of sales, and NGFS policy stringency (NPS) as defined in section 4.4. The variables are lagged by one year to account for potential endogeneity. Standard errors are clustered at the firm level and reported in parentheses. All independent variables are standardised for comparability across coefficients.

Variables	Full sample	Mining (B)	Industry (C + F)	Utilities (D+E)	Transportation (H)
	Dependent variable: $\Delta\log(e)\times100$				
Policy stringency					
BPS	1.42***	3.73**	2.40***	1.66***	4.01
	(0.26)	(1.66)	(0.59)	(0.32)	(2.94)
Financial variables					
Leverage_{t-1}	1.03*	-5.83	0.58	1.44	5.36
	(0.60)	(4.84)	(0.64)	(1.30)	(4.67)
Leverage^2_{t-1}	-0.64**	2.60	-0.23	-1.04**	-1.83
	(0.27)	(2.67)	(0.30)	(0.51)	(1.61)
$\text{Cash holding}_{t-1}$	0.44**	3.26**	0.15	1.16***	1.31
	(0.19)	(1.27)	(0.21)	(0.45)	(1.12)
Listed firm (Yes)	-0.15	1.66**	-0.27	-0.48	0.95
	(0.17)	(0.65)	(0.17)	(0.65)	(1.04)
ROA_{t-1}	0.61***	0.30	0.67***	0.76	1.16
	(0.20)	(1.47)	(0.22)	(0.49)	(1.03)
ROA^2_{t-1}	-0.23***	0.07	-0.27***	-0.26	-0.18
	(0.09)	(0.54)	(0.09)	(0.23)	(0.36)
Company-level characteristic					
$\log(\text{Fixed Assets})_{t-1}$	0.38***	0.07	0.39***	0.56***	-0.29
	(0.09)	(0.67)	(0.10)	(0.18)	(0.55)
$\Delta\log(\text{Sales})\times100$	5.43***	4.24**	4.96***	6.12***	8.16***
	(0.27)	(1.64)	(0.30)	(0.61)	(1.53)
log(Age of firm)	0.00	-0.69	-0.04	0.23	-2.59*
	(0.16)	(1.86)	(0.18)	(0.40)	(1.31)
ΔN. Installations	1.88***	2.56***	1.76*	2.29***	0.88
	(0.69)	(0.64)	(0.92)	(0.55)	(1.18)
Fixed effects					
Country	Y	Y	Y	Y	Y
NACE two-digits	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
NACE two-digits$\times Year$	Y	Y	Y	Y	Y
Num. obs.	27,177	495	17,539	8,302	841
R^2	0.12	0.26	0.10	0.10	0.34
AIC	258,982.93	4,474.45	159,173.06	83,716.11	8,363.66
BIC	262,332.67	4,819.23	161,357.04	84,327.22	8,728.23
Log Lik.	-129,083.47	-2,155.23	-79,305.53	-41,771.06	-4,104.83

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 9: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions ($\Delta\log(e)\times100$). The explanatory variables include: debt-to-total-assets ratio (leverage), fixed assets, cash holdings, return on assets (ROA), firm age, a dummy variable for listed companies, total assets, change in the number of installations, growth of sales, and Banking policy stringency (BPS) as defined in section 4.4. The variables are lagged by one year to account for potential endogeneity. Standard errors are clustered at the firm level and reported in parentheses. All independent variables are standardised for comparability across coefficients.

	Dependent variable: Δlog(e)$\times$100				
Variables	Current PS	PS (3-years)	PS (5-years)	PS (7-years)	PS (10-years)
Policy stringency					
Current PS	1.35^{***}				
	(0.25)				
ETS Policy stringency (3-years)		1.83^{***}			
		(0.27)			
ETS Policy stringency (5-years)			2.06^{***}		
			(0.27)		
ETS Policy stringency (7-years)				2.14^{***}	
				(0.27)	
ETS Policy stringency					2.20^{***}
					(0.27)
Financial variables					
Leverage$_{t-1}$	1.01^{*}	0.96	0.93	0.92	0.90
	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)
Leverage$^2_{t-1}$	-0.63^{**}	-0.63^{**}	-0.62^{**}	-0.62^{**}	-0.62^{**}
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
Cash holdings$_{t-1}$	0.43^{**}	0.44^{**}	0.44^{**}	0.44^{**}	0.44^{**}
	(0.20)	(0.19)	(0.20)	(0.20)	(0.20)
Listed firm (Yes)	-0.15	-0.14	-0.14	-0.14	-0.14
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
ROA$_{t-1}$	0.60^{***}	0.57^{***}	0.55^{***}	0.55^{***}	0.54^{***}
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
ROA$^2_{t-1}$	-0.23^{**}	-0.22^{**}	-0.22^{**}	-0.22^{**}	-0.22^{**}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Company-level characteristic					
log(Fixed Assets)$_{t-1}$	0.36^{***}	0.36^{***}	0.35^{***}	0.34^{***}	0.34^{***}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Δlog(Sales)$\times$100	5.46^{***}	5.47^{***}	5.48^{***}	5.49^{***}	5.49^{***}
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
log(Age of firm)	-0.00	-0.01	-0.02	-0.03	-0.03
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
ΔN. Installations	1.87^{***}	1.88^{***}	1.88^{***}	1.88^{***}	1.88^{***}
	(0.69)	(0.69)	(0.69)	(0.69)	(0.69)
Fixed effects					
Country	Y	Y	Y	Y	Y
NACE two-digits	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
NACE two-digits$\times Year$	Y	Y	Y	Y	Y
Num. obs.	27,177	27,177	27,177	27,177	27,177
R^2	0.12	0.12	0.12	0.12	0.12
AIC	258,990.99	258,967.75	258,954.33	258,949.49	258,946.25
BIC	262,340.72	262,317.48	262,304.06	262,299.22	262,295.98
Log Lik.	-129,087.49	-129,075.88	-129,069.17	-129,066.75	-129,065.12

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 10: The analysis covers the full sample period from 2013 to 2021, with the dependent variable being the annual change in the logarithm of emissions (Δlog(e)$\times$100). The explanatory variables include: debt-to-total-assets ratio (leverage), fixed assets, cash holdings, return on assets (ROA), firm age, a dummy variable for listed companies, total assets, changes in the number of installations, and growth of sales. This table compares the effects of different policy stringency specifications depending on the planning horizon: contemporaneous (Current PS as in 4), 3-years, 5-years, 7-years and 10-years (corresponding to our benchmark measure). The variables are lagged by one year to account for potential endogeneity. Standard errors are clustered at the firm level and reported in parentheses. All independent variables are standardized for comparability across coefficients.

References

Abrell, J., Cludius, J., Lehmann, S., Schleich, J., and Betz, R. (2022). Corporate emissions-trading behaviour during the first decade of the eu ets. *Environmental and Resource Economics*, 83(1):47–83.

Alam, M. S., Safiullah, M., and Islam, M. S. (2022). Cash-rich firms and carbon emissions. *International Review of Financial Analysis*, 81:102106.

Allcott, H. and Greenstone, M. (2012). Is there an energy efficiency gap? *Journal of Economic Perspectives*, 26(1):3–28.

Apergis, N., Eleftheriou, S., and Payne, J. E. (2013). The relationship between international financial reporting standards, carbon emissions, and rd expenditures: Evidence from european manufacturing firms. *Ecological Economics*, 88:57–66.

Back, K. (2010). Martingale pricing. *Annual Review of Financial Economics*, 2:235–250.

Baltagi, B. (2021). *Econometric Analysis of Panel Data*. 6th ed. Springer.

Bartram, S. M., Hou, K., and Kim, S. (2022). Real effects of climate policy: Financial constraints and spillover. *Journal of Financial Economics*, 143(1):668–696.

Baudry, M., Faure, A., and Quemin, S. (2021). Emissions trading with transaction costs. *Journal of Environmental Economics and Management*, 108:102468.

Benkraiem, R., Shuwaikh, F., Lakhal, F., and Guizani, A. (2022). Carbon performance and firm value of the world's most sustainable companies. *Economic Modelling*, 116:106002.

Bergé, L. (2018). Efficient estimation of maximum likelihood models with multiple fixed-effects: the r package fenmlm. Technical report, Department of Economics at the University of Luxembourg.

Bijnens, G. and Swartenbroek, C. (2022). Carbon emissions and the untapped potential of activity reallocation: Lessons from the eu ets. Economic Review No. 1, National Bank of Belgium.

Bissoondoyal-Bheenick, E., Brooks, R., and Do, H. X. (2023). Esg and firm performance: The role of size and media channels. *Economic Modelling*, 121:106203.

Bloom, N., Genakos, C., Martin, R., and Sadun, R. (2010). Modern management: Good for the environment or just hot air? *Economic Journal*, 120(544):551–572.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Calel, R. (2020). Adopt or innovate: Understanding technological responses to cap-and-trade. *American Economic Journal: Economic Policy*, 12(3):170–201.

Cantillon, E. and Slechten, A. (2018). Information aggregation in emissions markets with abatement. *Annals of Economics and Statistics*, (132):53–79.

Carradori, O., Giuzio, M., Kapadia, S., Salakhova, D., and Vozian, K. (2023). Financing the low-carbon transition in europe. *ECB Working Paper Series*.

Chao, H. and Wilson, R. (1993). Option value of emission allowances. *Journal of Regulatory Economics*, 5(3):233–249.

Cludius, J., de Bruyn, S., Schumacher, K., and Vergeer, R. (2020). Ex-post investigation of cost pass-through in the eu ets - an analysis for six industry sectors. *Energy Economics*, 91:104883.

Coase, R. H. (1960). The problem of social cost. *Journal of Law and Economics*, 3:1–44.

Colmer, J., Martin, R., Muûls, M., and Wagner, U. J. (2024). Does pricing carbon mitigate climate change? firm-level evidence from the european union emissions trading system. *The Review of Economic Studies*, pages 1–36.

Croissant, Y. and Millo, G. (2008). Panel data econometrics in R: The plm package. *Journal of Statistical Software*, 27(2):1–43.

Dechezleprêtre, A., Gennaioli, C., Martin, R., Muûls, M., and Stoerk, T. (2022). Searching for carbon leaks in multinational companies. *Journal of Environmental Economics and Management*, 112:102601.

European Central Bank (2022). The macroprudential challenge of climate change. Working Paper Research Project Team on climate risk monitoring, European Central Bank and European Systemic Risk Board.

Ferrell, A., Liang, H., and Renneboog, L. (2016). Socially responsible firms. *Journal of Financial Economics*, 122(3):585–606.

Gangadharan, L. (2000). Transaction costs in pollution markets: An empirical study. *Land Economics*, 76:601–614.

Haas, R. D., Martin, R., Muûls, M., and Schweiger, H. (2025). Managerial and financial barriers to the green transition. *Management Science*, 71(4):2751–3636.

Huij, J., Laurs, D., Stork, P. A., and Zwinkels, R. C. (2024). Pricing pollution: Asset-pricing implications of the eu emissions trading system. *Available at SSRN 5145959*.

Huisman, R. and Kiliç, M. (2015). Time variation in european carbon pass-through rates in electricity futures prices. *Energy Policy*, 86:239–249.

Ishikawa, J. and Okubo, T. (2017). Greenhouse-gas emission controls and firm locations in north–south trade. *Environmental and Resource Economics*, 67:637–660.

Kalantzis, F., Khalid, S., Solovyeva, A., and Wolski, M. (2024). Firms' response to climate regulations. IMF Working Papers 24/135, International Monetary Fund.

Khalid, F., Sun, J., Guo, J., and Srivastava, M. (2023). Green corporate image: Assessing the effects of climate change management practices on corporate reputation. *Corporate Social Responsibility and Environmental Management*, 31(3):1786–1801.

Kreutzer, J. (2006). Cap and trade: A behavioral analysis of the sulfur dioxide emissions market. *New York University Annual Survey of American Law*, 62:125–162.

Leszczensky, L. and Wolbring, T. (2019). How to deal with reverse causality using panel data? recommendations for researchers based on a simulation study. *Sociological Methods & Research*, 51(2):837–865.

Letout, S. (2022). Corporate Micro-Data in the EU Emission Trading System. Working Paper Research JRC127805, Publications Office of the European Union.

Martin, R., Muuls, M., de Preux, L., and Wagner, U. J. (2012). Anatomy of a paradox: Management practices, organizational structure and energy efficiency. *Journal of Environmental Economics and Management*, 63(1):208–223.

Martin, R., Muûls, M., and Wagner, U. J. (2015). Trading behavior in the eu emissions trading scheme. In Gronwald, M. and Hintermann, B., editors, *Emissions Trading as a Policy Instrument: Evaluation and Prospects*. MIT Press.

Meinerding, C., Shi, M., and Zhang, Y. (2024). The impact of climate policies on financial markets: Evidence from the eu carbon border adjustment mechanism. *Available at SSRN*.

Montero, J. P., Sanchez, J. M., and Katz, R. (2002). A market-based environmental policy experiment in chile. *Journal of Law and Economics*, 45:267–287.

Murphy, J. J. and Stranlund, J. K. (2007). A laboratory investigation of compliance behavior under tradable emissions rights: Implications for targeted enforcement. *Journal of Environmental Economics and Management*, 53:196–212.

OECD (2023). *Effective Carbon Rates 2023: Pricing Greenhouse Gas Emissions through Taxes and Emissions Trading*. OECD Series on Carbon Pricing and Energy Taxation. OECD Publishing.

Ortiz, M., López, L.-A., and Cadarso, M. (2020). Eu carbon emissions by multinational enterprises under control-based accounting. *Resources, Conservation and Recycling*, 163:105104.

Ovaere, M. and Proost, S. (2022). Cost-effective reduction of fossil energy use in the european transport sector: An assessment of the fit for 55 package. *Energy Policy*, 168:113085.

Patala, S., Juntunen, J. K., Lundan, S., and Ritvala, T. (2021). Multinational energy utilities in the energy transition: A configurational study of the drivers of fdi in renewables. *Journal of International Business Studies*, 52:930–950.

Pierce, J. R. and Schott, P. K. (2012). A concordance between ten-digit us harmonized system codes and sic/naics product classes and industries. *Journal of Economic and Social Measurement*, 37(1-2):61–96.

Pinkse, J., Demirel, P., and Marino, A. (2024). Unlocking innovation for net zero: constraints, enablers, and firm-level transition strategies. *Industry and Innovation*, 31(1):16–41.

Prosperi, L. and Zanin, L. (2024). A modelling framework for equity portfolio projections under different carbon price scenarios. *Journal of Climate Finance*, 6:100033.

Pryor, J., Agnolucci, P., de Oca Leon, M. M., Fischer, C., and Heine, D. (2023). Data for a Greener World: A Guide for Practitioners and Policymakers. Technical report, IMF.

Quemin, S. and Trotignon, R. (2021). Emissions trading with rolling horizons. *Journal of Economic Dynamics and Control*, 125:104099.

Ren, S., He, D., Zhang, T., and Chen, X. (2019). Symbolic reactions or substantive pro-environmental behaviour? an empirical study of corporate environmental performance under the government's environmental subsidy scheme. *Business Strategy and the Environment*, 28(6):1148–1165.

Rubin, J. D. (1996). A model of intertemporal emission trading, banking, and borrowing. *Journal of Environmental Economics and Management*, 31:269–286.

Sandoff, A. and Schaad, G. (2009). Does eu ets lead to emission reductions through trade? the case of the swedish emissions trading sector participants. *Energy Policy*, 37:3967–3977.

Schennach, S. M. (2000). The economics of pollution permit banking in the context of title iv of the 1990 clean air act amendments. *Journal of Environmental Economics and Management*, 40(3):189–210.

Taschini, L. (2021). Flexibility premium of emissions permits. *Journal of Economic Dynamics and Control*, 126(1):1–15.

Trinks, A., Mulder, M., and Scholtens, B. (2020). An efficiency perspective on carbon emissions and financial performance. *Ecological Economics*, 175:106632.

Vidovic, D., Marmier, A., Zore, L., and Moya, J. (2023). *Greenhouse gas emission intensities of the steel, fertilisers, aluminium and cement industries in the EU and its main trading partners.* Number JRC134682. Publications Office of the European Union, Luxembourg.

Wooldridge, J. (2010). *Econometric Analysis of Cross–Section and Panel Data.* 2nd edition. MIT Press.

World Bank Group (2024). State and Trends of Carbon Pricing 2024. Technical report, World Bank Group.

Yoon, B., Filipski, M., Landry, C. E., and Yoo, S. J. (2024). Endowment effects, expectations, and trading behavior in carbon cap and trade. *Energy Economics*, 139:107927.

Zanin, L. (2023). A flexible estimation of sectoral portfolio exposure to climate transition risks in the european stock market. *Journal of Behavioral and Experimental Finance*, 39:100824.

Zanin, L. (2025). Corporate carbon emissions and financial performance: A flexible copula-based model to address non-random sample selection. *Economics Letters*, 247(2):112188.

Zhang, S. (2023). Carbon Returns Across the Globe. *Journal of Finance*, 1:196–212.