Carbon Pricing and Investment

James R. Brown*, Gustav Martinsson†, Per Strömberg‡, Christian Thomann§

This version: May 10, 2026

Abstract

How does carbon pricing affect capital investment in emissions-intensive firms? While standard arguments predict disinvestment and relocation, carbon pricing also changes the relative return to investing in cleaner technologies. We study this tension using detailed firm-level data from Swedish manufacturing over 2000–2019, a period in which effective carbon emission costs rose by about 400 percent. Despite a significant decline in operating margins among high emitting firms, we find that carbon pricing increases capital investment in the most exposed industries. For firms in the highest emission intensity decile, a 10 percent increase in the firm-level cost of CO_2 emissions is associated with a 1.7 percent increase in investment. The response is driven by increased abatement capital and green R&D and is concentrated among firms with strong internal financial capacity. We find no comparable investment increase in high-emission industries outside Sweden. Our results show that sufficiently high and credible carbon prices can induce lumpy capital reallocation in the sectors central to decarbonization.

Keywords: Carbon pricing, Climate policy, Investment, Environmental taxes
JEL codes: Q53, Q54, G31

*Brown is at Texas A&M University, Mays Business School, Department of Finance, jrbrown@tamu.edu
†Stockholm University, SHoF & HOSS, gustav.martinsson@sbs.su.se
‡Stockholm School of Economics, CEPR, ECGI, SHoF, & HOSS, per.stromberg@hhs.se
§Royal Institute of Technology, SHoF, & HOSS, christian.thomann@hhs.se

1 Introduction

A central economic question in the transition to a low-carbon economy is how firms reallocate capital when environmental externalities are priced. Standard theory predicts that higher input costs reduce profitability and may contract production, yet price signals are also the primary mechanism through which market economies induce technological upgrading. In the context of carbon pricing, these forces point in opposite directions: higher carbon prices may discourage investment and induce relocation to less regulated jurisdictions (e.g., Ederington et al., 2005, Bartram et al., 2022), but they may also increase the return to cleaner technologies and accelerate capital reallocation (e.g., Popp, 2002, Acemoglu et al., 2016). How carbon pricing ultimately impacts real investment in emissions-intensive firms remains an open empirical question.

This paper studies how carbon pricing affects capital investment using detailed firm-level data from the Swedish manufacturing sector over the period 2000–2019. Sweden provides a uniquely informative setting. It combines rich micro data on investment and emissions with one of the highest and most sharply increasing carbon price paths in the world. After 2014, the marginal cost of emitting carbon faced by manufacturing firms rose by about 250 percent, reaching levels comparable to prominent estimates of the social cost of carbon (e.g., Nordhaus, 2019).[1] This sharp and policy-driven increase allows us to observe firm behavior when carbon pricing moves from being a modest operating expense to a material component of production costs.

Figure 1 shows how carbon pricing and manufacturing investment evolve in Sweden over the 2000–2019 period. Despite the sharp increase in the effective carbon price after 2014, aggregate manufacturing investment (relative to sales) is broadly flat. In sharp contrast, capital investment in the highest-emitting manufacturing industries increases by more than 80 percent as sector-specific carbon tax exemptions are phased out.[2] As a result, the share

[1] Sweden's carbon tax rate is consistently among the highest in the world (second highest as of 2025, see World Bank, 2025). However, these levels are sharply lower than recent estimates of the social cost of carbon in Bilal and Känzig (2026).

[2] We classify firms as high-emitting if they operate in a four-digit NACE sector in the top decile of carbon intensity. This measure is developed in Martinsson et al. (2024) and is based on the ratio of aggregate CO_2 emissions to PPI-adjusted sales for each four-digit sector in 1990, the year prior to the introduction of the

of total manufacturing investment accounted for by high-emitting industries increases from roughly 25 percent in 2000 to more than 33 percent by the end of the sample period. These patterns suggest that higher carbon prices may spur, rather than depress, capital investment in the most exposed firms.

We formalize this relationship by estimating how firm-level investment responds to changes in the firm-specific marginal cost of carbon emissions. The richness of the data allows us to estimate highly saturated specifications including firm and four-digit industry-by-year fixed effects. We first show that carbon pricing significantly reduces operating margins, particularly among high-emitting firms, consistent with limited pass-through of carbon costs to output prices (Ganapati et al., 2020). Despite this reduction in operating margins, we find a positive and statistically significant elasticity of investment with respect to the marginal cost of emitting carbon for high-emitting firms. A 10 percent increase in the marginal cost of carbon emissions is associated with a 1.7 percent increase in capital investment. The effect is economically larger when allowing for lagged investment responses and is statistically indistinguishable from zero for low-emission firms.

To examine the nature of this investment response, we exploit detailed data on environmental investment expenditures for a subset of firms. Abatement investment responds even more strongly to carbon pricing: in the highest-emission firms, the elasticity of abatement investment with respect to the marginal cost of carbon emissions is 0.700. High-emission firms also increase abatement investment as a share of total capital expenditures and expand R&D spending, including R&D directly related to emissions reduction. These findings indicate that higher carbon prices induce capital reallocation toward cleaner technologies rather than scale expansion of emissions-intensive capital.[3]

Next, we exploit the sharp increase in Swedish carbon prices after 2014 as a quasi-experimental shock and estimate difference-in-differences specifications comparing firms in the top decile of emissions intensity to other manufacturing firms. We confirm

carbon tax.

[3]Focusing solely on investment explicitly labeled "abatement investment" likely understates the full effect, as new capital is generally more energy-efficient and less polluting than existing capital (e.g., Xepapadeas and de Zeeuw, 1999).

a significant differential increase in capital expenditures among the dirtiest firms in the post-2014 period, consistent with lumpy capital adjustment triggered by a sufficiently large cost shock (and consistent with the aggregate evidence in Figure 1).

We then investigate the opportunity cost and funding source of the new capital investment. Sorting firms by internal and external financing capacity prior to the carbon price increase, we find that the investment response is driven by high-emission firms with strong internal financial resources. These firms reduce dividend payouts following the carbon price increase in magnitudes sufficient to fund the additional capital expenditures. We find similar patterns when sorting firms by ex ante internal cash flow. In contrast, we do not observe systematic differences in investment responses based on proxies for access to external finance. The evidence highlights the central role of internal resources in financing capital upgrading in response to higher carbon prices.

To address the concern that the Swedish carbon price increase coincided with a broader investment boom in high-emission industries, we assemble industry-level investment data for four-digit manufacturing industries across European Union member states. High-emitting industries in other EU countries operate under similar demand conditions and face comparable technological opportunities. We find no comparable increase in investment in high-emission industries outside Sweden over the 2015–2019 period. This evidence supports a causal interpretation linking higher effective carbon prices to increased capital spending.

We contribute to several related literatures on the real effects of climate policy. First, we advance the literature on the economic consequences of market-based emissions regulations (e.g., Martin et al., 2014, Fowlie et al., 2016, Bartram et al., 2022, Colmer et al., 2025). Most of this research focuses on how various climate policies affect emissions, energy use, or (aggregate) industry dynamics. In related work, Martinsson et al. (2024) show that higher carbon prices in Sweden are associated with reductions in CO_2 emissions in aggregate, but that industries with higher abatement costs – which tend to be the highest-emitting industries – have a lower emission sensitivity to carbon pricing.[4] Our work extends these findings

[4]Specifically, Martinsson et al. (2024) estimate a CO_2 emissions to carbon pricing elasticity for the overall manufacturing sector of around two. However, the elasticity for low emitting industries (where emissions likely are easier/cheaper to abate) is almost seven, compared to just above one for high emitting industries

by uncovering a direct micro-level mechanism through which carbon pricing can reduce emissions: new capital investment by high-emitting firms.[5] Our results also relate to recent theoretical work comparing carbon pricing to green finance as mechanisms for internalizing climate externalities. Pedersen (2026) develops a unifed model showing that sufficiently large increases in the cost of capital for carbon-intensive firms can replicate the effects of an optimal carbon tax; we provide complementary empirial evidence that sufficiently high carbon prices themselves induce the capital reallocation required for decarbonization.

Our study provides new evidence on how environmental taxes affect firm-level investment decisions, a margin on which existing evidence is limited and mixed. Jacob and Zerwer (2024) document a negative investment response to emission taxes in Spain, France, and Ireland, driven by tax incidence and financial flexibility rather than pollution intensity. In contrast, Colmer et al. (2025) find a positive capital stock response in Phase 2 of the EU ETS, while Bolton et al. (2023) report no investment effect in Phase 3, possibly reflecting anticipatory adjustment. We show that higher carbon pricing can substantially increase capital spending, particularly among the most exposed firms with sufficient internal resources.[6] Our setting also allows us to measure investment and firm-specific marginal carbon costs over two decades, enabling more precise long-run elasticity estimates than in prior work.

Our work also highlights the importance of focusing specifically on high-emitting (polluting) sectors to evaluate the effects of carbon pricing. Many empirical studies on the impact of environmental regulation suffer from so called *aggregation bias* (e.g., Ederington et al., 2005, Levinson and Taylor, 2008), wherein the consequences of environmental policy are under-stated (or missed entirely) because the costs of the policy are small relative to aggregate manufacturing costs or income.[7] Consistent with this idea, we find a modest

(where 80–85 percent of all emissions are located and where abatement likely is more costly).

[5]Moreover, we show that these investments only took off at the end of the sample period, after carbon prices sharply increased. These investments arguably take longer to implement before emission reductions are realized, which can explain why the Martinsson et al. (2024) study (which ends in 2015) finds a modest emission response in the highest polluting sectors.

[6]Consistent with Fang et al. (2025) and Lanteri and Rampini (2025), financially constrained firms invest less in abatement capital, partly due to its lower collateralizability.

[7]For example, this bias can explain the relative lack of empirical support for the *Pollution Haven Hypothesis* (e.g., Ederington et al., 2005, Levinson and Taylor, 2008). Ederington et al. (2005) show that some industries do relocate to low from high environmental regulatory settings; however, these "footloose" industries have low transportation costs and less fixed assets in place, and most importantly are not particularly pollution

investment response to carbon pricing in the full sample of manufacturing firms, but a substantial response in the top decile of polluting industries. In this way, we uncover a larger real investment response to market based climate policy than is reported in related studies.

We also contribute to the literature on environmental taxes and investment in pollution abatement technologies. For example, Calel and Dechezleprêtre (2016) find that the EU ETS facilitated low-carbon innovation in regulated firms. Brown et al. (2022) find that higher pollution taxes lead to more R&D investment in high-pollution firms. We show that carbon-intensive firms in Sweden respond to higher carbon prices by substantially increasing R&D spending, including R&D spending directly related to pollution abatement.

Finally, our work relates to the broader macroeconomic literature on the optimal design and aggregate effects of carbon pricing (e.g., Nordhaus, 1992, Golosov et al., 2014). These models hinge on how firms adjust capital in response to carbon emission costs. We provide micro-level evidence on this adjustment margin, showing that sufficiently high local carbon taxes can induce meaningful investment responses in emissions-intensive firms—consistent with recent work highlighting conditions under which subnational carbon pricing can be effective (e.g., Conte et al., 2025, Bilal and Känzig, 2025). Furthermore, while Känzig (2025) emphasizes the distributional consequences of carbon pricing across households, our findings highlight heterogeneity across firms: investment responses are concentrated among cash-rich, high-emission firms with the internal resources to finance capital upgrading.

Overall, the evidence indicates that sufficiently high and credible carbon prices induce emissions-intensive firms to undertake lumpy capital adjustments and reallocate internal resources toward cleaner technologies. Achieving deep decarbonization requires precisely such large-scale capital adjustment in sectors characterized by long-lived assets and high fixed costs. Rather than triggering disinvestment or relocation, carbon pricing in this setting accelerates capital upgrading in the sectors central to the low-carbon transition, operating through standard investment and corporate finance channels.

intensive. The most polluting sectors do not relocate due to higher environmental compliance costs because of very high fixed costs of moving.

2 Carbon Pricing and Firm Investment Responses

2.1 Adjustment margins in the literature

Carbon pricing increases the marginal cost of emissions-intensive production. Firms may respond along several margins. They can adjust operations (e.g., input substitution or energy efficiency: Martin et al., 2014, Fowlie et al., 2016), innovate in cleaner technologies (e.g., Popp, 2002, Aghion et al., 2016, Brown et al., 2022), pass costs to consumers (Ganapati et al., 2020), relocate activity across jurisdictions (Ederington et al., 2005, Dechezleprêtre and Sato, 2017), or undertake capital investment to replace emissions-intensive assets (Colmer et al., 2025, Jacob and Zerwer, 2024).

Which margin dominates depends on technological constraints and industry characteristics. Manufacturing emissions are highly concentrated in sectors characterized by large fixed assets and long-lived capital. Prior evidence shows that these sectors exhibit relatively low short-run emissions elasticities (Martinsson et al., 2024), suggesting limited scope for operational adjustment. In such settings, capital upgrading may be the primary adjustment margin.

Capital adjustment is lumpy and partially irreversible (Dixit and Pindyck, 1994). When switching technologies requires large fixed costs, firms may delay adjustment until carbon prices become sufficiently high and credible. In addition, because carbon pricing compresses operating margins, financially constrained firms may be unable to undertake capital-intensive upgrading even when it is privately efficient (Döttling and Rola-Janicka, 2025, Lanteri and Rampini, 2025). These considerations motivate a framework in which carbon pricing affects investment through profitability, technology reallocation, and financing channels.

2.2 Mechanism

Consider a firm that produces output using capital that differs in emissions intensity. An increase in carbon pricing raises the effective marginal cost of emissions-intensive production. This affects investment decisions through two forces.

First, higher carbon emission costs reduce operating margins and increase the user cost of emissions-intensive capital. If this profitability effect dominates, total investment declines.

Second, carbon pricing increases the relative return to emissions-reducing capital by lowering future carbon liabilities. Firms may respond by replacing emissions-intensive assets with cleaner technologies. If this reallocation effect dominates scale contraction, total investment increases, even as profitability falls.

Because capital adjustment is lumpy and partially irreversible, firms may only respond when carbon prices rise sufficiently to justify fixed switching costs. Financial constraints may further limit adjustment: if carbon pricing reduces internal funds, firms with weaker balance sheets may be unable to undertake large capital expenditures even when the long-run return is positive.

Exposure to carbon pricing scales with baseline emissions intensity. For a given carbon price increase, firms in emissions-intensive industries experience larger effective cost shocks. In the empirical analysis, we capture this heterogeneity using a pre-determined industry-level measure of emissions intensity.

2.3 Testable predictions

The framework yields four testable predictions.

Prediction 1 (Total investment). The effect of carbon pricing on total investment is theoretically ambiguous. Higher marginal emissions costs reduce profitability but increase the return to cleaner capital. The net effect depends on whether scale contraction or capital upgrading dominates.

Prediction 2 (Heterogeneity by emissions intensity). Because exposure scales with baseline emissions intensity, investment responses should be larger among firms in the most emissions-intensive industries.

Prediction 3 (Abatement investment). Carbon pricing increases the relative return to emissions-reducing technologies. Investment in emissions-treatment and emissions-prevention capital should increase with carbon prices, particularly among firms in the high emitting industries.

Prediction 4 (Financial capacity). Investment responses should be stronger among firms with greater internal financial capacity. Financially constrained firms may be unable to undertake lumpy capital adjustment even when carbon prices rise.

3 Institutional Setting

3.1 Carbon pricing in Sweden

Sweden introduced a carbon tax in 1991, levied per ton of carbon dioxide (CO_2) emissions from fossil fuel use. Over time, effective carbon tax rates increased substantially, making Sweden one of the highest carbon-pricing jurisdictions globally (World Bank, 2025). During our sample period (2000–2019), manufacturing firms were exposed to the Swedish carbon tax and, for a subset of firms, to the European Union Emissions Trading System (EU ETS).

A central institutional feature is the phase-out of carbon tax exemptions for manufacturing firms (NACE 10–33). Many energy-intensive manufacturing industries initially received reduced tax rates to mitigate competitiveness concerns. Although minor adjustments occurred earlier, the overwhelming majority of the exemption removal took place after 2014 (see Figure B.1). This reform generated a discrete and economically large increase in effective marginal carbon costs for manufacturing firms, raising them by about 250 percent over a short period.

Figure 2 plots marginal and average carbon prices separately for firms subject only to the Swedish carbon tax and for firms eventually regulated under the EU ETS. For firms taxed exclusively under the Swedish system, average and marginal carbon prices are nearly identical, reflecting the absence of free allowances. In contrast, for EU ETS firms, the relationship between average and marginal prices varies over time. During 2000–2007, when all emissions were taxed under the Swedish system, average prices exceed marginal prices. After 2008, the introduction of free allocation under the EU ETS lowers average carbon payments relative to emissions, while the marginal cost of emitting equals the market price of allowances. As a result, marginal prices exceed average prices for these firms in the ETS period.

Finally, we convert Swedish carbon prices to U.S. dollars per ton and benchmark them against estimates of the social cost of carbon (SCC) from Nordhaus (2019) in Figure 3.[8] Beginning in 2015, effective carbon emission costs for non–EU ETS manufacturing firms rise from approximately \$43 per ton—close to the DICE optimal SCC—to about \$125 per ton. Firms with some plants regulated under the EU ETS face lower average costs, reaching approximately \$82 per ton. These magnitudes indicate that the post-2014 increase moves Swedish carbon pricing into a range comparable to leading estimates of socially optimal carbon prices. Figure 3 also shows that EU ETS prices remain below Swedish carbon tax levels for most of the sample, with the sharp rise in EUA prices occurring after our study period.

The key source of policy variation arises from the phasing out of exemptions. Because exemption removal applied at the national level and was not targeted to individual firms, exposure was determined by regulatory classification rather than contemporaneous investment decisions. The magnitude of the marginal cost increase, however, varies with baseline emissions intensity: firms in emissions-intensive industries experience larger increases in costs of carbon emissions. Since emissions intensity is persistent and reflects underlying production technology, this interaction between regulatory exposure and pre-existing emissions intensity provides a natural source of variation for identifying investment responses.

3.2 Measuring climate mitigation investment

A central empirical challenge in studying carbon pricing and capital reallocation is measuring investment that is specifically directed toward reducing emissions. In this section, we describe

[8] We consider three different SCC estimates: i) the DICE optimal (blue short dashed line, lowest), ii) price needed to limit global warming to under 2°C (blue medium dashed line, middle), and iii) the price required to stay below 1.5°C (blue long dashed line, highest). The values are for year 2020 from Table 1 in Nordhaus (2019).

the investment measures available in our data and discuss their properties as measures of climate mitigation capital expenditure.

Our primary measure of climate mitigation investment comes from the annual Environmental Protection Expenditure Survey conducted by Statistics Sweden, which follows the Classification of Environmental Protection Activities (CEPA) framework developed by Eurostat (European Parliament and Council, 2011). CEPA distinguishes between two broad categories of environmental capital expenditure: end-of-pipe investments, which treat pollution after it is generated (e.g., filters or scrubbers), and integrated or prevention investments, which reduce emissions by modifying the production process itself. Our abatement investment variable, which we denote *Abate Inv*, captures both categories and is scaled by sales. Critically, for prevention investments, firms are instructed to report only the *incremental* cost of the cleaner alternative relative to a conventional investment that would otherwise have been made. The full replacement cost of the cleaner equipment is therefore not captured.

This survey design has a direct implication for how we interpret our abatement investment estimates. Because prevention expenditures reflect only the marginal environmental premium rather than the full cost of the cleaner asset, *Abate Inv* understates the true capital expenditure attributable to climate mitigation purposes. A concrete illustration from within our sample period makes this clear. In September 2019, SCA announced a SEK 7.5 billion investment at its Obbola kraftliner mill in Umeå — a firm operating in one of the D10 industries in our sample (NACE 1712, manufacture of paper and paperboard) and one of the largest industrial capital investments in Sweden during our sample period (SCA, 2019). Of the total, approximately SEK 1 billion was explicitly earmarked for environmental improvements, including the elimination of roughly 8,000 cubic meters of annual oil consumption and upgrades to water treatment capacity, with the full investment bringing SCA's industrial processes to 97 percent fossil-free. Under CEPA reporting conventions, a firm making this investment would report only the SEK 1 billion environmental premium — the marginal cost of choosing the cleaner configuration over a conventional alternative — while the remaining SEK 6.5 billion in capital expenditure, which physically embodies the transition to near-fossil-free production, would be recorded only in total capex. A firm that replaces emissions-intensive assets in this way would therefore appear to have modest abatement investment relative to large total capital expenditure, exactly the pattern we observe in our data for high-emitting firms.The degree of understatement scales with the cost gap between clean and conventional alternatives, which is largest precisely in the high-emitting industries at the center of our analysis. Our elasticity estimates for abatement investment should therefore be interpreted as lower bounds on the true investment response to carbon pricing.

This measurement property motivates our use of two complementary dependent variables throughout the empirical analysis. Total capital expenditure (*Inv*) captures the full investment response of firms to higher carbon prices without taking a stand on the purpose of individual investments. Abatement investment (*Abate Inv*) isolates the directional reallocation toward emissions-reducing capital, but understates its magnitude. When both measures respond positively to carbon pricing — as we find for high-emitting firms — this provides stronger evidence of climate-motivated capital reallocation than either measure alone. The fact that the share of abatement investment in total capital expenditure also increases (Table 7, columns 6–7) further supports the interpretation that higher carbon prices induce compositional upgrading rather than scale expansion, even accounting for the conservative nature of the abatement investment measure.

4 Data and Descriptive Evidence

4.1 Sample construction

We construct the main sample by combining five administrative datasets. The primary source is the annual capital investment survey conducted by Statistics Sweden, covering 2000–2019. We merge these data with: (i) firm- and plant-level CO_2 emissions from the Swedish Environmental Protection Agency (SEPA); (ii) abatement investment data from the Environmental Protection Expenditure Survey (Statistics Sweden); (iii) group-level R&D investment data from consolidated accounts; and (iv) firm balance sheet and income statement data from the Serrano dataset. Appendix section A provides detailed descriptions of each source. Firm-level observations are consolidated to the corporate group level.

The baseline sample - defined as the intersection of capital investment, CO_2 emissions, and firm financial statement data — contains just under 10,000 firm-year observations over 2000–2019. Abatement investment data are available from 2002 onward and cover a smaller set of firms, resulting in approximately 2,000 observations. The R&D sample comprises roughly 5,200 firm-years.

4.2 Industry-level emissions intensity

Carbon emissions are highly concentrated across manufacturing industries. We classify firms based on four-digit NACE industry-level emissions intensity, defined as aggregate CO_2 emissions divided by producer-price-adjusted sales in 2000. Industries are ranked by this measure and divided into deciles, from the highest-emissions-intensity industries (*D10*) to the lowest (D1). Using PPI-deflated sales ensures that the emissions-to-sales ratio approximates emissions per unit of output rather than reflecting variation in output prices.[9] We group industries into three categories: low (*D1–D4*), mid (*D5–D9*), and high (*D10*) emissions intensity.[10]

Table 1 documents substantial heterogeneity across deciles. In 2000–2002, *D10* industries account for 83 percent of manufacturing emissions; by 2017–2019, this share rises to 89 percent. In terms of aggregate output, *D10* industries account for 22.5% of output at the beginning of the time period, and 17.4% in 2017–2019. Thus, the dirtiest industries account for a much larger share of pollution than output. Emissions are therefore highly concentrated relative to production.

Panel A of Table 1 reports time-series changes in emissions intensity. In 2000–2002, emissions intensity in *D10* industries is 28 times higher than in *D1–D4* and 8 times higher than in *D5–D9*. Emissions intensity declines across all groups over time. For *D10* industries,

[9] Because most manufacturing firms are exporters, revenues are sensitive to fluctuations in world prices and exchange rates. PPI-deflation mitigates this concern.

[10] Eighteen industries are classified in *D10* based on 2000 data; 14 of these are also in *D10* when using 1990 emissions intensity as in Martinsson et al. (2024). Results are robust to alternative baseline years.

it falls from 0.0235 to 0.0152 between 2000–2002 and 2017–2019 (a 35 percent decline). Because emissions intensity declines more sharply in lower-emission industries, emissions become increasingly concentrated in *D10* over time. By the end of the sample, emissions intensity in *D10* is 82 (15) times that of *D1–D4* (*D5–D9*).

Figure 4a, Figure 4b, and Figure 4c illustrate these dynamics. Emissions intensity declines steadily in lower-emission industries throughout the sample (72 percent lower in 2019 relative to 2000). High-emission industries experience reductions prior to the financial crisis (approximately 30 percent), but little additional decline thereafter; emissions intensity in *D10* is largely flat after 2012–2013.

Panels B and C of Table 1 relate the emissions-intensity classification to alternative industry characteristics used in the literature. In the absence of direct measures of marginal abatement costs (Gillingham and Stock, 2018), we examine pollution abatement costs and expenditures (PACE) (e.g., Becker, 2005) and asset mobility (e.g., Ederington et al., 2005). All *D10* industries exhibit high PACE, and 61 percent are characterized by both high PACE and low mobility.[11]

Panel C further shows that 93 percent of *D10* industries are included on the EU carbon leakage list, primarily due to high emissions intensity.[12] Using U.S. PACE data yields similar classifications. Overall, the emissions-intensity deciles align closely with independent measures of abatement costs and regulatory exposure.

4.3 Firm-level characteristics

Table 2 reports summary statistics for the full sample (Panel A), firms in the high emitting industries (D10; Panel B), and firms in the less emitting industries (deciles 1–9; Panel C). On average, capital expenditures exceed explicitly classified abatement investment across firms. Relative to lower-emission firms, *D10* firms are larger and invest more in total capital and

[11] High PACE and low mobility are defined relative to industry medians; we follow (e.g., Ederington et al., 2005) and consider industries with high levels of fixed assets to total assets facing higher costs to move production.

[12] European Commission (2009) includes the initial carbon leakage list. Firms in a given four digit industry can be considered at risk of carbon leakage if it has i) high costs of carbon pricing (i.e., industries with high emission intensity ("Emission"), ii) high level of international competition (i.e., high levels of trade outside of the EU ("Trade only") or, iii) being exposed to both of these factors.

in abatement (both fixed capital and R&D). They exhibit lower general R&D intensity, rely less on long-term bank debt, and experience slower sales growth. EBIT margins and cash flows are similar across high- and low-emission industries.

4.4 Carbon prices and aggregate investment

Figure 1 plots aggregate capital investment-to-sales ratios (three-year moving averages) for the manufacturing sector (black dashed line), firms in high (D10, black solid line), and low emitting industries (D1–D9, grey dashed line). The figure also reports the average carbon price (grey dotted line, right axis).

Carbon prices remain relatively stable during 2000–2010 (approximately 0.22–0.25 SEK per kilogram CO_2), increase modestly in 2011–2014 (to roughly 0.35), and rise sharply after 2014 (to approximately 1.15 SEK per kilogram), representing an increase of about 250 percent between 2014 and 2019. During the period of relatively low and stable carbon prices (2000–2014), investment-to-sales ratios decline across manufacturing, with similar trends for high- and low-emission firms. Over this period, the investment ratio falls by 23 percent for manufacturing overall (16 percent for high emitting firms and 27 percent for low emitting firms).

After 2014, investment trends diverge. The investment-to-sales ratio increases by 83 percent for high emitting firms (from approximately 0.03 to 0.05), compared to a 16 percent increase for lower-emission industries (from 0.021 to 0.024). Figure B.2 presents indexed investment-to-sales ratios (normalized to 100 in 2000–2002). Investment declines similarly across groups through 2014 (approximately 35 percent for both high- and low-emission industries). After 2014, investment rises by 55 percent in high emitting industries and by 10 percent in low emitting industries. Over the full sample, investment-to-sales declines by 25 percent in lower-emission industries but increases by 22 percent in high emitting industries.

The shift in investment is reflected in the composition of aggregate manufacturing capital expenditure. The share of investment accounted for by high emitting industries increases from approximately 25 percent to 33 percent over the sample period (Figure 5a). In real terms, aggregate capital expenditures increase by 12 billion over the period, of which high emitting industries account for roughly 7 billion (Figure 5b). Finally, Figure 5c relates investment to internal finance. For high emitting firms, the investment-to-cash-flow ratio increases from 0.325 to 0.500 over the sample period. In contrast, the ratio declines for lower-emission industries. We next turn to formal regression analysis of these patterns.

5 Carbon Pricing and Firm Investment

5.1 Baseline specification

We estimate the relationship between carbon pricing and firm investment using a specification similar to Shapiro and Walker (2018) and Martinsson et al. (2024):

$$\ln(\mathrm{Inv}_{i,t}) = \alpha + \sum_{s=0}^{q} \beta_s \ln(C_{i,t-s}) + \gamma X_{i,t-1} + \eta_i + \eta_{j,t} + \epsilon_{i,t}. \tag{1}$$

The dependent variable, $\mathrm{Inv}_{i,t}$, is capital expenditure divided by sales for firm i in year t. The variable $C_{i,t}$ denotes firm-specific carbon emissions cost intensity, defined as the marginal cost of emitting CO_2 multiplied by total emissions and scaled by PPI-deflated sales. Lagged values of $C_{i,t}$ allow for delayed investment responses to changes in carbon pricing.[13]

Firm fixed effects η_i absorb time-invariant heterogeneity across firms. Industry-by-year fixed effects $\eta_{j,t}$ control for shocks common to firms within the same four-digit industry in a given year, including industry-specific demand and investment trends unrelated to carbon pricing. The vector $X_{i,t-1}$ includes lagged firm-level controls: cash flow, log total assets, long-term debt, and PPI-adjusted sales growth.

5.2 Carbon pricing and operating margins

Before turning to investment, we examine whether carbon pricing affects firm profitability, consistent with incomplete pass-through. We estimate a version of Equation 1 using only the contemporaneous carbon emission cost term ($s = 0$), replacing the dependent variable

[13] Investment decisions depend on the marginal cost of emissions; we therefore measure carbon pricing at the margin (Cropper and Oates, 1992).

with operating margins (EBIT divided by sales). Because EBIT can be negative, operating margins are normalized to lie between zero and one before being log-transformed.

Table 3 reports the results. Column 1 shows a statistically significant negative association between carbon pricing and operating margins. Increases in the marginal carbon emissions cost are associated with economically meaningful reductions in profitability.

Given substantial heterogeneity in emissions intensity across industries, we next estimate the specification separately for low-, medium-, and high-emission industries. For firms in low- and medium emitting industries (columns 2 and 3), the estimated coefficients are similar in magnitude to the full-sample estimate, though less precisely estimated. In contrast, column 4 shows that the effect for high emitting (D10) firms is nearly three times larger and highly statistically significant. For these firms, a 10 percent increase in carbon prices is associated with a 0.9 percent decline in EBIT-to-sales.

These results highlight two points. First, the profitability impact of carbon pricing varies systematically with emissions intensity. Second, the negative margin response for high-emission firms is consistent with incomplete pass-through of carbon emission costs.

5.3 Carbon pricing and capital investment

Table 4 reports estimates of Equation 1. Columns 1–4 include only the contemporaneous carbon emission cost term ($s = 0$), while columns 5–7 incorporate up to three lags.

Column 1, which includes only year fixed effects, yields an elasticity of 0.108. Adding firm fixed effects, four-digit industry-by-year fixed effects, and firm-level controls reduces the contemporaneous elasticity to 0.055 (column 4). This estimate implies that a 10 percent increase in carbon prices is associated with a 0.6 percent increase in investment. Columns 5–7 allow for delayed responses. The contemporaneous effect remains positive and statistically significant. When three lags are included (column 7), the cumulative elasticity is 0.123, approximately 60 percent larger than the contemporaneous estimate alone.

Table B.2 reports robustness checks. Alternative constructions of firm-level carbon emission cost intensity —using sales- or asset-weighted plant measures — yield similar results (columns 1–2). Scaling investment and carbon emission cost by total assets (column

3) or estimating the model at the plant level (column 4) does not materially alter the estimates. Including lagged investment ratios (columns 6–7) leaves the baseline elasticity largely unchanged.

5.4 Heterogeneous effects by emissions intensity

We next estimate Equation 1 separately by emissions-intensity group. Table 5 reports results for firms in *D1–D4* (columns 1–2), *D5–D9* (columns 3–4), and *D10* (columns 5–6), with contemporaneous specifications in odd-numbered columns and the full lag structure in even-numbered columns. Because the emissions-intensity classification is measured at the beginning of the sample period, heterogeneity results are not driven by endogenous sorting in response to carbon pricing.

For low- and medium-emission industries, the estimated elasticities are small and statistically indistinguishable from zero. In contrast, the response is economically large and precisely estimated for high emitting firms. The contemporaneous elasticity is 0.168 (column 5). Allowing for lags increases the cumulative elasticity to 0.309 (column 6), consistent with delayed adjustment.[14]

Table B.4 examines alternative industry classifications. Firms in high-abatement-cost industries exhibit a positive and significant investment response to carbon pricing, whereas firms in low-abatement-cost industries do not. The response is concentrated among firms in industries characterized by both high abatement costs and low asset mobility. Similarly, firms in industries included on the EU carbon leakage list display a significant response.

Finally, Table 6 shows that the strongest effects occur among firms that are both high-emitting (D10) and operate in high-abatement-cost industries. In contrast, firms in hard-to-abate or leakage-exposed industries that are not high-emitting exhibit small and statistically insignificant elasticities. Overall, the investment response to carbon pricing is concentrated in emissions-intensive and costly-to-abate sectors.

[14] We report results in Table B.3 with the contemporaneous marginal cost regressions (odd numbered columns in Table 5) using the same sample as in the even numbered columns to attain comparability.

5.5 Abatement and the composition of investment

For a subset of firms, we observe capital expenditures on emissions treatment and air emissions prevention equipment from the annual Environmental Protection Expenditure Survey conducted by Statistics Sweden.[15] We scale this varriable by sales and denote it as *Abate Inv*. We first re-estimate the baseline specification using the abatement sample and total capital investment as the dependent variable to ensure comparability. As reported in Table B.5, the investment-to-carbon-price elasticity in this subsample is 0.157, compared to 0.055 in the full manufacturing sample.

Columns 1–3 of Table 7 report estimates using *Abate Inv* as the dependent variable. The elasticity of abatement investment with respect to carbon pricing is 0.440 for the full subsample. Splitting by emissions intensity reveals strong heterogeneity: the elasticity is close to zero for firms in low emitting industries and 0.700 for firms in high emitting industries. Columns 4–5 examine abatement capital spending divided by total capital expenditures. Investment in abatement rise significantly faster among high emitting firms, while no systematic change is observed for lower-emission industries. The relative increase in the abatement spending suggests that the response reflects compositional upgrading rather than purely scale expansion.

Finally, columns 6–7 separates abatement investment into spending designated to treatment of actual pollution (*Treatment*) and the prevention of future of pollution (*Prevent*). The abatement spending appear to be driven by investment in preventing future pollution.

Taken together, these results indicate that the investment response to carbon pricing in high-emission industries reflects a substantial reallocation toward emissions-reducing capital.

5.6 Carbon pricing and R&D investment

We next examine whether carbon pricing affects investment in innovation activity. Using R&D expenditures scaled by sales (*R&D*) as the dependent variable, columns 1–3 of Table 8 report estimates analogous to the baseline investment specification. Sample coverage is

[15] The purpose of this survey is to capture environmental expenditures and therefore the sub-sample of firms covered are slightly more emitting than the average manufacturing firm and it begins in 2002.

substantially smaller than for capital investment.

For the full R&D sample, the estimated elasticity is close to zero and statistically insignificant. Splitting by emissions intensity reveals heterogeneity: the response is negligible for firms in low emitting industries (D1–D9, column 2), while firms in high emitting industries exhibit a positive and statistically significant elasticity (D10, column 3). For these firms, a 10 percent increase in carbon prices is associated with a 2.75 percent increase in R&D expenditures.

Columns 4–6 focus on R&D expenditures explicitly directed toward emissions abatement (*Abate R&D*). Because this measure is available for only about 150 firm-years, statistical power is limited. Nevertheless, for firms in high emitting industries, the estimated elasticity is 0.712 and statistically significant (column 6), while no systematic response is observed among lower-emission industries.

Taken together, the results indicate that the investment response to higher carbon prices in high-emission industries extends beyond physical capital to innovative activity, with particularly strong responses in emissions-related R&D.

6 Causal Evidence and Mechanisms

6.1 Quasi-experimental evidence and internal finance

We exploit the sharp increase in effective carbon prices beginning in 2015 as a quasi-experimental shock. Specifically, we compare investment responses of firms in high emitting industries (*D10*) to other manufacturing firms before and after the policy change. This event-based design complements the elasticity estimates by isolating discrete shifts in the carbon pricing regime and allows us to expand the sample beyond firms for which plant-level emissions data are available. We estimate the following difference-in-differences specification:

$$Inv_{i,t} = \sigma + \omega \cdot D10\ firm_i + \kappa \cdot Post_t + \phi(D10\ firm_i \cdot Post_t) + \epsilon_{i,t}. \tag{2}$$

In Equation 2, *D10 firm* equals one if the firm operates in a top-decile emissions-intensity industry. *Post* equals one for years 2015–2019 and zero for 2010–2014. Identification relies on the assumption that, absent the post-2014 carbon price increase, investment trends in *D10* and other manufacturing industries would have evolved similarly. Pre-2015 investment trends are comparable across groups, consistent with this assumption (Figure 1). The coefficient of interest, ϕ, captures the differential change in investment for *D10* firms in the post period.

We report estimates of Equation 2 for the full manufacturing sample in the first three columns of Table 9. In column 1, without fixed effects, both *D10 firm* and *Post* enter positively, indicating that high-emission firms invest at higher rates on average and that investment increases economy-wide after 2015. Most importantly, the interaction term is positive and statistically significant, indicating a differential post-2015 investment increase among D10 firms.

Including firm fixed effects absorbs time-invariant differences in investment levels across industries, while year fixed effects absorb aggregate investment shocks common to all firms. Because year fixed effects capture macroeconomic conditions, the identifying variation arises from differential changes across emissions-intensity groups within the same year. The interaction coefficient remains positive and statistically significant when these controls are included (columns 2 and 3). Robustness checks reported in Table B.7 confirm that results are similar when collapsing the data to one pre- and one post-period per firm and when restricting the sample to firms with emissions data.

We next examine whether internal financial capacity conditions the investment response. Our preferred proxy is whether the firm paid dividends during 2010–2014. We define *Div Firm* as an indicator equal to one for firms distributing dividends in the pre-period. We augment Equation 2 with interactions between *Div Firm*, *D10 firm*, and *Post*. The interaction between *D10 firm* and *Post* now captures the response of high emitting firms that did not distribute dividends prior to 2015.

The results (column 4 of Table 9) indicate that the differential post-2015 investment response among *D10* firms is concentrated among firms that distributed dividends prior to the policy change. High emitting firms that did not pay dividends exhibit no statistically significant post-period investment response.

One interpretation is that dividend-paying firms differ systematically in unobserved quality. An alternative interpretation is that dividend payments proxy for internal financial capacity. To distinguish between these explanations, we examine whether previously dividend-paying *D10* firms reduce payouts when investment increases. Using dividend payments scaled by cash flows as the dependent variable, columns 5–8 show that high emitting firms reduce dividend payouts relative to cash flows in the post period, and that this reduction is driven entirely by firms that paid dividends prior to 2015. The magnitude of the reduction is economically large and sufficient to finance the observed increase in capital expenditures.

Descriptive statistics in Table B.6 corroborate this pattern: the triple-difference estimates reflect a sharp increase in investment and a corresponding reduction in dividend payouts among previously dividend-paying *D10* firms. In contrast, non-dividend-paying *D10* firms exhibit little change in investment, and firms outside *D10* industries show no meaningful differential response.

We further consider alternative measures of financial capacity. We construct firm-level pre-period averages (2010–2014) of cash flow to assets and sort firms by whether they are above or below the median. We also examine proxies for access to external finance, including credit ratings and long-term debt ratios. In contrast to internal finance measures, proxies for external financing capacity do not generate differential post-2015 responses within *D10* industries. The estimated interaction coefficient remains similar in magnitude and significance when conditioning on these measures. This pattern suggests that internal liquidity, rather than external borrowing capacity, is central to financing the capital adjustment.

Finally, we examine firm exit and find no evidence of differential exit rates among *D10* firms following the carbon price increase (see Tables B.8 and B.9 in the appendix, section A). Taken together, the event-study evidence supports the interpretation that the post-2014 increase in carbon pricing triggered differential investment responses among high emitting firms, and that these responses were financed primarily through reductions in internal payouts.

6.2 Cross-country evidence

The increase in investment among Swedish *D10* firms could reflect broader European trends in high emitting industries, such as global shifts in technology costs or demand conditions. To address this possibility, we construct a country-by-industry panel using four-digit manufacturing data from Eurostat and compare investment patterns in Sweden to those in other EU member states.

We augment the event-study specification with an indicator for Swedish observations (*Sweden*) and interact it with *D10*, and *Post*. This yields a triple-difference design in which identification comes from comparing the post-2015 change in investment among high-emission industries in Sweden relative to (i) cleaner Swedish industries and (ii) high-emission industries in other EU countries.

As a preliminary comparison, Table B.10 reports average capital expenditure-to-sales ratios across 2010–2014 and 2015–2019 for Sweden and the rest of the EU. High emitting Swedish industries increase investment intensity by 0.016 in the post period, while cleaner Swedish industries exhibit little change. In contrast, high emitting industries in the EU excluding Sweden show only modest increases (approximately 0.002), and this pattern is similar when restricting the sample to EU15 countries or excluding the Nordic countries.

Regression estimates of the augmented specification are reported in Table 10. In the pre-period, high emitting industries display higher investment intensity across countries. There is also a general increase in manufacturing investment in the post period across the EU. However, high emitting industries outside Sweden do not experience a differential post-2015 increase relative to cleaner industries.

In the fully saturated specification - including country-industry, industry-year, and country-year fixed effects — the coefficient on the *Sweden* $\times$ *D10* $\times$ *Post* interaction is positive and statistically significant (0.012). Country-industry fixed effects absorb time-invariant differences across country-industry pairs; industry-year fixed effects absorb common industry-wide shocks across Europe; and country-year fixed effects absorb macroeconomic conditions specific to each country. The remaining variation therefore captures differential post-2015 investment changes in high emitting Swedish industries relative to comparable industries elsewhere in the EU.

The magnitude of the triple-difference estimate closely matches the corresponding estimate in the firm-level event specification reported above. Taken together, these results are consistent with the interpretation that the post-2014 increase in Swedish carbon prices, rather than broader European trends, drove the observed investment response among high-emission industries.

7 Conclusion

A central concern in climate policy is whether carbon pricing discourages real investment in emissions-intensive sectors or instead accelerates capital reallocation toward cleaner technologies. This margin is critical for evaluating whether market-based environmental regulation can induce technological upgrading in the sectors most central to decarbonization.

Using detailed firm-level data from Swedish manufacturing over two decades, we show that sufficiently large increases in carbon pricing are associated with higher capital investment among the most emitting firms. While carbon pricing compresses operating margins—particularly in high emitting industries—it also induces a reallocation of capital toward emissions-reducing investment and innovation. The investment response is concentrated in industries with the highest emissions intensity and among firms with sufficient internal financial capacity to finance adjustment. These patterns are consistent with carbon pricing operating through standard corporate finance channels: higher carbon emission costs reduce payouts and trigger reinvestment into cleaner capital.

The evidence does not support the view that carbon pricing primarily leads to disinvestment or relocation in this setting. Instead, when prices rise to economically meaningful levels, firms undertake lumpy capital adjustments and expand abatement and R&D spending. Cross-country comparisons indicate that these patterns are not driven by broader European trends in high-emission industries.

Our findings suggest that the effectiveness of carbon pricing depends not only on statutory rates, but also on the magnitude, credibility, and persistence of policy changes. When carbon prices reach levels that materially affect profitability, they reshape capital allocation decisions within firms. More broadly, the results suggest that well-designed carbon pricing can function as a capital reallocation mechanism, steering private investment toward emissions-reducing technologies through standard market incentives.

References

Acemoglu, D., Akcigit, U., Hanley, D., and Kerr, W. (2016). Transition to clean technology. *Journal of political economy*, 124(1):52–104.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., and Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1):1–51.

Bartram, S. M., Hou, K., and Kim, S. (2022). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*, 143(2):668–696.

Becker, R. A. (2005). Air pollution abatement costs under the clean air act: evidence from the pace survey. *Journal of environmental economics and management*, 50(1):144–169.

Bilal, A. and Känzig, D. R. (2025). Does unilateral decarbonization pay for itself? In *AEA Papers and Proceedings*, volume 115, pages 369–373. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Bilal, A. and Känzig, D. R. (2026). The macroeconomic impact of climate change: Global versus local temperature. *The Quarterly Journal of Economics*, page qjag011.

Bolton, P., Lam, A., and Muûls, M. (2023). Do carbon prices affect stock prices? *Journal of Financial Research.*

Brown, J. R., Martinsson, G., and Thomann, C. (2022). Can environmental policy encourage technical change? emissions taxes and r&d investment in polluting firms. *The Review of financial studies*, 35(10):4518–4560.

Calel, R. and Dechezleprêtre, A. (2016). Environmental policy and directed technological change: evidence from the european carbon market. *Review of Economics and Statistics*, 98(1):173–191.

Colmer, J., Martin, R., Muûls, M., and Wagner, U. J. (2025). Does pricing carbon mitigate climate change? firm-level evidence from the european union emissions trading system. *Review of Economic Studies*, 92(3):1625–1660.

Conte, B., Desmet, K., and Rossi-Hansberg (2025). On the geographic implications of carbon taxes. *Economic Journal, forthcoming.*

Cropper, M. L. and Oates, W. E. (1992). Environmental economics: a survey. *Journal of economic literature*, 30(2):675–740.

Dechezleprêtre, A. and Sato, M. (2017). The impacts of environmental regulations on competitiveness. *Review of Environmental Economics and Policy*, 11:183–206.

Dixit, A. K. and Pindyck, R. S. (1994). *Investment under uncertainty.* Princeton university press.

Döttling, R. and Rola-Janicka, M. (2025). Too levered for Pigou? Carbon pricing, financial constraints, and leverage regulation. *Journal of Financial Economics*, 172:104105.

Ederington, J., Levinson, A., and Minier, J. (2005). Footloose and pollution-free. *Review of Economics and Statistics*, 87(1):92–99.

European Commission (2009). Determining, pursuant to directive 2003/87/ec of the European Parliament and of the council, a list of sectors and subsectors which are deemed to be exposed to a significant risk of carbon leakage. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32010D0002&from=EN.

European Parliament and Council (2011). Regulation (EU) no 691/2011 of the European Parliament and of the Council on European environmental economic accounts.

Fang, M., Hsu, P.-H., and Tsou, C.-Y. (2025). Financial frictions and pollution abatement over the life cycle of firms. *Available at SSRN 4390975*.

Fowlie, M., Reguant, M., and Ryan, S. P. (2016). Market-based emissions regulation and industry dynamics. *Journal of Political Economy*, 124(1):249–302.

Ganapati, S., Shapiro, J. S., and Walker, R. (2020). Energy cost pass-through in us manufacturing: Estimates and implications for carbon taxes. *American Economic Journal: Applied Economics*, 12(2):303–342.

Gillingham, K. and Stock, J. H. (2018). The cost of reducing greenhouse gas emissions. *Journal of Economic Perspectives*, 32(4):53–72.

Golosov, M., Hassler, J., Krusell, P., and Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88.

Jacob, M. and Zerwer, K. L. (2024). Emission taxes and capital investments: The role of tax incidence. *The Accounting Review*, pages 1–32.

Justitiedepartementet L1. Bokföringslag (1999:1078).

Justitiedepartementet L1. Årsredovisningslag (1995:1554).

Känzig, D. R. (2025). The unequal economic consequences of carbon pricing. Technical report, National Bureau of Economic Research.

Lanteri, A. and Rampini, A. (2025). Financing the adoption of green technology. *NBER Working Paper*, 33545.

Levinson, A. and Taylor, M. S. (2008). Unmasking the pollution haven effect. *International economic review*, 49(1):223–254.

Martin, R., De Preux, L. B., and Wagner, U. J. (2014). The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics*, 117:1–14.

Martinsson, G., Sajtos, L., Strömberg, P., and Thomann, C. (2024). The effect of carbon pricing on firm emissions: Evidence from the swedish co2 tax. *The Review of Financial Studies*, 37(6):1848–1886.

Nordhaus, W. (2019). Climate change: The ultimate challenge for economics. *American Economic Review*, 109(6):1991–2014.

Nordhaus, W. D. (1992). An optimal transition path for controlling greenhouse gases. *Science*, 258(5086):1315–1319.

Pedersen, L. H. (2026). Carbon pricing versus green finance. *The Journal of Finance*.

Popp, D. (2002). Induced innovation and energy prices. *American economic review*, 92(1):160–180.

SCA (2019). SCA invests in Obbola kraftliner mill. Press release, September 2, 2019, Svenska Cellulosa Aktiebolaget SCA.

Shapiro, J. S. and Walker, R. (2018). Why is pollution from US manufacturing declining? the roles of environmental regulation, productivity, and trade. *American Economic Review*, 108(12):3814–54.

World Bank (2025). State and trends of carbon pricing 2025.

Xepapadeas, A. and de Zeeuw, A. (1999). Environmental policy and competitiveness: the porter hypothesis and the composition of capital. *Journal of Environmental Economics and Management*, 37(2):165–182.

Figure 1: Investment and carbon prices in Swedish manufacturing

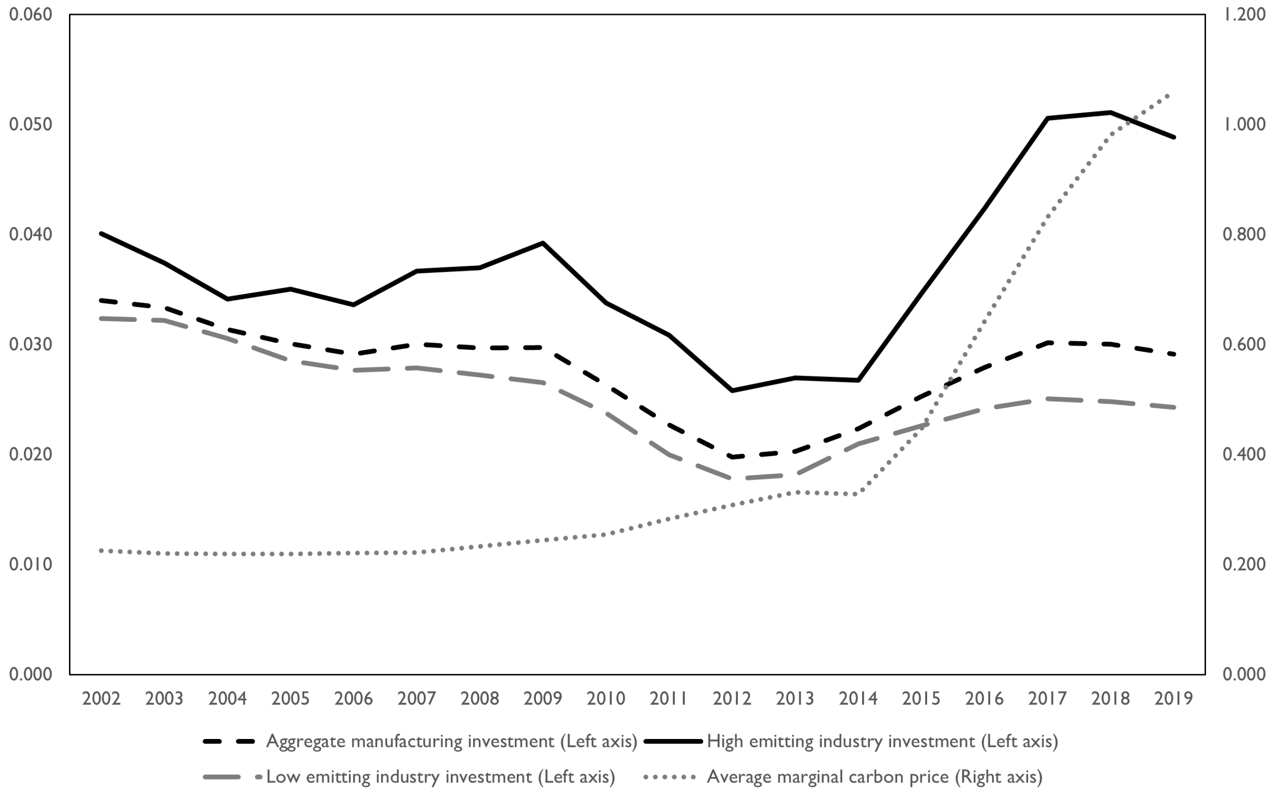


Figure 1 displays aggregate capital investment-to-sales ratios for (i) all manufacturing firms (dashed black line), (ii) high emitting industries (D10; solid black line), and (iii) low- and medium emitting industries (D1–D9; dashed gray line). The gray dotted line (right axis) shows the average marginal carbon price. Low emitting, or D1–D9 industries (high emitting or D10 industries) include firms in the four-digit industries in the lowest nine (highest) deciles in terms of carbon emissions to sales in 2000. All time series are expressed as a rolling moving average from t to t-2 for the time period 2000–2019.

Figure 2: Average and marginal carbon costs under Swedish policy

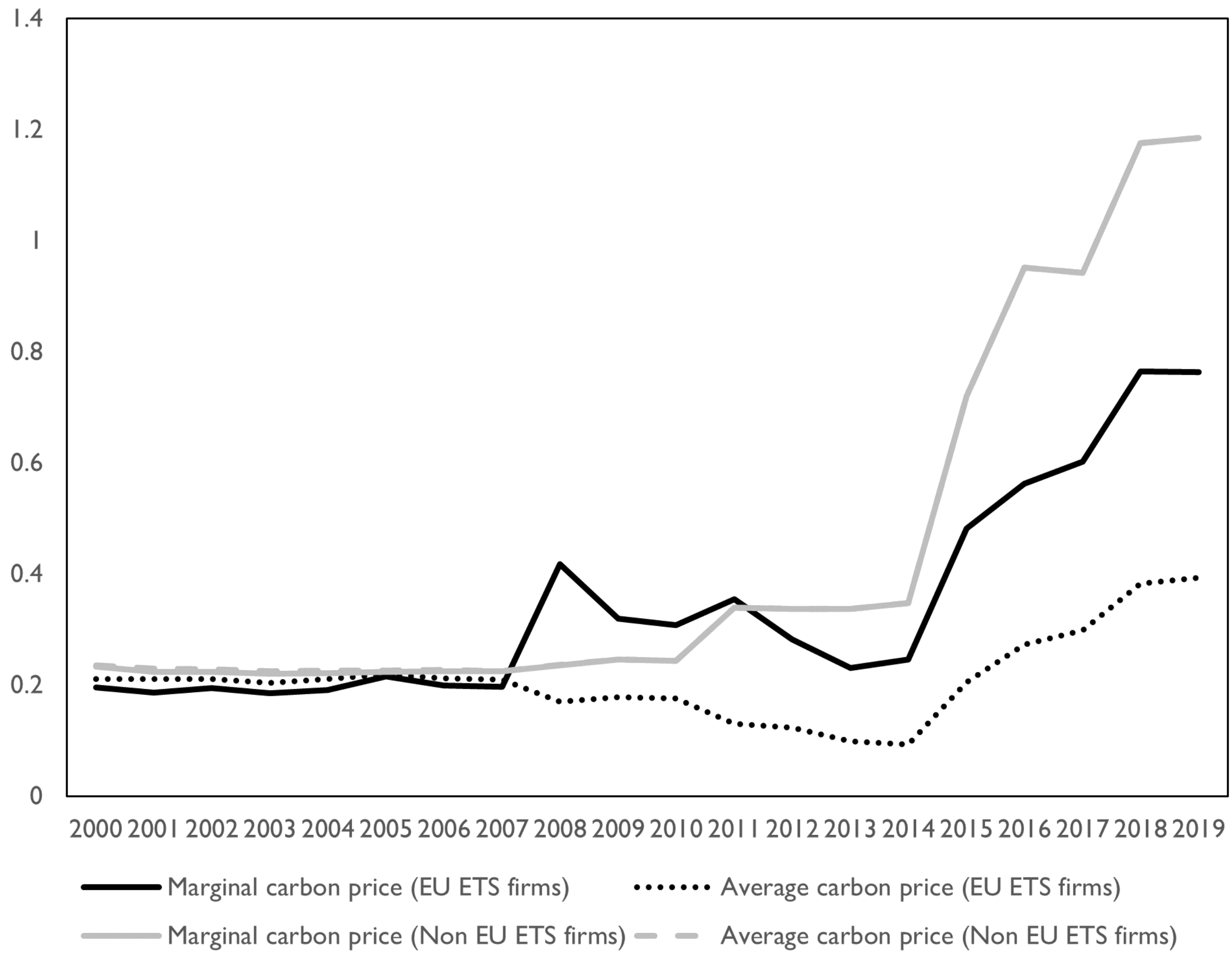


Figure 2 displays the marginal carbon price (solid black line) and average carbon price (dotted black line) for firms regulated by the EU ETS. Under the EU ETS, free allocation drives a wedge between average and marginal carbon costs. Before EU ETS firms enter EU ETS the price refers to the Swedish carbon tax rate. The marginal carbon price (solid gray line) and average carbon price (dashed gray line) for firms only taxed under the Swedish carbon tax.

Figure 3: Swedish carbon prices and Social Cost of Carbon estimates

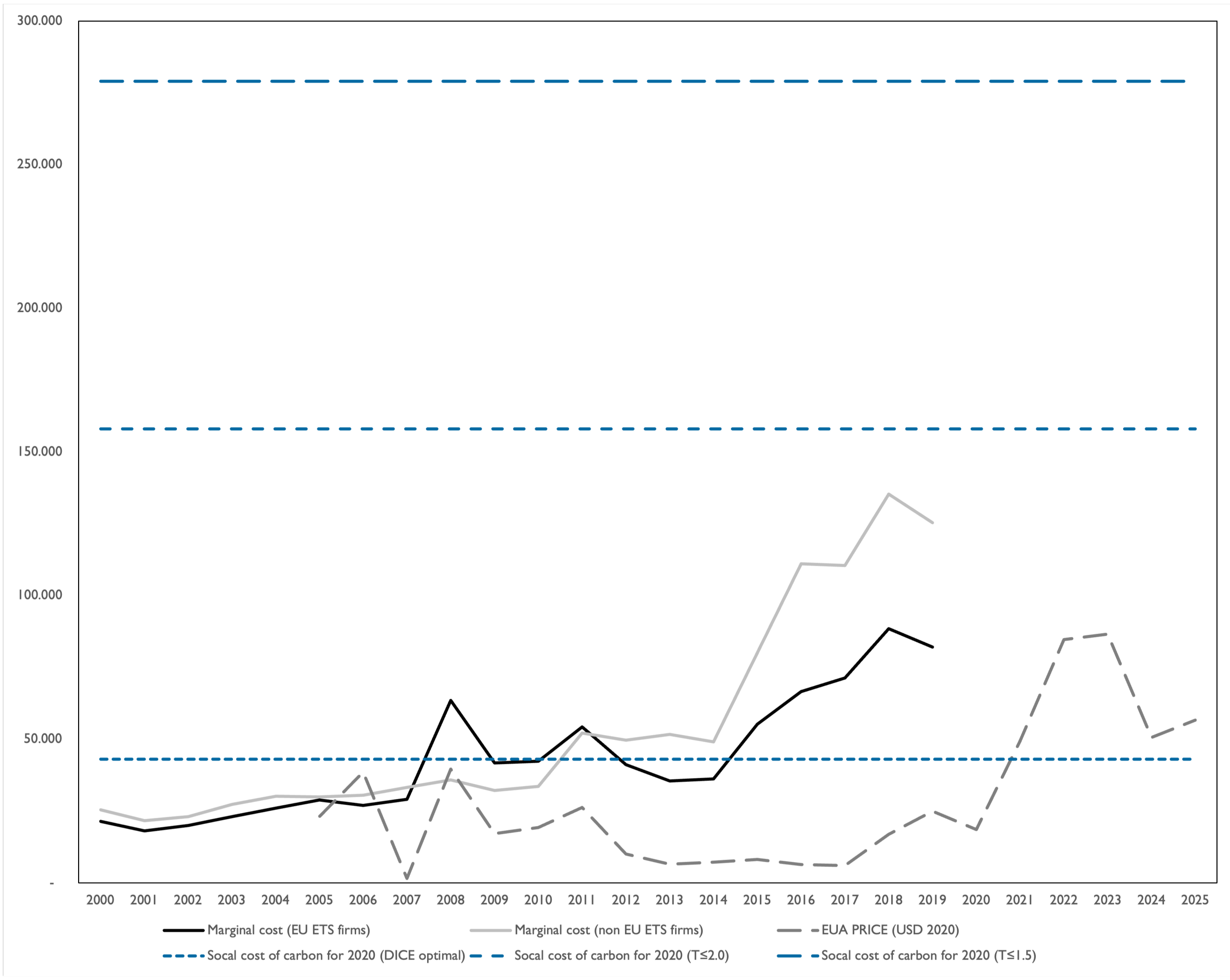
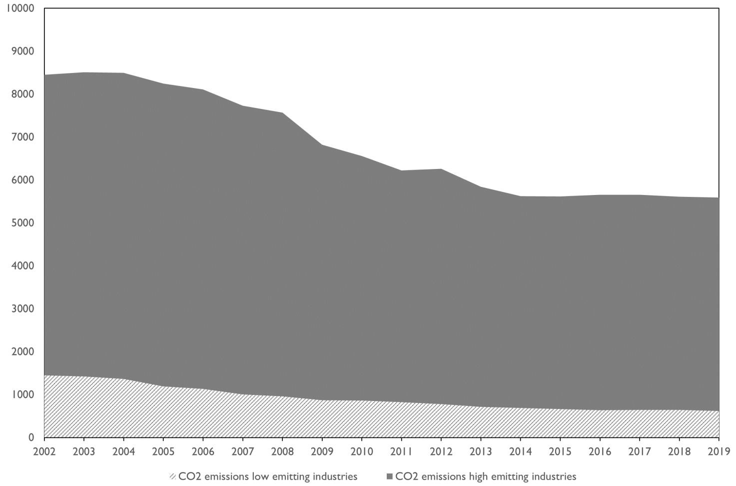


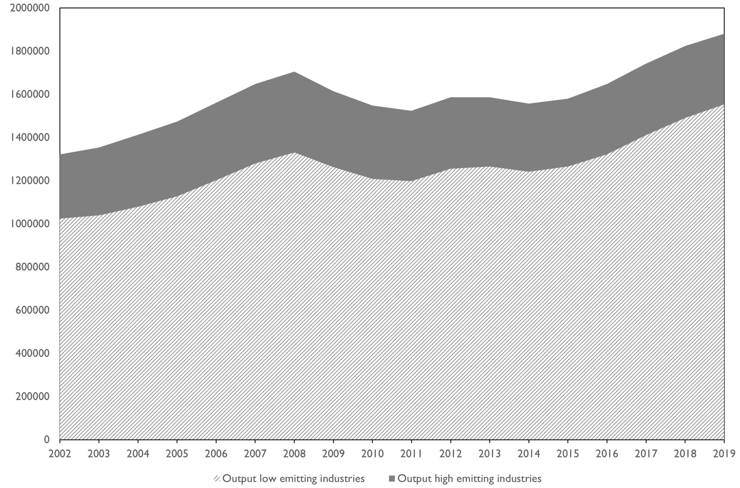
Figure 3 displays the marginal carbon price (solid black line) for firms regulated by the EU ETS converted to US dollar per ton emission (before EU ETS firms enter EU ETS the price refers to the Swedish carbon tax rate). The marginal carbon price (solid gray line) for firms only taxed under the Swedish carbon tax converted to US dollar per ton emission. The EUA price, EU allowances price in constant 2020 US dollars. Social cost of carbon (SCC) for 2020 are from Nordhaus (2019) and represent the baseline optimal DICE estimate (blue short dashed line, lowest), the SCC for targets of 2°C or under (blue medium dashed line, middle) and the SCC for targets of 1.5°C or under (blue long dashed line, highest).

Figure 4: Carbon emissions and output in Swedish manufacturing

(a) Aggregate carbon emissions (kt)



(b) Aggregate output (BSEK)



(c) Aggregate carbon emissions to output (kg per SEK)

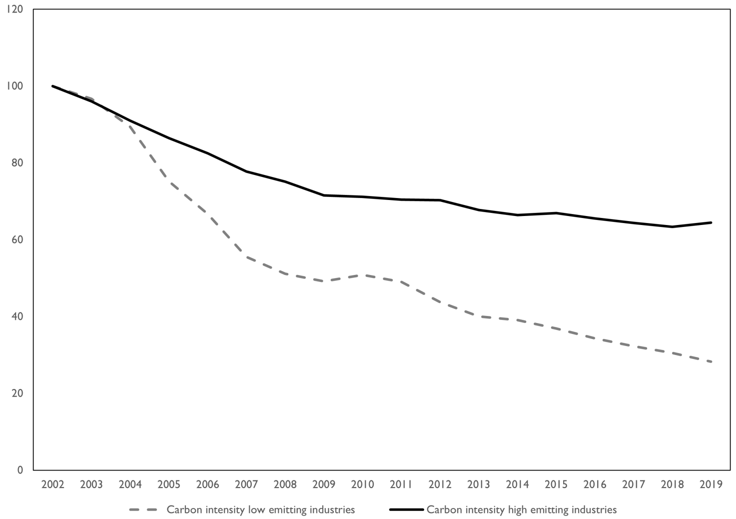
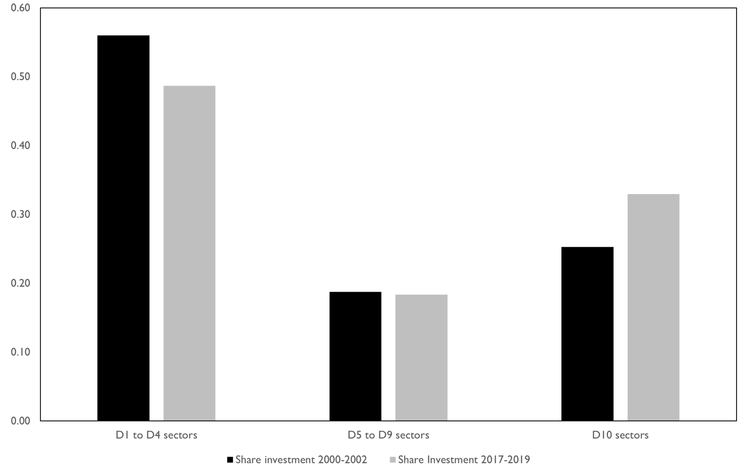


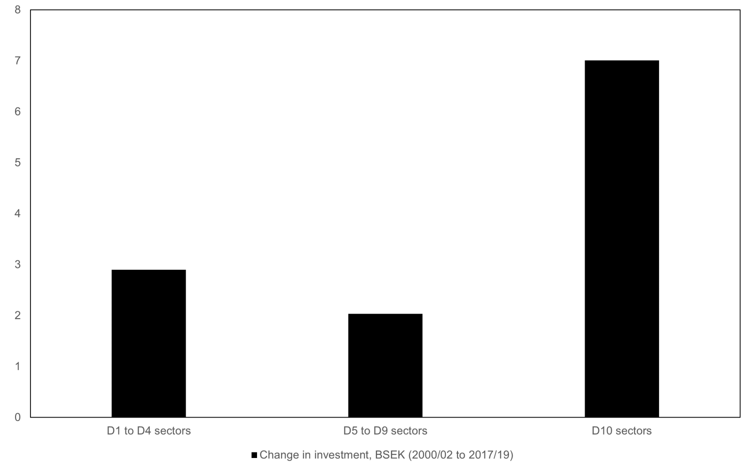
Figure 4 displays carbon emissions (output, BSEK) in panel A(B) for high emitting industries (dark grey) and low emitting industries (white, light grey). Panel C displays aggregate carbon emissions over (PPI deflated) output for for high emitting (solid black line) and low emitting industries (grey dashed line) with 2002 as base year. Low emitting, or D1–D9 industries (high emitting or D10 industries) include firms in the four-digit industries in the lowest nine (highest) deciles in terms of carbon emissions to sales in 2000. All time series are expressed as a rolling moving average from t to t-2 for the time period 2000–2019.

Figure 5: Investment shares and financing by emissions intensity groups

(a) Share of investment



(b) Aggregate investment (BSEK)



(c) Investment to cash flow

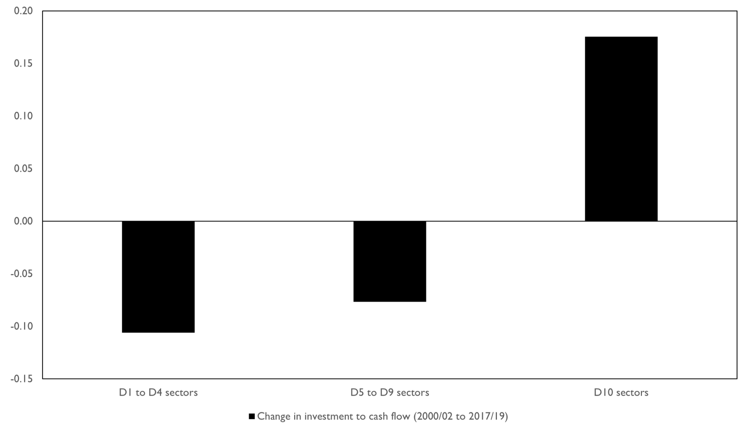


Figure 5 displays (in panel A) the share of total manufacturing investment accounted for by D10 industries, (in panel B) aggregate real capital expenditures over time, and (in panel C) investment-to-cash-flow ratios by emissions intensity group. Investment measures are three-year moving averages. D1–D4 include firms in the four-digit industries in the first to fourth deciles (bottom 40 percent) in terms of carbon emissions to sales in 2000, D5–D9 represent firms in the fifth to ninth decile in terms of carbon emissions to sales in 2000 and D10 the top decile.

Table 1: Sorting the manufacturing sector in to emission decile groups

	ALL	D1–D4	D5–D9	D10
Panel A: Distribution of emissions, output and carbon intensity				
Share CO_2 2000–2002	1.000	0.076	0.095	0.828
Share CO_2 2017–2019	1.000	0.038	0.073	0.889
Share output 2000–2002	1.000	0.568	0.206	0.225
Share output 2017–2019	1.000	0.614	0.210	0.174
CO_2 to output 2000–2002	0.0064	0.0009	0.0030	0.0235
CO_2 to output 2017–2019	0.0030	0.0002	0.0010	0.0152
Panel B: Pollution abatement costs and mobility				
Low PACE	0.497	0.616	0.520	0.000
High PACE	0.503	0.384	0.480	1.000
Low Mobility	0.486	0.298	0.608	0.640
High Mobility	0.514	0.702	0.392	0.360
Low PACE & Low Mobility	0.146	0.106	0.221	0.000
Low PACE & High Mobility	0.351	0.506	0.305	0.000
High PACE & Low Mobility	0.337	0.174	0.410	0.613
High PACE & High Mobility	0.167	0.215	0.064	0.387
Panel C: EU leakage list and US based PACE measure				
Share firms on EU Carbon leakage list	0.484	0.545	0.334	0.930
On list for outside EU trade concern	0.371	0.540	0.287	0.117
On list for high emissions concern	0.113	0.005	0.048	0.813
Low PACE US	0.511	0.706	0.472	0.012
High PACE US	0.489	0.294	0.528	0.988

Table 1 reports statistics across decile groupings: D1–D4 include firms in the four-digit industries in the first to fourth deciles (bottom 40 percent) in terms of carbon emissions to sales in 2000, D5–D9 represent firms in the fifth to ninth decile in terms of carbon emissions to sales in 2000 and D10 the top decile. Panel A reports aggregate shares of CO_2 emissions and output (PPI deflated sales) and aggregate carbon emissions to output averaged over 2000–2002 and 2017–2019. ratios across deciles and time in panels A and B and the difference in shares and ratios in panel C. Panel B reports the share of firms across deciles that are in low (high) PACE sectors measured as below (above) the median in the four-digit sector's ratio of abatement investment to sales the first year of abatement data (in 2002). It also reports the share of firms across deciles that are in low (high) mobility sectors measured as above (below) the median in the four-digit sector's ratio of fixed assets to total assets the first year of asset data (in 2000). The final four rows in panel B reports firms across low PACE & low mobility (below the median in PACE and mobility); low PACE & high mobility (below the median in PACE and above the median in mobility); high PACE & low mobility (above the median in PACE and below the median in mobility); high PACE & high mobility (above the median in PACE and mobility). Panel C reports reports firms based on if they operate in sectors that are on European Union's (EU) carbon leakage list (also divided by if the sector is on the list for trade concerns or high emission concerns). The final two rows reports the share of firms across deciles that are in low (high) PACE sectors measured as below (above) the median in the four-digit sector's ratio of abatement investment to shipments using US data from 2005 from the Environmental Protection Agency).

Table 2: Summary statistics

	OBS	Mean	25th	Median	75th	St Dev
		Panel A: Full sample				
Inv	9,839	0.031	0.007	0.017	0.035	0.045
C	9,839	0.0011	0.0001	0.0003	0.0010	0.0021
Abate Inv	1,320	0.002	0.000	0.000	0.001	0.003
Abate to Total	1,320	0.072	0.004	0.016	0.059	0.141
R&D Inv	5,267	0.010	0.000	0.000	0.007	0.027
Abate R&D Inv (x 10)	1,320	0.0005	0.0000	0.0000	0.0000	0.0018
EBIT	9,839	0.044	0.012	0.044	0.081	0.110
Cash flow	9,185	0.122	0.051	0.097	0.150	0.195
Total assets (BSEK)	9,839	3.469	0.066	0.237	0.970	18.800
Long term debt	9,839	0.144	0.000	0.061	0.228	0.200
Sales gwth	9,099	0.131	-0.055	0.022	0.116	0.755
		Panel B: Firms in decile 10 sectors				
Inv	1,058	0.042***	0.012	0.025	0.048	0.055
C	1,058	0.0033***	0.0006	0.0019	0.0044	0.0039
Abate Inv	383	0.003***	0.000	0.001	0.003	0.004
Abate to Total	383	0.084***	0.010	0.030	0.082	0.140
R&D Inv	658	0.006	0.000	0.000	0.004	0.014
Abate R&D Inv (x 10)	383	0.0011***	0.0000	0.0000	0.0001	0.0025
EBIT	1,058	0.047	0.014	0.051	0.092	0.113
Cash flow	956	0.109	0.047	0.091	0.136	0.177
Total assets (BSEK)	1,058	9.436***	0.268	1.089	5.923	32.300
Long term debt	1,058	0.118	0.000	0.001	0.167	0.207
Sales gwth	947	0.090	-0.059	0.009	0.086	0.650
		Panel C: Firms in deciles 1–9 sectors				
Inv	8,781	0.029	0.007	0.016	0.033	0.043
C	8,781	0.0008	0.0000	0.0003	0.0008	0.0016
Abate Inv	937	0.001	0.000	0.000	0.001	0.003
Abate to Total	937	0.067	0.003	0.012	0.050	0.141
R&D Inv	4,609	0.011***	0.000	0.000	0.007	0.028
Abate R&D Inv (x 10)	937	0.0003	0.0000	0.0000	0.0000	0.0014
EBIT	8,781	0.043	0.012	0.043	0.080	0.109
Cash flow	8,229	0.123	0.052	0.097	0.152	0.197
Total assets (BSEK)	8,781	2.750	0.060	0.201	0.803	16.300
Long term debt	8,781	0.148***	0.000	0.070	0.231	0.199
Sales gwth	8,152	0.136***	-0.055	0.024	0.120	0.766

Table 2 reports summary statistics of the key variables used in this study across decile groupings: D1–D9 (D10) in panel B (C) include firms in the four-digit industries in the lowest nine (highest) deciles in terms of carbon emissions to sales in 2000. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2000–2019. Prices are expressed in constant 2020 Swedish Krona (sek). *Inv* is the capital expenditure to sales ratio. *C* is the marginal cost of emitting CO_2 (Marginal cost×total CO_2 emissions) divided by sales. *Abate Inv* is the air pollution abatement capital expenditure to sales ratio. *Abate to Total* is the air pollution abatement capital expenditure divided by the total capital investment. *R&D* is the research and development (R&D) expenditure to sales ratio. *Abate R&D* is the abatement R&D expenditure to sales ratio. *EBIT* is the earnings before interest and taxes to sales ratio. *Cash flow* is cash flow divided by total assets. *Total assets* is the book value of total assets. *Long term debt* is long term bank debt divided by total assets. *Sales gwth* is the annual log difference in PPI-adjusted sales. ***, **, and * in panels B and C indicate whether differences in means are significantly larger at the 1%, 5%, and 10% levels.

Table 3: Carbon pricing and operating margins

	(1)	(2)	(3)	(4)
	All	**D1–D4**	**D5–D9**	**D10**
$\ln(C_{i,t})$	-0.003***	-0.003*	-0.002*	-0.009***
	(0.001)	(0.002)	(0.001)	(0.003)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	6,234	2,483	3,071	680
Adjusted R^2	0.460	0.543	0.499	0.207

Table 3 reports OLS estimates of Equation 1. $ln(EBIT)_{i,t}$ is the dependent variable, where *EBIT* is the earnings before interest and taxes to sales ratio, standardized between zero and one, for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000-3300) with capital expenditure and CO_2 emissions data during 2000–2019. D1–D4 include firms in the four-digit industries in the first to fourth deciles (bottom 40 percent) in terms of carbon emissions to output in 2000, D5–D9 represent firms in the fifth to ninth decile in terms of carbon emissions to output in 2000 and D10 is the top decile. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: $Cash\ flow_{i,t-1}$, $ln(Total\ assets)_{i,t-1}$, $Long\ term\ debt_{i,t-1}$, and $Sales\ gwth_{i,t-1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 4: Carbon pricing and capital investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(C_{i,t})$	0.108***	0.045***	0.059***	0.055**	0.077***	0.084***	0.073**
	(0.013)	(0.016)	(0.022)	(0.025)	(0.029)	(0.030)	(0.035)
$\ln(C_{i,t-1})$					-0.001	0.005	0.020
					(0.029)	(0.033)	(0.038)
$\ln(C_{i,t-2})$						0.019	0.028
						(0.028)	(0.031)
$\ln(C_{i,t-3})$							0.002
							(0.034)
Cash $\text{flow}_{i,t-1}$				0.510***	0.589***	1.286***	1.493***
				(0.188)	(0.234)	(0.382)	(0.376)
$\ln(\text{Total assets}_{i,t-1})$				0.017	0.030	-0.007	0.074
				(0.044)	(0.075)	(0.074)	(0.085)
Long term $\text{debt}_{i,t-1}$				-0.694***	-0.734***	-0.636***	-0.684***
				(0.198)	(0.210)	(0.218)	(0.244)
Sales $\text{gwth}_{i,t-1}$				-0.031	-0.056	-0.032	-0.182**
				(0.036)	(0.045)	(0.087)	(0.078)
$\sum \ln(C)$					0.076**	0.108***	0.123**
					(0.020)	(0.008)	(0.030)
Firm fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No	No	No
Industry × Year effects	No	No	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes	Yes
Observations	9,839	9,043	7,869	6,242	5,477	4,681	3,653
Adjusted R^2	0.039	0.453	0.442	0.447	0.457	0.476	0.479

Table 4 reports OLS estimates of Equation 1. $ln(Inv)_{i,t}$ is the dependent variable. *Inv* is the capital expenditure to sales ratio for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2000–2019. Regressions in columns 2–7 include firm fixed effects. Regressions in columns 1–2 include year fixed effects and columns 3–7 include four digit industry-year fixed effects. Regressions in columns 4–7 include the following firm control variables: *Cash flow*$_{i,t-1}$, *ln(Total assets)*$_{i,t-1}$, *Long term debt*$_{i,t-1}$, and *Sales gwth*$_{i,t-1}$. The standard errors are clustered at the firm level. $\sum \Delta\ln(C)$ present an F-test of joint significance. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 5: Carbon pricing and capital investment: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	D1–D4		D5–D9		D10	
$\ln(C_{i,t})$	0.013	-0.025	0.051	0.090**	0.168***	0.207***
	(0.039)	(0.061)	(0.036)	(0.044)	(0.058)	(0.066)
$\ln(C_{i,t-1})$		-0.027		0.075		0.056
		(0.069)		(0.044)		(0.088)
$\ln(C_{i,t-2})$		0.105*		-0.070		0.094***
		(0.062)		(0.054)		(0.033)
$\ln(C_{i,t-3})$		0.057		-0.008		-0.048
		(0.050)		(0.053)		(0.082)
Cash $\text{flow}_{i,t-1}$	0.646**	2.011***	0.609**	1.500***	-0.118	1.044
	(0.277)	(0.744)	(0.263)	(0.483)	(0.537)	(0.831)
ln(Total $\text{assets}_{i,t-1}$)	-0.090	-0.157	0.077	0.214*	0.086	-0.054
	(0.077)	(0.217)	(0.053)	(0.113)	(0.149)	(0.190)
Long term $\text{debt}_{i,t-1}$	-0.751**	-1.038**	-0.673**	-0.345	-0.352	-0.359
	(0.320)	(0.504)	(0.300)	(0.360)	(0.460)	(0.525)
Sales $\text{gwth}_{i,t-1}$	-0.066	-0.053	-0.015	0.236*	-0.024	-0.216*
	(0.051)	(0.148)	(0.053)	(0.121)	(0.099)	(0.122)
$\sum$ ln(C)		0.110		0.087		0.309***
		(0.370)		(0.251)		(0.007)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,486	1,407	3,075	1,744	681	502
Adjusted R^2	0.405	0.444	0.449	0.463	0.467	0.510

Table 5 reports OLS estimates of Equation 1. *ln(Inv)*$_{i,t}$ is the dependent variable. *Inv* is the capital expenditure to sales ratio for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2000–2019. D1–D4 include firms in the four-digit industries in the first to fourth deciles (bottom 40 percent) in terms of carbon emissions to output in 2000, D5–D9 represent firms in the fifth to ninth decile in terms of carbon emissions to output in 2000 and D10 is the top decile. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: *Cash flow*$_{i,t-1}$, *ln(Total assets)*$_{i,t-1}$, *Long term debt*$_{i,t-1}$, and *Sales gwth*$_{i,t-1}$. The standard errors are clustered at the firm level. $\sum \Delta\ln(C)$ present an F-test of joint significance. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 6: Carbon pricing and capital investment: Other industry sorts and deciles

	(1)	(2)	(3)	(4)	(5)	(6)
	PACE		**Leakage list**		**PACE US**	
	High	**High**	**Yes**	**Yes**	**High**	**High**
	D1–D9	**D10**	**D1–D9**	**D10**	**D1–D9**	**D10**
$\ln(C_{i,t})$	0.051	0.168***	0.011	0.176***	0.069	0.168***
	(0.041)	(0.060)	(0.039)	(0.057)	(0.042)	(0.058)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,973	628	2,256	637	2,224	681
Adjusted R^2	0.374	0.474	0.446	0.469	0.396	0.467

Table 6 reports OLS estimates of Equation 1. *ln(Inv)*$_{i,t}$ is the dependent variable. *Inv* is the capital expenditure to sales ratio for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. Columns 1–2 reports results for firms that are in high PACE sectors measured as above the median in the four-digit sector's ratio of abatement investment to sales the first year of abatement data (in 2002) Columns 3–4 reports results firms based on if they operate in sectors that are on European Union's (EU) carbon leakage list. Columns 5–6 report results for firms in high PACE sectors measured as above the median in the four-digit sector's ratio of abatement investment to shipments using US data from 2005 from the Environmental Protection Agency). Results for firms located in D1–D9 (D10) industries in odd (even) numbered columns. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2000–2019. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: *Cash flow*$_{i,t-1}$, *ln(Total assets)*$_{i,t-1}$, *Long term debt*$_{i,t-1}$, and *Sales gwth*$_{i,t-1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 7: Carbon pricing and firm level abatement investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						Abate Inv	
		Abate Inv		Abate to Total		Treatment	Prevent
	All	D1–D9	D10	D1–D9	D10	All	All
$\ln(C_{i,t})$	0.440***	0.016	0.700***	-0.038	0.510**	0.232	0.692**
	(0.161)	(0.294)	(0.181)	(0.417)	(0.217)	(0.216)	(0.267)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	484	251	233	197	223	268	222
Adjusted R^2	0.331	0.362	0.133	0.229	0.074	0.267	0.160

Table 7 reports OLS estimates of Equation 1. *ln(Abate Inv)*$_{i,t}$ is the dependent variable in columns 1–3, where *Abate Inv* is the abatement capital expenditure to sales ratio for firm i in year t. *ln(Abate to Total)*$_{i,t}$ is the dependent variable in columns 4–5, where *Abate to Total* is the air pollution abatement capital expenditure divided by the total capital investment for firm i in year t. *ln(Abate Inv: Treatment)*$_{i,t}$ is the dependent variable in column 6, where *Abate Inv: Treatment* is the air pollution abatement capital expenditure with the purpose to treat actual pollution for firm i in year t. *ln(Abate Inv: Prevent)*$_{i,t}$ is the dependent variable in column 6, where *Abate Inv: Treatment* is the air pollution abatement capital expenditure with the purpose to prevent future pollution for firm i in year t. *MC* is the cost of emitting CO_2 divided by sales for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure, abatement investment and CO_2 emissions data during 2002–2019. D1–D9 include firms in the four-digit industries in the first to ninth deciles (bottom 90 percent) in terms of carbon emissions to output in 2000 and D10 is the top decile. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: *Cash flow*$_{i,t-1}$, *ln(Total assets)*$_{i,t-1}$, *Long term debt*$_{i,t-1}$, and *Sales gwth*$_{i,t-1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 8: Carbon pricing and R&D investment

	(1)	(2)	(3)	(4)	(5)	(6)
	R&D Inv			**Abate R&D Inv**		
	All	**D1–D9**	**D10**	**All**	**D1–D9**	**D10**
$\ln(C_{i,t})$	-0.017	-0.047	0.275***	0.462	-0.312	0.712**
	(0.047)	(0.049)	(0.081)	(0.309)	(0.237)	(0.327)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	782	646	136	146	78	68
Adjusted R^2	0.820	0.770	0.838	0.720	0.815	0.579

Table 8 reports OLS estimates of Equation 1. $ln(R\&D)_{i,t}$ is the dependent variable in columns 1–3, where *R&D* is the R&D to sales ratio for firm i in year t. $ln(Abate\ R\&D)_{i,t}$ is the dependent variable in columns 4–6, where *Abate R&D* is the abatement R&D expenditure to sales ratio for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with R&D and CO_2 emissions data during 2000–2019 in columns 1–3 and with abatement R&D and CO_2 emissions data during 2002–2019 in columns 4–6. D1–D9 include firms in the four-digit industries in the first to ninth deciles (bottom 90 percent) in terms of carbon emissions to output in 2000 and D10 is the top decile. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: $Cash\ flow_{i,t-1}$, $ln(Total\ assets)_{i,t-1}$, $Long\ term\ debt_{i,t-1}$, and $Sales\ gwth_{i,t-1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 9: Carbon pricing and firm level investment and dividend payments: Event results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inv				Div			
D10 Firm	0.010***				0.044			
	(0.004)				(0.064)			
Post	0.003***	0.001			0.049***	0.071***		
	(0.001)	(0.001)			(0.014)	(0.018)		
D10 Firm x *Post*	0.012**	0.012***	0.012***	0.000	-0.183**	-0.207**	-0.209**	0.014
	(0.005)	(0.005)	(0.005)	(0.004)	(0.077)	(0.087)	(0.087)	(0.059)
Post x *Div firm*				0.002				-0.038
				(0.002)				(0.033)
D10 Firm x *Post* x *Div firm*				0.020**				-0.351**
				(0.008)				(0.140)
Firm fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	8,597	8,108	8,108	7,404	8,596	8,108	8,108	7,404
Adjusted R^2	0.013	0.396	0.397	0.377	0.002	0.196	0.199	0.199

Table 9 reports OLS estimates of Equation 2 with $Inv_{i,t}$ as the dependent variable in columns 1–4 and $Div_{i,t}$ as the dependent variable in columns 5–8. *Inv* is the capital expenditure to sales ratio for firm i in year t and *Div* is the dividend payment to cash flow ratio for firm i in year t. *D10 Firm* is an indicator variable taking on the value one (zero) if the firm is (not) in a decile 10 industry. *Post* is an indicator variable taking on the value one (zero) for years 2015–2019 (2010–2014). *Div firm* is an indicator variable taking on the value one (zero) if the firm paid dividend in the period 2010–2014 and zero otherwise. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2010–2019. Regressions in columns 2–4, and 5–8 include firm fixed effects. Regressions in columns 3–4 and 7–8 include year fixed effects. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 10: Industry level investment across EU countries during, 2010–2019

	(1)	(2)	(3)	(4)	(5)
D10	0.010***				
	(0.002)				
Post	0.004**	0.003*			
	(0.002)	(0.001)			
D10 × Post	-0.002	-0.001	-0.001		
	(0.002)	(0.002)	(0.002)		
Sweden	-0.010***				
	(0.003)				
D10 × *Sweden*	0.004**				
	(0.002)				
Post × Sweden	-0.003*	-0.002	-0.002	-0.002	
	(0.002)	(0.001)	(0.001)	(0.002)	
D10 × *Post* × *Sweden*	0.010***	0.016***	0.016***	0.011***	0.012***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Country-industry effects	No	Yes	Yes	Yes	Yes
Year effects	No	No	Yes	No	No
Industry × year effects	No	No	No	Yes	Yes
Country × year effects	No	No	No	No	Yes
Observations	35,635	35,426	35,426	35,422	35,422
Adjusted R^2	0.010	0.405	0.405	0.409	0.422

Table 10 reports OLS estimates of a version of Equation 2 using data on four digit industries in the European Union. $Inv_{ij,t}$ is the dependent variable. *Inv* is the capital expenditure to sales ratio for a country-industry *ij* in year *t*. *D10* is an indicator variable taking on the value one (zero) if it is (not) a decile 10 industry. *Post* is an indicator variable taking on the value one (zero) for years 2015–2019 (2010–2014). The standard errors are clustered at the country level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

A Appendix

We build our sample data based on several sources. The study is based on administrative data on manufacturing Swedish limited liability companies (Swedish: Aktiebolag) from 1999 to 2020. The Swedish Companies Registration Office (SCRO) (Swedish: Bolagsverket) assigns each Swedish limited liability company an unique and permanent identifier entitled organization number. We link the data using the unique identifier by years. Due to privacy policy, all real identifiers related to micro objects are removed, the data is anonymized and handled by Statistics Sweden (SCB).

Firm-level financial data: First, we get accounting data of Swedish limited liability companies from Bisnode Serrano database. This database integrates financial information from balance sheets, income statements, bankruptcy records, as well as NACE Rev.2 industrial classifications from 1998 to 2020. All variables are converted into the respective calendar year. Since firms can switch industry during our research period, we take the latest 5-digit industrial classification codes (NACE Rev.2) to make it consistent across time.

We build a consolidated dataset at the group and year level by integrating the accounting variables within the same group. We merge accounting variables with corporate structure data from the knc file of serrano database. Each firm identity in a specific year is linked to a unique parent company identifier. In the absence of a group identity, we replace it with the firm's organization number and consider it as an independent entity. We establish coherent NACE Rev.2 for group using the classification of the subsidiary with the most sales or employees. If no entity provides NACE2007 information based on sales or employees, we choose the most recent one among the group. All required values are deflated by Consumer Price Index (CPI), and Swedish Producer Price Index (PPI) at four-digit NACE Rev.2 level with the base year of 2020. For a stand-alone firm, the consolidated figure will be its own value; for firms matched with corporate structure file, we aggregate figures of all subsidiaries within the same group.

General investments data: We have firm-level general investment data from the survey conducted by Statistics Sweden (SCB). This data contains information on implemented and planned general investments from 2000 to 2019, which is aligned with the European System of Accounts (ESA) framework. The investments are categorized into (a) buildings and facility, (b) machinery and equipment, and (c) housing for only real estate companies (NACE Rev.2 sector 68). Table A.2 provides an overview of the sample selection criteria over time based on data description documents from SCB. Table A.3 provides information on sample size with observable investments, which is between 4,100 and 4,900, with an average of 4,600 firms. Figure A.1 displays the coverage of micro data to the aggregated public investments in manufacturing sectors provided by Statistics Sweden.

Environmental investments data: We obtain firm-level environmental expenditures from the survey conducted by Statistics Sweden (SCB), which adheres to EU Regulation [16] and utilizes the accounting system for environmental protection expenditure defined by Eurostat. This dataset consists of firms' environmental investment statistics from 2002 to 2019. The survey includes all firms with 250 or more employees and a selection of firms with 50-249 employees. Surveyed firms are required by law to provide data to SCB (Lag (2001:99) om den officiella statistiken, 7 §). Accordingly on average, 88.5

[16] Regulation (EU) No 691/2011 of the European Parliament and of the Council of 6 July 2011 on European environmental economic accounts, https://eur-lex.europa.eu/eli/reg/2011/691/oj

percent of the surveyed firms in the years 2002-2019 complete the survey.[17] Environmental investments encompass expenditures aimed at reducing or treating pollution. This includes the total expenditure when the sole purpose or direct function is environmental protection (e.g., end-of-pipe equipment or the environmental adaptation of existing equipment). Partial expenditures are considered when a part of the equipment or machinery serves an environmental function and can be separately identified; in such cases, only the cost for that specific part is classified as an environmental investment (e.g., a catalytic converter in a car). Marginal costs related to environmental benefits of an investment are included when a decision has been made to purchase more expensive, environmentally beneficial equipment compared to standard alternatives. The additional cost attributable to these environmental benefits is regarded as part of the environmental investment. If the primary purpose of the equipment is environmental protection but the environmental component cannot be separately estimated, total costs are used as a proxy for environmental investment. Conversely, expenditures are excluded from environmental protection investment if the primary purpose is not environmental protection and the environmental component cannot be estimated separately.[18]

R&D expenditures: The data of business R&D expenses are derived from two sources. i. we have annual total R&D expenses of firms using functional accounting, from the bokslut file in Serrano database; ii. we get biennial R&D data for business sectors from the survey conducted by Statistics Sweden (SCB). The R&D questionnaire contains various components, such as external and internal costs, different funding sources, usages, and anticipated R&D values. This survey ranges from 1997 to 2021. Table A.6 shows the selection thresholds over time, we have around 460 manufacturing firms with valid R&D expenses on yearly average. Figures A.2 and A.3, which are segmented by internal and outsourced R&D expenses, illustrate how our sample data compares to the publicly available aggregated data released by SCB.

To get observable values for even years, we assume that the total external and internal R&D expenditures follow linear trends within the same firm in adjacent years. We generate imputed values by filling in the gaps with the average values of adjacent years when the values are either 0 or missing. We solve fewer than fifty percent of the value gaps by this approach, since larger firms exist the entire time, while smaller ones are rolling depending on the selection cut-off. Additionally, we consider values from accounting type F and K3 firms as benchmarks. If a firm with F(K3) accounting type has a zero total external or internal R&D expense and a missing R&D value from the questionnaire, we replace the missing value with zero. Figure A.2 displays the process of establishing imputed values for data from the questionnaire. Table A.7 exhibits the sample size with observable R&D expenses (both raw and imputed), we have more than 10,000 firms including estimated values on yearly average, which covers around 75 percent of aggregated R&D expenses of Swedish manufacturing sectors.

The R&D variables at firm level apply functional accounting, which is comparable to the sum of external and internal R&D expenditures from the questionnaire. However, the number of firms using functional accounting declined dramatically since 2014, According to Swedish Annual Accounts Act (Årsredovisningslag) Justitiedepartementet L1 (b) and Accounting Board's Guidance

[17]The detailed information the survey, including lapse can be found here [in Swedish]: `https://www.scb.se/hitta-statistik/statistik-efter-amne/miljo/miljoekonomi-och-hallbar-utveckling/miljoskyddskostnader/`. An example of the web survey used for abatement investments in year 2019 can be found here [in Swedish] `https://www.scb.se/contentassets/5c671de894c247a7aa6560cdb0b06e34/mi1302_staf_2019_ml_201014.pdf`

[18]For a decision tree see: `https://www.scb.se/contentassets/f7af32625bdd49f6be7b747299c23d3e/tf_off2000.pdf`

(Bokföringsnämndens vägledninga, 2012:1 Justitiedepartementet L1 (a)) , the updated accounting framework entitled K3 has been made obligatory for larger companies since January 1, 2013.[19] Firms are defined as larger at current year if two of the same conditions have been fulfilled in the last two consecutive years: (i. the average number of employees are at least 50; (ii. the average balance sheet total (Balansomslutning, common name for total assets in Swedish) are at least 40 million SEK; (iii. the average sales are at least 80 million SEK (Bokföringsnämndens vägledninga, 2012:1 Justitiedepartementet L1 (a)). We consider K3 firms which fulfill these criteria as F firms to solve the drastically decreased sample.

Emission data: We acquire annual CO2 emissions at installation level from 1990 to 2021 from Environmental Protection Agency (SEPA). We also have CO2 emissions and allowances at installation level from EU emissions trading system (EU ETS) since 2005. Below we describe our steps to process the emission data.

1. Firstly, we collect Swedish carbon tax rates and generate primary carbon tax payments by multiplying applicable tax rate with corresponding carbon emissions. We measure average cost and marginal cost incurred by firms when emitting an extra unit of CO2 using the summarized tax scheme and approach developed by Martinsson et al. (2024). In our research period, manufacturing sectors were subjected to the "0.8 percent rule" from 1997 to 2006, which indicated that firms paid carbon tax with a maximum of 0.8 percent of their sales, and 25 percent of the initial marginal tax rate was applied to the exceeding part of the payments. Subsequently, the exemption cap was raised from 0.8 percent to 1.2 percent during 2011 to 2014, and then was eliminated in 2015. While for high-emitting industries as cement and glass lime, the highest possible payment is 1.2 percent of sales until 2007, see Table 1 by Martinsson et al. (2024) for details.

2. The European Union Emissions Trading Scheme (EU ETS) comprises four distinct phases. We assess if the firm qualifies for EU ETS exemptions for each phase in accordance with the established rules specific to industries. We acquire EU ETS emissions and free allowances data since 2005 from the European Union Transaction Log and link it with our sample data. We develop a dummy identifier to track firms that have ever been part of the EU ETS. At the consolidated-group level, we consider the group under EU ETS if at least one subsidiary belongs to the system. The marginal costs of emissions for installations under EU ETS align with the sum of the carbon tax rate and allowance prices since 2008. Then we aggregate total CO2 emissions, EU ETS emissions and sum of allowances, CPI-deflated carbon tax payments, weighted marginal costs and allowance prices by sales and tangible fixed assets at group level.

3. As SEPA only collects emissions on bigger installations from 2003 to 2006, we have relatively fewer observations during this period (see Table A.9). We follow the same approach as we developed for R&D expenditure to solve this issue. With the assumption that the emission intensity within a firm between 2002 and 2007 is linear, we interpolate missing values if there are at least two observable emissions, i.e., neither missing or zero during this period. We further

[19] If a company prepares fiscal annual report including information of year 2014, it needs to adopt the new accounting standards and principles starting from January 1, 2013, to ensure consistency in the presentation of comparable statistics. The implementation date has been extended to January 1, 2014 for smaller firms which have no need to modify comparative values (Bokföringsnämndens vägledninga, 2012:1 Justitiedepartementet L1 (a)).

multiply the imputed emission intensity by deflated sales to scale the imputed emissions. Finally, we integrate data on specific industries identified as being at a high risk of carbon leakage, and produce decile dummy variables based on ascending-sorted emission intensity in 1990 at four-digit industrial level, see Martinsson et al. (2024) for details.

Finally, We link data of general investments, environmental investments, biennial R&D expenditures, accounting R&D expenses and accounting values for all manufacturing firms by organization numbers and years. Our sample data is from 1999 to 2020 and at unit of firm and year level.

Exits: Our main analysis uses consolidated firm groups: subsidiaries with ownership shares of at least 50 percent are aggregated to the top-mother level using a (scrambled) unique identifier. This consolidation allows us to measure firm size consistently, but changes in group ownership can mechanically generate apparent "exits" even when underlying operating entities continue.

To focus on proper exits rather than ownership reorganization, we therefore estimate exit patterns at the legal-firm level. We start from firms observed in the baseline year (2009) and included in the investment survey in that year. We define an exit in the post period (2015–2019) as either (i) the firm not being observed in any post-year or (ii) the firm being observed but reporting zero sales in all years of the post period.

Following Colmer et al. (2025), we define this exit indicator and test whether exit is systematically related to our key firm characteristics. Following the difference-in-differences setup in Section subsection 6.1, we estimate probit models for this binary outcome with controls for decile-10 status (d10) and dividend-paying status, and we additionally consider specifications controlling for baseline size (log sales). Results are unchanged when using a linear probability model. The baseline selection which we present in Table B.8 yields 1,213 firms. In the post period, 61 firms are observed with zero sales and 43 firms are not observed. Among these, 4 (zero-sales) and 3 (missing) firms belong to decile 10. Splitting by dividend status, 608 firms pay dividends and 605 do not. Exit is more prevalent among non-dividend-paying firms: 51 are observed with zero sales and 43 are not observed in 2015–2019. All decile-10 firms that are missing (3) or report zero sales (4) in the post period are in the non-dividend group. Among dividend-paying firms, 10 report zero sales and 4 are not observed in the post period. Across probit specifications, decile-10 status is not a statistically significant predictor of exit. This conclusion is unchanged when adding controls for baseline size (log sales), dividend-paying status and two-digit industry controls. We report the regression estimates in Table B.9.

EU aggregates: In addition to the Swedish micro-data, we compare our empirical investigation to the European Union (EU) level. The country-level financial and investment data for 27 EU member states are obtained from Eurostat Structural Business Statistics (SBS) database. Following a significant legislative transition in the collection and reporting of European business statistics, the SBS framework was partitioned into two distinct datasets. Data prior to 2021 are sourced from *SBS - historical data* coded as *sbs_na_ind_r2* [20] while data from 2021 onwards are obtained from *SBS - Enterprise statistics on the whole business population* coded as *sbs_ovw_act*[21]. Our final dataset spans from 2008 to 2023 and encompasses all four-digit manufacturing industries categorized under NACE

[20]SBS database before 2021 on Eurostat: https://ec.europa.eu/eurostat/databrowser/view/sbs_na_ind_r2__custom_19374189/default/table

[21]SBS database after 2021 on Eurostat: https://ec.europa.eu/eurostat/databrowser/view/sbs_ovw_act/default/table

Rev.2 (Sector C). We focus on gross investments in machinery and equipment (variable name *Gross investment in machinery and equipment – million euro* coded as *V15150* from 2008 to 2020 and *Gross investment in machinery and equipment - million euro* coded as *GRSINV_MAC_MEUR* from 2021 to 2023). To scale our investment variable, we use sales/turnover (variable name *Turnover or gross premium written – million euro* coded as *V12110* from 2008 to 2020 and *Net turnover - million euro* coded as *NETTUR_MEUR* from 2021 to 2023).[22] Observations with missing values were excluded from the final sample. To maintain consistency with the primary firm-level analysis, we applied an identical decile-based classification methodology to this cross-country dataset.

[22]In our final dataset, we use the variable name *gross investments in machinery and equipment* coded as *inv_mach_equipment_meur* and *turnover* coded as *turnover_meur*.

A.1 Additional Tables and Figures

Figure B.1: Economy-wide vs Manufacturing Carbon Tax Rate 1990–2024

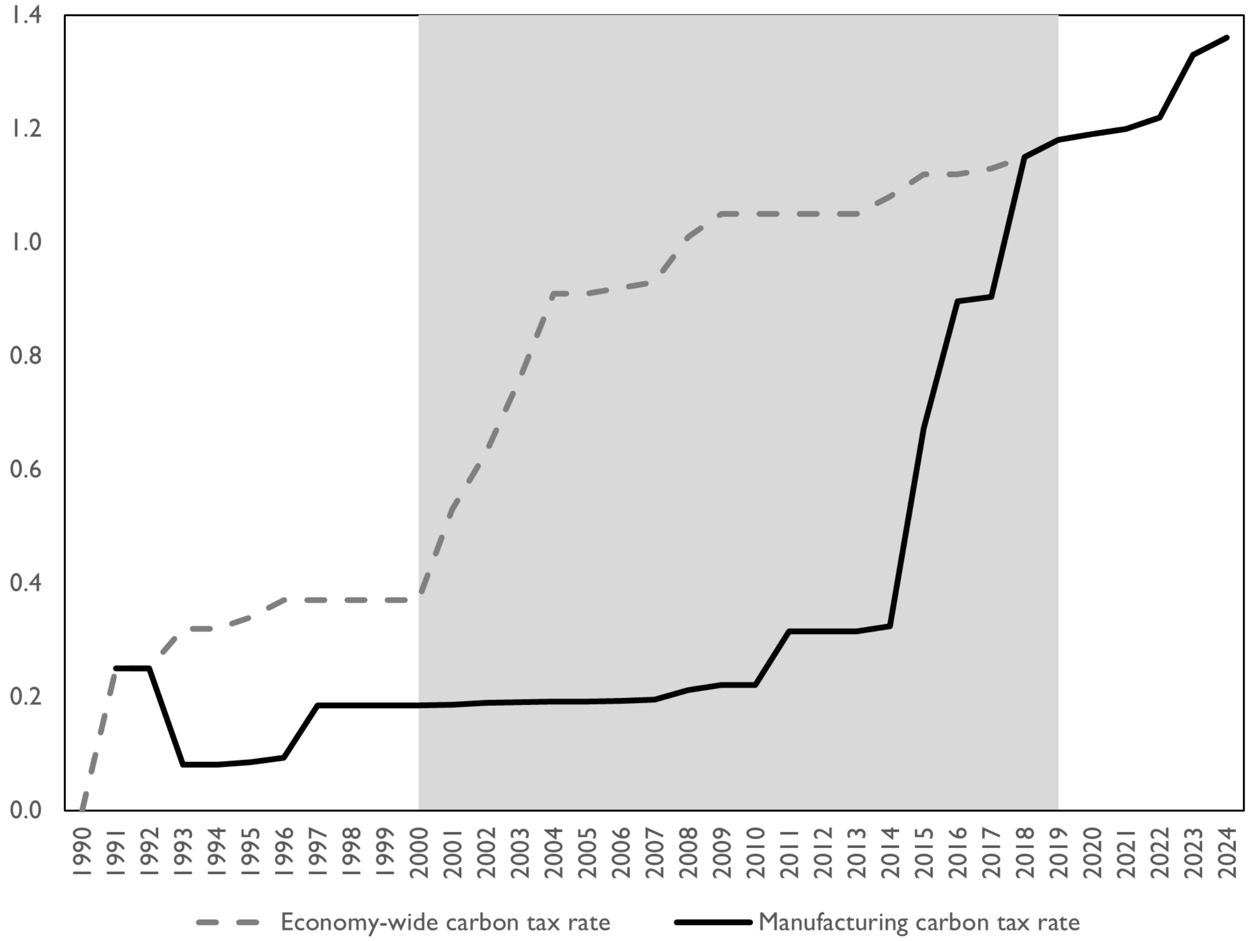


Figure B.1 displays the economy-wide carbon tax rate (grey dashed line) and the manufacturing carbon rate (black solid line) after exemptions. All exemptions were phased out in 2018.

Figure B.2: Capital investment in the manufacturing sector, with 2000–2002 as base years

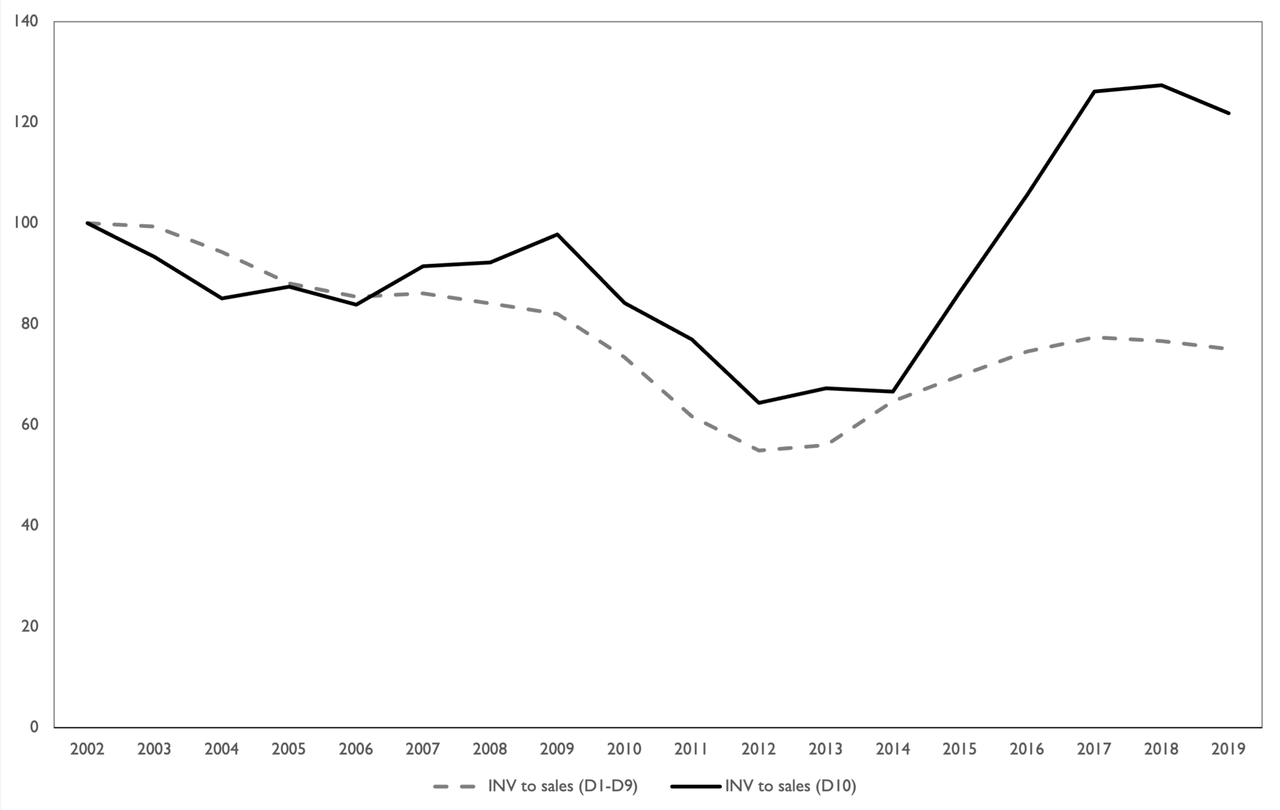


Figure B.2 displays the aggregate capital investment to sales ratio (expressed as a rolling moving average from t to t-2) for decile 10 industries, D10 (solid black line) and for decile 1-9 industries, D1–D9 (dashed grey line), indexed with 2000–2002 as base year. D1–D9 (D10) include firms in the four-digit industries in the lowest nine (highest) deciles in terms of carbon emissions to sales in 2000. All time series are expressed as a rolling moving average from t to t-2 for the time period 2000–2019.

Table B.1: Decile 10 industries

NACE	Four digit industries	Decile in 2000	Decile in 1990
1062	Starches and starch products	10	10
1081	Manufacture of sugar	10	10
1106	Manufacture of malt	10	10
1330	Finishing of textiles	10	10
1712	Manufacture of paper and paperboard	10	10
1920	Refined petroleum products	10	10
2013	Other inorganic basic chemicals	10	10
2016	Plastics in primary forms	10	10
2313	Manufacture of hollow glass	10	10
2351	Manufacture of cement	10	10
2352	Manufacture of lime and plaster	10	10
2362	Plaster products for construction purposes	10	10
2399	Other non-metallic mineral products n.e.c.	10	10
2410	Basic iron and steel and of ferro-alloys	10	10
1711	Manufacture of pulp	10	9
2014	Other organic basic chemicals	10	9
2341	Manuf of ceramic household articles	10	9
2370	Cutting, shaping and finishing of stone	10	7
1621	Veneer sheets and wood-based panels	8	10
2320	Manufacture of refractory products	9	10
2364	Manufacture of mortars	7	10

Table B.1 reports the four-digit NACE industries that make up decile 10 in 1990 and in 2000. Decile 10 is defined as four-digit industries that are in the 10th decile (top 10 percent) in terms of carbon emissions to output in 2000.

Table B.2: Some robustness

	(1)	(2)	(3)	(4)	(5)	(6)
			Inv	**Uncons-**		
	Inv		**Scaled TA**	**olidated**	**Inv**	
$\ln(\mathrm{C_{i,t}}$ - Sales weighted)	0.064***					
	(0.022)					
$\ln(\mathrm{C_{i,t}}$ - Fixed assets weighted)		0.070***				
		(0.021)				
$\ln(\mathrm{C_{i,t}}$ - Scaled by Total Assets)			0.093***			
			(0.027)			
$\ln(\mathrm{C_{i,t}})$					0.055**	0.065***
					(0.026)	(0.011)
$\ln(\mathrm{C_{i,t}}$ - Unconsolidated)				0.046***		
				(0.017)		
$\ln(\mathrm{Inv_{i,t\text{-}1}})$					0.017	0.492***
					(0.025)	(0.020)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	No
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,242	6,154	6,243	10,621	5,161	5,664
Adjusted R^2	0.448	0.434	0.489	0.401	0.472	0.342

Table B.2 reports OLS estimates of Equation 1. $ln(Inv)_{i,t}$ is the dependent variable in columns 1–2, where *Inv* is the capital expenditure to sales ratio for firm i in year t. $ln(Inv\ Scaled\ TA)_{i,t}$ is the dependent variable in column 3, where *Inv Scaled TA* is the capital expenditure to total assets ratio for firm i in year t. $ln(Inv\ unscaled_{i,t}$ is the dependent variable in column 4, where *Inv unscaled* is the capital expenditure for firm i in year t. *C - Sales weighted* is the unconsolidated firm sales weighted cost of emitting CO_2 divided by sales for firm i in year t. *C - Fixed assets weighted* is the unconsolidated firm fixed assets weighted cost of emitting CO_2 divided by sales for firm i in year t. *C - Scaled by TA* is the cost of emitting CO_2 divided by total assets for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2000–2019. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: *Cash flow*$_{i,t\text{-}1}$, *ln(Total assets)*$_{i,t\text{-}1}$, *Long term debt*$_{i,t\text{-}1}$, and *Sales gwth*$_{i,t\text{-}1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.3: Carbon pricing and firm level capital investment: Robustness deciles

	(1)	(2)	(3)
	D1–D4	**D5–D9**	**D10**
$\ln(C_{i,t})$	-0.009	0.109**	0.239***
	(0.067)	(0.042)	(0.057)
Firm fixed effects	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Observations	1,407	1,744	502
Adjusted R^2	0.443	0.463	0.508

Table B.3 reports OLS estimates of Equation 1. $ln(Inv)_{i,t}$ is the dependent variable. *Inv* is the capital expenditure to sales ratio for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2000–2019 and with firm-years in C in four consecutive years. D1–D4 include firms in the four-digit industries in the first to fourth deciles (bottom 40 percent) in terms of carbon emissions to output in 2000, D5–D9 represent firms in the fifth to ninth decile in terms of carbon emissions to output in 2000 and D10 the top decile. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: *Cash flow*$_{i,t-1}$, *ln(Total assets)*$_{i,t-1}$, *Long term debt*$_{i,t-1}$, and *Sales gwth*$_{i,t-1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.4: Carbon pricing and firm level capital investment: Other industry sorts

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: PACE and Mobility					
	Low PACE	**High PACE**	**Low PACE**	**Low PACE**	**High PACE**	**High PACE**
			Low Mobility	**High Mobility**	**Low Mobility**	**High Mobility**
$\ln(C_{i,t})$	0.030	0.084**	0.046	0.031	0.098**	0.054
	(0.040)	(0.035)	(0.090)	(0.043)	(0.045)	(0.048)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,441	2,601	685	1,736	1,751	825
Adjusted R^2	0.468	0.401	0.544	0.417	0.399	0.414
	Panel B: EU leakage list and US PACE data					
	Leakage list		**Leakage list Yes**		**PACE US**	
	No	**Yes**	**Trade only**	**Emission**	**Low**	**High**
$\ln(C_{i,t})$	0.041	0.069*	0.052	0.098**	0.006	0.099***
	(0.034)	(0.035)	(0.050)	(0.043)	(0.034)	(0.035)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,349	2,893	2,175	718	3,142	2,905
Adjusted R^2	0.435	0.467	0.445	0.389	0.461	0.416

Table B.4 reports OLS estimates of Equation 1. $ln(Inv)_{i,t}$ is the dependent variable. *Inv* is the capital expenditure to sales ratio for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. Panel A reports results for firms that are in low (high) PACE industries measured as below (above) the median in the four-digit industry's ratio of abatement investment to sales the first year of abatement data (in 2002) (columns 1–2); for firms in low PACE & low mobility (below the median in PACE and mobility) (column 3); low PACE & high mobility (below the median in PACE and above the median in mobility) (column 4); high PACE & low mobility (above the median in PACE and below the median in mobility) (column 5); high PACE & high mobility (above the median in PACE and mobility) (column 6). Panel B reports results for firms based on if they operate in industries that are on European Union's (EU) carbon leakage list or not (columns 1–2) as well as if the industry is on the list for trade concerns (column 3) or high emission concerns (column 4), for firms in low (high) PACE industries measured as below (above) the median in the four-digit industry's ratio of abatement investment to shipments using US data from 2005 from the Environmental Protection Agency) (columns 5–6). The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2000–2019. All regressions include firm and four digit industry-year fixed effects and the following firm control variables: $Cash\ flow_{i,t-1}$, $ln(Total\ assets)_{i,t-1}$, $Long\ term\ debt_{i,t-1}$, and $Sales\ gwth_{i,t-1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.5: Carbon pricing and firm level capital investment: Abatement investment sub-sample

	(1)	**(2)**	**(3)**	**(4)**
$\ln(C_{i,t})$	0.113***	0.080***	0.160***	0.157***
	(0.019)	(0.024)	(0.049)	(0.041)
Firm fixed effects	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No
Industry × Year effects	No	No	Yes	Yes
Firm controls	No	No	No	Yes
Observations	2,046	1,845	995	815
Adjusted R^2	0.046	0.497	0.487	0.470

Table B.5 reports OLS estimates of Equation 1. $ln(Inv)_{i,t}$ is the dependent variable. *Inv* is the capital expenditure to sales ratio for firm i in year t. C is the cost of emitting CO_2 divided by sales for firm i in year t. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure, abatement investment and CO_2 emissions data during 2002–2019. Regressions in columns 2–4 include firm fixed effects. Regressions in columns 1–2 include year fixed effects and columns 3–4 include four digit industry-year fixed effects. Regression in column 4 includes the following firm control variables: *Cash flow*$_{i,t\text{-}1}$, *ln(Total assets)*$_{i,t\text{-}1}$, *Long term debt*$_{i,t\text{-}1}$, and *Sales gwth*$_{i,t\text{-}1}$. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.6: Investment and dividend before and after the event

	2010–2014	2015–2019	Diff periods	Diff-in-diff	Triple Diff
Panel A: Investment spending					
Div firm (D10)	0.032	0.051	0.019		
No div firm (D10)	0.031	0.029	-0.002		
Diff Groups (D10)	0.001	0.022		0.021	
Div firm (D1–D9)	0.022	0.025	0.003		
No div firm (D1–D9)	0.021	0.022	0.001		
Diff groups (D1–D9)	0.001	0.003		0.002	
Triple Diff					0.019
Panel B: Dividend to cash flow					
Div firm (D10)	0.346	0.064	-0.282		
No div firm (D10)	0.000	0.108	0.108		
Diff Groups (D10)	0.346	-0.044		-0.390	
Div firm (D1–D9)	0.281	0.314	0.033		
No div firm (D1–D9)	0.000	0.109	0.109		
Diff groups (D1–D9)	0.281	0.205		-0.076	
Triple Diff					-0.314

Table B.6 report summary statistics for *Inv* (investment to sales) in panel A and *Div* dividend payments to cash flow in panel B. *Div firm* (*No div firm*) is an indicator variable taking on the value one (zero) if the firm paid dividend in 2010–2014. D1–D9 (D10) include firms in the four-digit industries in the lowest nine (highest) deciles in terms of carbon emissions to sales in 2000. Values are expressed as averages for *Inv* (*Div*) in the first two columns in panel A (B). The table also reports difference in periods and groups as well as differences-in-differences within D1–D9 and D10 groups respectively across dividend paying status and triple differences to compare across firms in different decile groups.

Table B.7: Carbon pricing and firm level capital investment: event results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Collapsed	**Firm-years with emissions data**			**FM: Cash flow**			**FM: Credit ratings**			**FM: Long term debt**		
D10 Firm	0.004	0.012***			0.009**			0.010*			0.012**		
	(0.004)	(0.004)			(0.004)			(0.005)			(0.005)		
Post	0.000	0.004***	0.002*		0.003*	0.000		0.001	0.000		0.004**	0.001	
	(0.001)	(0.001)	(0.001)		(0.002)	(0.002)		(0.001)	(0.002)		(0.001)	(0.001)	
D10 Firm × Post	0.011**	0.012**	0.012**	0.012**	0.005	0.006	0.006	0.012**	0.015**	0.015**	0.009	0.014**	0.014**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
FM					0.008***			0.004***			0.001		
					(0.002)			(0.002)			(0.002)		
D10 Firm × *FM*					0.005			0.000			-0.005		
					(0.007)			(0.002)			(0.007)		
Post × *FM*					0.001	0.001	0.001	0.004*	0.003	0.003	-0.001	-0.001	-0.001
					(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
D10 Firm × *Post* × *FM*					0.011	0.017*	0.017*	-0.008	-0.005	-0.005	-0.002	-0.007	-0.007
					(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Firm fixed effects	No	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year effects	No	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	2,144	5,594	5,096	5,096	7,309	7,026	7,026	7,309	7,309	7,026	7,309	7,026	7,026
Adjusted R^2	0.007	0.023	0.444	0.444	0.025	0.384	0.384	0.017	0.383	0.383	0.012	0.383	0.383

Table B.7 reports OLS estimates of Equation 2 with $Inv_{i,t}$ as the dependent variable. *Inv* is the capital expenditure to sales ratio for firm i in year t. *D10 Firm* is an indicator variable taking on the value one (zero) if the firm is (not) in a decile 10 industry. *Post* is an indicator variable taking on the value one (zero) for years 2015–2019 (2010–2014). *FM* (Finance Measure) is an indicator variable taking on the value one (zero) if the firm's average cash flow to assets in 2010–2014 is above (below) the median among decile 10 firms (or decile 1–9 firms) in columns 5–7, in terms of credit ratings in columns 8–10, and long term debt (bank plus bond debt) to assets in columns 11–13. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2010–2019. The sample in column 1 is two observations per firm, one pre (averaged over 2010–2014) and one post (average over 2015–2019). The sample in columns 2–4 conditions the firm to have emissions data as in the baseline specification. Regressions in columns 3–4, 6–7, 9–10, and 12–13 include firm fixed effects. Regressions in columns 4, 7, 10 and 13 include year fixed effects. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.8: Number of firm exits

	All firms			Dividend firms			No dividend firms		
	# Firms	**# Exits**	**Exit rate**	**# Firms**	**# Exits**	**Exit rate**	**# Firms**	**# Exits**	**Exit rate**
All deciles	1,213	43	0.035	608	4	0.007	605	39	0.064
D1–D9	1,123	40	0.036	567	4	0.007	556	36	0.065
D10	90	3	0.033	41	0	0.000	49	3	0.061

Table B.8 reports number of exits across deciles and firms. A firm is considered to exit if it exists in 2010–2014 but does not show up in 2015–2019. *D10 Firm* is an indicator variable taking on the value one (zero) if the firm is (not) in a decile 10 industry. *Div firm* is an indicator variable taking on the value one (zero) if the firm paid dividend in the period 2010–2014 and zero otherwise.

Table B.9: Carbon pricing and firm exit

	(1)	(2)	(3)
D10 Firm	-0.030	-0.006	0.019
	(0.264)	(0.020)	(0.021)
Div Firm		-0.069***	
		(0.016)	
Size control			-0.011***
			(0.004)
Observations	1,213	1,213	1,213
Log likelihood	-185.8	-168.7	-181.3
Pseudo R^2	0.000	0.092	0.025

Table B.9 reports average marginal effects from Probit versions of Equation 2. *Firm exit* is the dependent variable which takes on the value one if a firm exits and zero otherwise. A firm is considered to exit if it is observed in 2010–2014 but does not appear in any of the years from 2015–2019. *D10 Firm* is an indicator variable taking on the value one (zero) if the firm is (not) in a decile 10 industry. *Div firm* is an indicator variable taking on the value one (zero) if the firm paid dividend in the period 2010–2014 and zero otherwise. The sample comprises Swedish manufacturing firms (NACE: 1000–3300) with capital expenditure and CO_2 emissions data during 2010–2019. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.10: Capital investment to sales in Sweden vs Europe

	Decile 10 industries			Decile 1–9 industries			
	2010–2014	**2015–2019**	**Diff Periods**	**2010–2014**	**2015–2019**	**Diff Periods**	**Diff-in-diff**
Sweden	0.048	0.063	0.016	0.030	0.033	0.003	0.013
EU excl Sweden	0.024	0.027	0.002	0.026	0.026	0.000	0.002
EU 15 excl Sweden	0.024	0.025	0.002	0.024	0.022	-0.001	0.003
EU excl Nordics	0.024	0.026	0.002	0.026	0.026	0.000	0.002

Table B.10 reports average, aggregate capital investment to sales ratios for 2010–2014 and 2015–2019 for decile 10 and decile 1–9 industries respectively in Sweden compared to in the European Union (EU).