The Unequal Burden of Carbon Policy: Distributional Effects on Firm-Level Investment*

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Abstract

This paper examines the heterogeneous effects of carbon policy shocks on firm-level investment using a large panel of non-financial corporations in Germany, France, Italy, and Spain (approximately 7.9 million firm-year observations, 2000–2019) sourced from the ORBIS database. Using high-frequency carbon policy shocks from Känzig (2021) and panel local projections, the analysis finds that a restrictive carbon policy shock reduces tangible investment by 1.24–1.35 percentage points at the one- to two-year horizon. This average decline reflects two complementary supply-side mechanisms. The direct cost channel produces a clear monotonic gradient along the energy intensity of firms' assigned sector-country-year: those in the top tercile cut investment by roughly 75 percent more than those in the bottom tercile. Beyond this direct exposure, supply chain linkages generate a further contraction—firms whose suppliers are carbon-intensive reduce investment substantially more than otherwise comparable firms. Financial conditions and productivity then determine which firms can absorb these cost shocks. Large firms show no statistically significant response, while micro and small firms adjust the most. Among the latter, the least productive firms drive the investment cut while the most productive remain broadly unresponsive at short horizons. Together, these results suggest that carbon policy generates a broad investment contraction that spreads through production networks and whose burden falls disproportionately on firms with limited financial and technological capacity relative to their direct exposure to energy costs.

JEL codes: E22, Q43, Q50
Keywords: Investment, firm heterogeneity, carbon pricing, carbon policy transmission, input-output linkages, energy-intensity

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1 Introduction

The European Union's commitment to achieving climate neutrality by 2050 has placed carbon pricing at the center of the policy agenda. The EU Emissions Trading System (EU ETS), established in 2005, is the world's largest cap-and-trade system and a cornerstone of European climate policy (European Commission, 2021). The European Commission's recent *Fit for 55* package further extends carbon pricing to buildings and transportation, intensifying the discussion around the distributional consequences of climate policy (European Commission, 2021). Understanding how carbon policy affects firm-level investment decisions is therefore essential for designing complementary measures that support the green transition without imposing disproportionate costs on vulnerable firms.

While a growing literature studies the aggregate effects of carbon pricing on output and emissions (see Section 2), much less is known about how carbon policy transmits to firm-level investment decisions. Känzig (2023) identifies exogenous carbon policy shocks using high-frequency variation in EU ETS futures prices and shows that regulatory tightening raises energy prices and reduces industrial production. At the firm level, Matzner and Steininger (2024) examine the response of firm investment to carbon policy shocks. However, the specific mechanisms through which carbon cost increases propagate across firms—in particular, the role of production network linkages and financial constraints—remain largely unexplored.

The present study fills this gap by documenting the heterogeneous effects of carbon policy shocks on firm investment using granular micro-data. The analysis combines a rich firm-level dataset from the ORBIS database—covering over one million non-financial corporations (approximately 7.9 million firm-year observations) in Germany, France, Italy, and Spain from 2000 to 2019—with exogenous carbon policy shocks identified through high-frequency variation in European carbon futures prices around regulatory announcements (Känzig, 2023). The dynamic effects are estimated using panel local projections (Jordá, 2005), following the firm-level applications of Cloyne et al. (2018), Jeenas (2019), Ottonello and Winberry (2020), and Durante et al. (2022).

The main findings are as follows. First, a restrictive carbon policy shock reduces tangible investment significantly, with the effect peaking at 1.25 percentage points (pp) one year and 1.35 pp two years after the shock; intangible investment shows a small positive but statistically insignificant response, so the response of total fixed investment is somewhat smaller than the tangible-only effect. Second, sectoral carbon exposure—measured through the CPRS classification—generates only modest cross-sectoral differences: high-carbon firms (CPRS 1–6) and low-carbon firms (CPRS 7–9) respond by similar magnitudes, indicating that the impact of carbon policy is far broader than the set of directly regulated sectors. EU ETS-covered firms themselves display a comparatively muted response. Third, the direct cost channel is quantitatively important: firms in the top tercile of the sector-country-year energy-intensity measure reduce investment by 1.90 pp at the two-year horizon—about 75 percent more than firms in the bottom tercile. Fourth, supply chain linkages constitute an independent transmission mechanism: firms with high upstream exposure to carbon-intensive suppliers reduce investment by up to 1.78 pp at the two-year horizon, and the effect survives once the assigned energy-intensity measure is included in the same specification. Fifth, financial constraints shape the response: large firms (≥ 250 employees) do not show a statistically significant response at any horizon, while micro, small, and medium firms reduce investment substantially; highly leveraged firms also show stronger contemporaneous declines, consistent with a credit channel. Sixth, the investment cut is concentrated among less productive firms, whereas the most productive firms are largely unresponsive on impact and respond by less at one- and two-year horizons, even after using a value-added-based productivity measure that strips out intermediate-input intensity. Seventh, across broad sectors, investment responses are qualitatively similar, consistent with input-output linkages diffusing carbon-induced cost changes throughout the economy.

The contribution is threefold. First, the analysis decomposes the transmission of carbon policy shocks into a direct energy cost channel and an indirect supply chain channel. A sector-country-year energy-intensity proxy assigned to firms produces a monotonic investment gradient consistent with the quantitative importance of the direct cost mechanism, while a measure of upstream carbon-cost exposure, constructed from input-output tables, identifies supply chain propagation as an independent amplifier[1]. Including both channels jointly in the same regression confirms that each remains significant. Second, the analysis provides novel evidence on the role of finan-

[1] Throughout the paper, this measure refers to the input-share-weighted average of suppliers' *energy* intensity through all rounds of production; it is interpreted as a proxy for upstream *carbon-cost* pass-through, since carbon policy primarily raises the cost of fossil-energy inputs, and is not a direct CO_2-emission measure.

cial constraints—firm size, leverage, and age—in shaping the investment response to carbon policy, showing that large firms do not respond significantly while micro and small firms bear the burden of adjustment. Third, the analysis links the carbon policy literature to the productivity-and-reallocation literature: the most productive firms are largely unresponsive on impact and adjust by less at one- and two-year horizons, while less productive firms bear a disproportionate share of the adjustment burden, and this gradient is robust to the choice of productivity measure, whether sales-based or value-added-based. Together, these findings extend the growing body of work on the macroeconomic effects of carbon policy (Känzig, 2023; Metcalf and Stock, 2020; Känzig and Konradt, 2023) to the firm level, showing that its incidence is shaped as much by firms' financial and technological capacity as by their direct exposure to energy costs.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data, variable construction, and classifications used. Section 4 describes the methodology, covering both the aggregate analysis and the firm-level local projection specification. Section 5 reports the average results. Section 6 examines heterogeneous responses along several dimensions, including carbon exposure, supply chain linkages, and financial constraints. Section 7 discusses robustness checks. Section 8 concludes.

2 Literature review

The analysis relates to three main strands of the literature: the macroeconomic effects of carbon policy, firm-level heterogeneity in the response to aggregate shocks, and the channels through which energy and carbon cost shocks propagate.

A growing empirical literature examines the aggregate consequences of carbon pricing. Metcalf (2019) and Metcalf and Stock (2020) study carbon tax implementations across European countries and find no robust evidence of negative effects on GDP or employment. Andersson (2019) evaluates Sweden's carbon tax and confirms substantial emission reductions without measurable output losses. Konradt and Weder di Mauro (2021) shows that carbon taxes in Europe and Canada have not generated significant inflationary pressure, particularly in countries with revenue-recycling schemes. On the identification front, Känzig (2023) develops a novel approach to identifying carbon policy shocks using high-frequency variation in European carbon futures prices around EU ETS regulatory announcements, finding that a regulatory tightening raises energy prices, reduces industrial production, and achieves persistent emission reductions. Känzig and Konradt (2023) compare EU ETS carbon pricing with national carbon taxes and highlight that the economic costs associated with the European carbon market are larger than those for national carbon taxes, with factors such as revenue recycling, sectoral coverage, and spillovers shaping the transmission. At the firm level, Matzner and Steininger (2024) extend this line of work by examining how carbon policy shocks affect firm-level investment using ORBIS data for European firms.

A large literature has documented that firm characteristics shape investment responses to aggregate shocks. Gertler and Gilchrist (1994) shows that small manufacturing firms account for a disproportionate share of investment declines following aggregate tightening, while Cloyne et al. (2018) find that younger firms paying no dividends exhibit the largest responses. Ottonello and Winberry (2020) show that firms with low default risk are more responsive because they face a flatter marginal cost curve for external finance. Jeenas (2019) documents that balance sheet liquidity, rather than leverage per se, predicts investment sensitivity. Durante et al. (2022), using a comparable ORBIS-based European dataset, find that age and durable goods production are important dimensions of heterogeneity. Financial constraint proxies such as firm size, leverage, and age have been validated by Hadlock and Pierce (2010) and Ferrando and Mulier (2015). The present analysis applies these same proxies—firm size, leverage, and age—to document how financial constraints amplify the firm-level investment response to carbon policy shocks.

Regarding the specific channels of transmission, Hamilton (2009) identifies three pathways through which energy price shocks affect firm investment: the marginal cost of production, demand contraction as consumers reduce expenditure, and uncertainty about future energy prices. The present analysis contributes to this literature by decomposing the carbon policy transmission into two distinct supply-side channels. The first is the direct energy cost channel: firms operating in more energy-intensive sector-country-year cells are more exposed to increases in energy-related production costs, producing a monotonic investment gradient consistent with the mechanism emphasized by Acemoglu et al. (2016) and the empirical findings of Martin et al. (2014). The second is an indirect supply chain mechanism that has received less attention in the firm-level literature on carbon policy shocks: input-output linkages amplify and diffuse carbon cost shocks through production networks (Acemoglu et al., 2012). The upstream carbon exposure measure constructed from FIGARO input-output tables provides novel evidence that supply chain propagation is a quantitatively important and independent amplifier of the investment response, even after controlling for the sector-country-year energy-intensity measure assigned to each firm.

3 The data

This section presents the two main data sources: the carbon policy shocks and the firm-level dataset. It also describes the variable construction, the matching procedure, and the classifications used for heterogeneity analysis.

3.1 Carbon policy shocks

The carbon policy shocks are identified following the methodology of Känzig (2023). The EU Emissions Trading System (EU ETS) was established in 2005 to reduce greenhouse gas emissions through a cap-and-trade mechanism. Regulated firms trade emission allowances within the cap in secondary spot and futures markets. Importantly, the system has undergone numerous regulatory updates to enhance market effectiveness and expand coverage.

Känzig (2023) compiles 113 regulatory events from 2005 to 2019 and identifies carbon policy surprises using high-frequency price movements in European carbon futures around these announcements. The surprise series is shown to be neither autocorrelated nor forecastable by macroeconomic and financial variables. Since the surprise series captures only part of the regulatory shock, it is used as an external instrument for identifying the dynamic causal effects in a monthly VAR. The heteroskedasticity-robust F-statistic of the instrument is 17.51 (critical value 15.06), confirming its strength (Olea and Pflueger, 2013). The carbon policy shocks are extracted from the VAR and normalized so that a unit monthly shock ε_k^m increases the HICP energy component by one percent on impact. The 12-month cumulative shock $\varepsilon_{i,t}$ therefore has units of cumulative energy-price pressure over the firm's fiscal year, and its magnitude depends on the number and direction of monthly shocks within the window.[2]

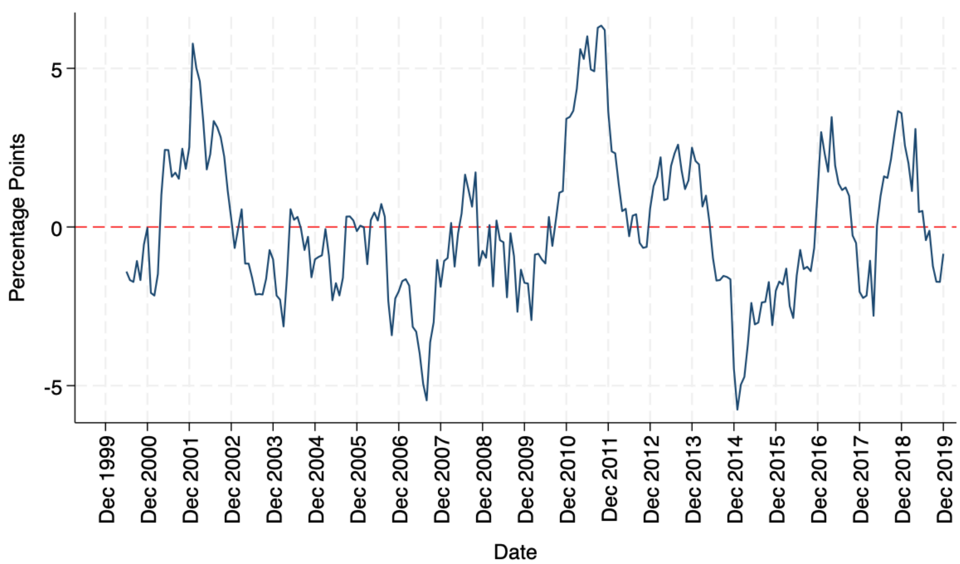
[2] For the full details of the identification procedure, the external instrument approach, and the validity checks, see Känzig (2023).

The shocks are monthly, while the firm-level data are annual. Following Durante et al. (2022), a 12-month moving sum of the carbon policy shocks is constructed and matched with each firm's fiscal year using the "closing month" variable from the ORBIS database. Specifically, let $m_{i,t}$ be the month when firm i closes its accounts in year t. Then the 12-month cumulative shock for firm i in year t is

$$\varepsilon_{i,t} = \sum_{k=0}^{11} \varepsilon^{m}_{m_{i,t}-k}. \tag{1}$$

This matching captures firm-specific variation in the timing of shock exposure, since firms that close their accounts in different months of the same year experience the past shocks differently. Figure 1 displays the 12-month moving sum of the carbon policy shocks, and Table 1 reports the corresponding summary statistics by country.

Figure 1: 12-month moving sum of carbon policy shocks



Note: The figure displays the 12-month moving sum of the carbon policy shock series from Känzig (2023). The shocks are normalized to increase the HICP energy component by one percent on impact.

Table 1: Summary statistics for Carbon Policy Shocks (pp, 12-month cumulative)

	DE	ES	FR	IT	Pooled
mean	0.10	-0.17	0.03	0.03	-0.04
std	2.61	2.28	2.41	2.45	2.38

3.2 Firm-level dataset

The firm-level data are obtained from the Amadeus/ORBIS database provided by Bureau van Dijk (BvD). The analysis covers the four largest EU economies—Germany, France, Italy, and Spain—for the period 2000 to 2019 with annual frequency. The database provides detailed balance sheet and income statement information, including total assets, tangible and intangible fixed assets, sales, employment, cash flow, and industry classification (NACE Rev. 2). A distinguishing feature of ORBIS is its coverage of both listed and unlisted firms, including very small firms, which provides the statistical power necessary to detect heterogeneous effects.

The cleaning procedure follows the methodology of Gopinath et al. (2017) and Kalemli-Özcan et al. (2015) and proceeds in several stages. First, when multiple financial statements exist for the same firm-year, the observation with the highest consolidation level is retained, with priority given to consolidated accounts (C2, C1) over unconsolidated (U1, LF, U2). Fiscal years are assigned to calendar years using a June 1 cutoff: accounts closing before June 1 are assigned to the previous calendar year.[3] Second, a set of validation filters removes companies that report unrealistic balance sheet figures. Following Gopinath et al. (2017), firms are dropped if they report negative or zero total assets, negative employment, negative sales, negative tangible fixed assets, or if key balance sheet ratios—such as employment-to-assets, employment-to-sales, or sales-to-assets—exceed the 99.9th percentile. Additional checks verify accounting identities: observations where total liabilities exceed 110 percent of total assets or fall below 90 percent, or where long-term debt exceeds total non-current liabilities, are removed. Seven component-to-total balance sheet ratios are trimmed at the 0.1st and 99.9th percentiles. Third, all financial variables are converted to a common unit, deflated using

[3]This re-assignment applies only to the alignment of balance sheet variables with calendar years, following Kalemli-Özcan et al. (2015). The carbon policy shock is matched to each firm using its actual fiscal year closing date—not the re-assigned year—so that the 12-month cumulative sum in Equation (1) always covers the firm's true reporting window. Only 3.9% of firm-year observations have a closing month before June, so this distinction has negligible impact on the results.

industry-level (two-digit NACE) deflators where available and GDP deflators otherwise, and expressed in constant euros. Fourth, we construct financial ratios including investment rates, leverage, cash flow to assets, and liquidity. To handle outliers, the main dependent variables (investment rates) are winsorized at the 2nd and 98th percentiles, while all other ratios are winsorized at the 1st and 99th percentiles. Finally, the focus is on non-financial corporations. The financial sector (NACE K), real estate (L), public administration (O), education (P), health (Q), households (T), and extraterritorial bodies (U) are excluded. Firms with fewer than four consecutive years of observations are excluded, as the analysis requires lagged variables and forward projections.[4]

The final sample includes approximately 1.21 million firms and 7.86 million firm-year observations, representing a substantial increase in coverage relative to prior work. Table 2 reports the summary statistics by country and for the pooled sample. The average tangible net investment rate (pooled) is 13.75 percent, with a standard deviation of 99.17 percent, reflecting the vast heterogeneity in the firm-level data. The average firm is 20 years old. Italy and Spain contribute the largest shares of observations, while Germany, despite contributing fewer firms, has the highest average total assets.

[4]When firms have gaps in their reporting, consecutive spells of at least four years are retained as separate units.

Table 2: Summary statistics

	DE	ES	FR	IT	Pooled
Tangible net investment (percent)					
mean	10.00	12.31	14.02	15.25	13.75
std	72.72	93.70	108.30	98.11	99.17
min	-73.49	-85.89	-99.92	-69.05	-99.92
max	693.34	608.14	592.46	641.99	693.34
Total assets (log euro)					
mean	21.34	13.57	13.34	14.05	13.78
std	4.12	1.51	1.68	1.48	1.87
min	9.79	8.38	8.79	9.08	8.38
max	25.98	18.55	23.58	22.13	25.98
Age (years)					
mean	32	18	20	20	20
std	31	10	13	13	13
min	5	5	5	5	5
max	689	149	166	1005	1005
Sales growth (percent)					
mean	4.61	4.16	0.43	5.99	3.77
std	31.22	50.05	26.88	55.94	47.06
min	-59.28	-87.57	-99.90	-76.31	-99.90
max	302.46	462.54	158.82	836.78	836.78
Cash flow / Total assets (percent)					
mean	10.40	5.84	9.97	5.84	7.04
std	10.20	9.14	11.27	7.88	9.59
min	-21.02	-29.93	-24.37	-21.01	-29.93
max	61.00	48.91	56.69	44.51	61.00
Obs.	110,481	2,913,022	2,172,035	2,665,434	7,860,972
N. firms	21,753	436,143	378,422	372,423	1,208,741

3.3 Variable definitions and classifications

The benchmark dependent variable is the tangible net investment rate $I_{i,t}$, which measures the net change in tangible fixed assets as a percentage of the beginning-of-period stock.[5] The control vector includes two lags of the carbon policy shock, two lags of the first difference of the investment rate, two lags of the first difference of sales growth, and two lags of the first difference of cash flow relative to total assets. A comprehensive

[5] Year t refers to the firm's accounting year, identified by the closing date of its accounts. Formally, $I_{i,t} = (\text{Tangible fixed assets}_{i,t} - \text{Tangible fixed assets}_{i,t-1})/\text{Tangible fixed assets}_{i,t-1} \times 100$. The dependent variable in the local projection is $\Delta_h^* I_{i,t-1} = I_{i,t+h} - I_{i,t-1}$, so a coefficient of -1.25 means that a one-unit increase in the cumulative carbon policy shock reduces the investment rate by 1.25 percentage points of the beginning-of-period tangible asset stock at the one-year horizon.

description of all variables is provided in Table A1 in the Appendix.

Firms are classified into four macro sectors using NACE Rev. 2 sections: manufacturing (Section C), construction (Section F), services (Sections G, H, I, J, M, N), and primary & utilities (Sections A, B, D, E). For carbon exposure, the analysis uses the Climate Policy Relevant Sectors (CPRS) classification developed by Battiston et al. (2017), which maps NACE codes into groups based on their relevance to carbon pricing. The CPRS framework identifies nine categories reflecting different forms of exposure to climate policy—from fossil fuel extraction (CPRS 1) through energy-intensive manufacturing (CPRS 3) to low-carbon services (CPRS 9). Following this framework, firms are categorized into three tiers: *energy-intensive sectors* (CPRS 1–3: fossil fuels, utilities, energy-intensive manufacturing), *carbon-exposed sectors* (CPRS 4–6: buildings, transportation, agriculture), and *low-carbon sectors* (CPRS 7–9: finance, R&D, services). For the binary analysis, energy-intensive and carbon-exposed firms are combined into the "high-carbon" category.

In addition to the standard tercile-based classifications, the analysis uses the European Commission's SME classification based on employee headcount (European Commission, 2003): micro ($<$ 10 employees), small (10–49), medium (50–249), and large ($\geq$ 250). This classification aligns with the policy-relevant size thresholds used in EU industrial and competition policy.

To measure indirect supply chain exposure, an upstream carbon exposure variable is constructed using Eurostat's FIGARO inter-country input-output tables (industry-by-industry), which provide transaction matrices for EU countries at a 64-sector NACE classification. For each sector s, country c, and year t, a matrix of Leontief technical coefficients is first computed from the domestic sub-matrix of the FIGARO table. Each element $A_{s's,c,t}$ represents the share of sector s's gross output accounted for by purchases from sector s':

$$A_{s's,c,t} = \frac{Z_{s's,c,t}}{x_{s,c,t}} \tag{2}$$

where $Z_{s's,c,t}$ is the value of inputs from sector s' purchased by sector s in country c at time t, and $x_{s,c,t}$ is the gross output of sector s (total intermediate inputs plus value added). The Leontief inverse $L_{c,t} = (I - A_{c,t})^{-1}$ is then computed, where each element $L_{s's,c,t}$ captures the total—direct and indirect—requirement of sector s''s output needed to deliver one unit of sector s's final demand, accounting for all rounds of production. Sectoral energy intensity $\text{EI}_{s',c,t}$ is constructed from Eurostat data as energy use in terajoules divided by gross value added in million euros and is used to compute the upstream carbon exposure as:

$$\text{Upstream}_{s,c,t} = \sum_{s'} L_{s's,c,t} \cdot \text{EI}_{s',c,t} \tag{3}$$

This variable captures the total energy intensity embodied in a sector's entire supply chain, including not only direct suppliers but also suppliers' suppliers through all subsequent production rounds.[6] A sector with high upstream exposure faces large carbon cost increases even if it is not itself energy-intensive, because cost shocks propagate and amplify through the production network. The measure focuses on domestic supplier links and varies by country and year; a time-invariant version—averaging the exposure across all available FIGARO years (2010–2021)—is also constructed to extend coverage to the full sample period. Each firm is assigned the upstream exposure value of its primary NACE two-digit sector in its country and year. The network propagation of cost shocks through input-output linkages is a theoretically well-established mechanism (Acemoglu et al., 2012). Table A3 in the Appendix reports the top 20 sectors by upstream exposure.

4 Methodology

4.1 Aggregate investment response

Before turning to the firm-level analysis, the aggregate investment response to carbon policy shocks is examined. Let $GFCF_{j,q}$ denote the chain-linked gross fixed capital formation of country j in quarter q, obtained from Eurostat national accounts[7]. The carbon policy shocks are summed over each quarter to match the frequency. Following

[6]The construction uses sectoral *energy* intensity, which is available at finer country-sector-year resolution. The variable is therefore best interpreted as a measure of *upstream carbon-cost exposure*: the channel through which a carbon-policy shock raises the input costs of sector s via its energy-intensive suppliers.

[7]Note that GFCF in the national accounts is constructed to include both tangible (machinery, equipment, structures) and intangible (R&D, software, mineral exploration, artistic originals) assets under the ESA 2010 methodology, so the aggregate measure is broader than the firm-level tangible-only benchmark and closer in scope to the total fixed investment series reported in Appendix B.

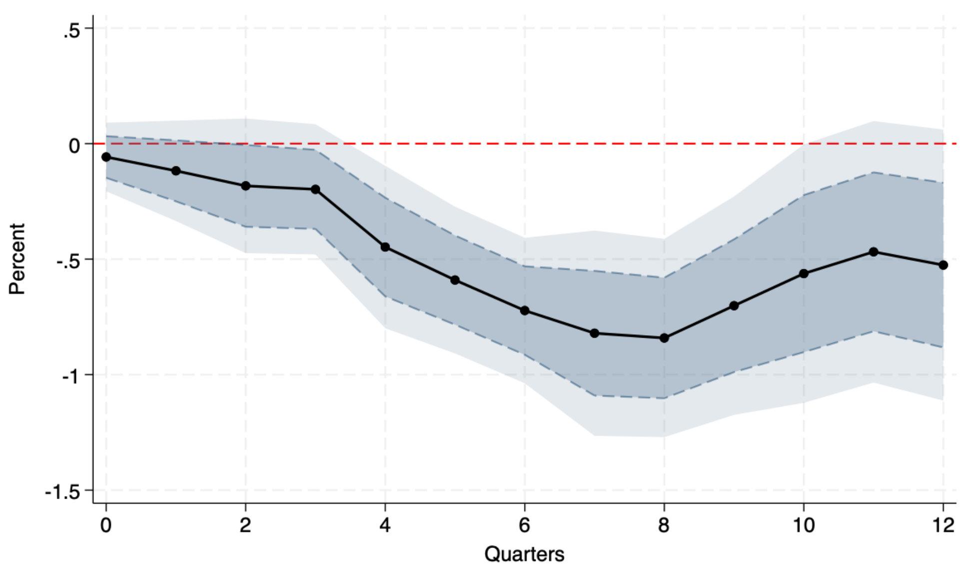
Jordá (2005), the impulse response is estimated via local projections:

$$\log(GFCF)_{j,q+h} - \log(GFCF)_{j,q-1} = \alpha_j^h + \beta^h \cdot \varepsilon_q + u_{j,q+h} \tag{4}$$

where j denotes the country, h the horizon (quarters), and α_j^h is a country fixed effect. The coefficient β^h captures the cumulative response of aggregate investment to a one percentage point increase in the carbon policy shock at horizon h. Standard errors are robust.

Figure 2 displays the pooled aggregate response, and Table 3 reports the estimates. Tightening carbon policy reduces aggregate investment, with the effect building gradually over time. The point estimates become sizable by the fourth quarter (-0.45 pp) and reach statistical significance at the two-year horizon (-0.84 pp, significant at the 5 percent level). Country-specific estimates, reported in the Appendix (Figure A8), show qualitatively similar patterns.

Figure 2: The impact of carbon policy shocks on aggregate investment (pooled)



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are robust. The estimation pools Germany, France, Italy, and Spain with country fixed effects.

Table 3: Effect of Carbon Policy Shocks on Aggregate GFCF (Pooled, Chain-Linked)

	ΔI^*_{it0}	ΔI^*_{it2}	ΔI^*_{it4}	ΔI^*_{it6}	ΔI^*_{it8}	ΔI^*_{it10}	ΔI^*_{it12}
ϵ_t	-0.058	-0.183	-0.448	-0.723**	-0.841**	-0.563	-0.526
	(0.090)	(0.177)	(0.214)	(0.191)	(0.261)	(0.340)	(0.357)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	324	316	308	300	292	284	276

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Firm-level local projections

Following Jordá (2005) and Cloyne et al. (2018), the dynamic firm-level investment responses to carbon policy shocks are estimated using panel local projections (LP). The dependent variable is the h-year forward difference in the investment rate, defined as $\Delta^*_h I_{i,t-1} = I_{i,t+h} - I_{i,t-1}$. For the average effect, the specification is:

$$\Delta^*_h I_{i,t-1} = \alpha_i^h + \beta^h \cdot \varepsilon_{i,t} + \Gamma^h \Delta X_{i,t-1} + u_{i,t+h} \tag{5}$$

where α_i^h is a firm fixed effect controlling for time-invariant heterogeneity at each horizon h, $\varepsilon_{i,t}$ is the 12-month moving sum of the carbon policy shock from Equation (1), and $\Delta X_{i,t-1}$ is the control vector. The sequence of estimated coefficients $\hat{\beta}^0, \hat{\beta}^1, \ldots, \hat{\beta}^H$ traces the impulse response function.

To study heterogeneous effects across groups of firms, the specification is extended to interact the shock with group indicator variables:

$$\Delta^*_h I_{i,t-1} = \alpha_i^h + \sum_{g=1}^{G} \beta_g^h \cdot D^g_{i,t-1} \cdot \varepsilon_{i,t} + \sum_{g=1}^{G} \gamma_g^h \cdot D^g_{i,t-1} + \Gamma^h \Delta X_{i,t-1} + u_{i,t+h} \tag{6}$$

where $D^g_{i,t-1}$ is an indicator that equals one if firm i belongs to group g at time $t-1$, and zero otherwise. Group membership is determined by lagged characteristics to avoid simultaneity concerns. For continuous characteristics (size, leverage, liquidity), firms are sorted into terciles based on lagged values. The coefficients β_g^h capture the impulse response for group g at horizon h. The coefficients γ_g^h control for level differences in investment across groups; these drop from the regression when group membership is time-invariant, as the firm fixed effect absorbs them.

Standard errors are two-way clustered at the firm and month-year levels to account for both cross-sectional and temporal dependence.[8] All available observations are used at each horizon; since firms entering the sample close to the end of the period cannot be followed forward, the sample shrinks at longer horizons.

5 Average effect on tangible investment

Figure 3 displays the impulse response function of the average firm-level tangible investment rate to a carbon policy shock, and Table 4 reports the full regression results including all control variables.

A restrictive carbon policy shock produces a sizable and persistent decline in tangible investment. The contemporaneous response is -0.52 pp, not statistically significant at conventional levels. The effect intensifies sharply to -1.25 pp at the one-year horizon (significant at the 1 percent level) and peaks at -1.35 pp at the two-year horizon (significant at the 5 percent level). By the third year, the point estimate attenuates to -0.58 pp and loses significance, indicating that the bulk of the investment adjustment occurs within the first two years following the shock. The hump-shaped pattern—an insignificant impact effect followed by a significant, deepening response at horizons one and two—is consistent with the gradual pass-through of carbon costs into energy and input prices, the time required for firms to revise investment plans, and the lagged realization of project cancellations or postponements.

The control variables behave as expected and provide reassurance about the specification. Lagged investment differences enter with large negative coefficients (-0.68 and -0.34 for the first and second lags, respectively, $p < 0.01$), reflecting strong mean reversion in firm-level investment rates. Lagged cash flow differences enter positively and significantly at shorter horizons ($+0.32$ at $h = 0$, $+0.11$ at $h = 1$), consistent with the internal finance channel: firms with improving cash flow positions invest more, in line with the predictions of models with financial frictions (Fazzari et al., 1988). Sales growth lags are positive and significant ($+0.04$ pp, $p < 0.01$), capturing the demand-driven component of investment.

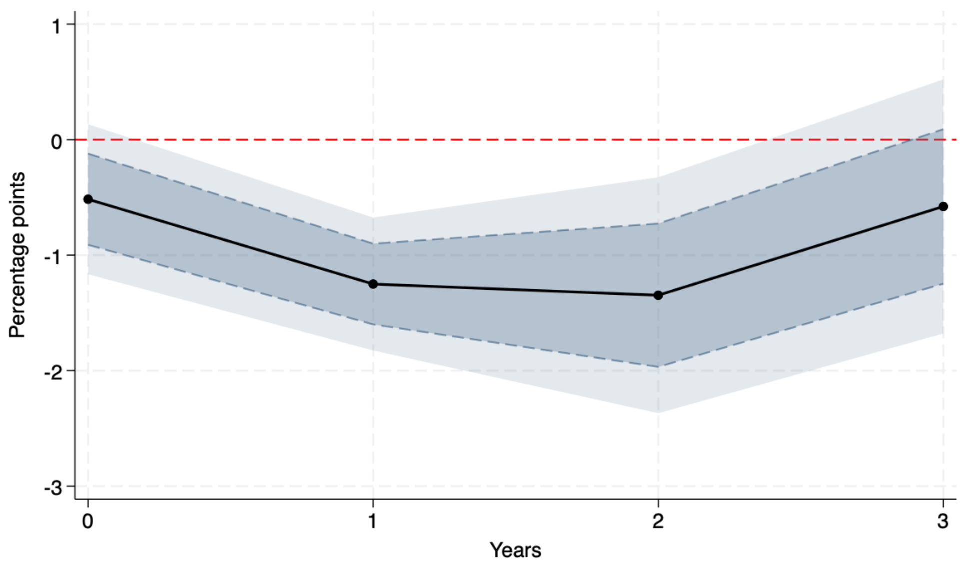
The first lag of the carbon policy shock ($\varepsilon_{i,t-1}$) enters significantly and negatively at $h = 0$ (-1.04 pp, $p < 0.01$) and $h = 1$ (-1.01 pp, $p < 0.01$), indicating that past carbon

[8] Clustering at the month-year level is warranted because firms closing their accounts in the same month share the same realization of the carbon policy shock.

policy shocks continue to depress current investment. This persistence is economically important: it implies that a sequence of tightening shocks has cumulative effects on investment, as each successive shock compounds the depressive effect of earlier ones. The second lag ($\varepsilon_{i,t-2}$) is insignificant at all horizons, suggesting that the investment response to a given shock is largely exhausted within two years.

The aggregate and firm-level analyses are consistent. Both exhibit a hump-shaped response with the largest effects at the one- to two-year horizon. The aggregate analysis, based on only 324 quarterly observations across four countries, achieves significance at the two-year ($h = 8$ quarters) horizon (-0.84 pp). The firm-level analysis, with nearly 7.9 million observations, provides sharply more precise estimates and detects significant effects one year earlier, underscoring the statistical power gained from granular micro data.

Figure 3: The impact of carbon policy shocks on average firm-level tangible investment



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels.

Table 4: Effect of Carbon Policy Shocks on Tangible Investment (Average)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.52	-1.25***	-1.35**	-0.58
	(0.39)	(0.35)	(0.62)	(0.67)
ϵ_{it-1}	-1.04***	-1.01***	-0.23	-0.19
	(0.30)	(0.33)	(0.44)	(0.44)
ϵ_{it-2}	-0.68	0.36	0.40	1.06
	(0.45)	(0.54)	(0.65)	(0.70)
ΔI_{it-1}	-0.68***	-0.68***	-0.68***	-0.67***
	(0.01)	(0.01)	(0.01)	(0.01)
ΔI_{it-2}	-0.34***	-0.33***	-0.33***	-0.32***
	(0.01)	(0.01)	(0.01)	(0.01)
ΔSG_{it-1}	0.04***	0.04***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
ΔSG_{it-2}	0.04***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
ΔCF_{it-1}	0.32***	0.11***	0.04*	0.04
	(0.02)	(0.02)	(0.02)	(0.03)
ΔCF_{it-2}	0.22***	0.06***	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The analysis also examines alternative investment measures. The intangible investment rate shows a positive but statistically insignificant response across all horizons (see Table A5 and Figure A1 in the Appendix), suggesting that firms may redirect investment toward intangible assets (e.g., patents, carbon allowances) in response to carbon policy. Total fixed investment, which combines tangible and intangible components, shows a negative response (-0.71 pp and -0.73 pp at $h = 1$ and $h = 2$, respectively; see Table A6 and Figure A2 in the Appendix), though smaller in magnitude than the tangible-only measure, consistent with partial offsetting by intangible investment.

6 Heterogeneous responses

This section investigates how the investment response to carbon policy varies across firm characteristics. The analysis proceeds along five dimensions: sectoral carbon exposure, the direct and upstream energy-cost channels, financial constraints, firm-level productivity, and broad sectoral composition.

6.1 Carbon exposure

This subsection investigates how the investment response to carbon policy varies with sectoral carbon exposure, using the Climate Policy Relevant Sectors (CPRS) classification described in Section 3.3. The analysis proceeds from a broad binary classification—high-carbon (CPRS 1–6) versus low-carbon (CPRS 7–9)—to a finer three-tier decomposition that distinguishes energy-intensive sectors (CPRS 1–3), carbon-exposed sectors (CPRS 4–6), and low-carbon sectors (CPRS 7–9).[9] A central finding is that the investment response is remarkably broad-based across sectors.

6.1.1 Binary analysis: high-carbon versus low-carbon firms

As an initial heterogeneity analysis, firms are classified into a high-carbon group (CPRS 1–6, encompassing fossil fuels, utilities, energy-intensive manufacturing, construction, transportation, and agriculture) and a low-carbon group (CPRS 7–9, comprising finance, R&D, advanced services, and other low-policy-relevance sectors). This binary split is a natural first pass, though subsequent analysis will show that it masks important within-group variation.

Figure 4 displays the impulse response functions for the two groups, with full regression results in Table A7. Both groups exhibit economically and statistically significant investment declines. High-carbon firms reduce investment by -0.67 pp at impact, with the effect deepening to -1.28 pp at the one-year horizon ($p < 0.01$) and reaching -1.63 pp at $h = 2$ ($p < 0.05$) before attenuating to -0.86 pp by year 3. Low-carbon firms follow a similar trajectory: -0.48 pp at impact, -1.24 pp at $h = 1$,

[9] This grouping captures sector-level emission intensity and does not correspond one-to-one with actual EU ETS participation, which depends on installation-level thresholds. Many firms in CPRS 1–3 are not ETS-covered, and some firms in CPRS 4–6 (e.g., aviation) are. See Table A2 in the Appendix for the detailed mapping of CPRS categories to NACE Rev. 2 codes.

and -1.28 pp at $h = 2$ (both significant at the 1 percent level), with the year-3 effect fading to -0.52 pp.

The differential between the two groups, shown in panel (c) of Figure 4 and reported in Table A8, is small and statistically insignificant at most horizons. This finding is noteworthy: even firms classified as low-carbon experience substantial, persistent investment declines in response to carbon policy shocks. Three mechanisms can account for this broad-based response. First, supply chain propagation transmits carbon-induced cost increases to downstream firms in all sectors, since virtually all firms purchase energy-intensive inputs such as electricity, fuels, and basic materials (see Section 6.2.2). Second, aggregate demand effects reduce revenue for firms throughout the economy when carbon policy contracts demand for energy-intensive goods. Third, policy uncertainty may cause firms across the board to postpone investment until the long-run profitability implications of the regulatory shift become clearer. Disentangling these mechanisms requires the finer disaggregation undertaken in the following subsections.

6.1.2 Three-tier CPRS classification: energy-intensive, carbon-exposed, and low-carbon sectors

To determine if the magnitude of the investment decline corresponds directly to a sector's level of carbon exposure, this subsection presents the results using a three-tier classification system. Energy-intensive sectors (Tier 1, CPRS 1–3) include fossil fuel extraction, utilities, and energy-intensive manufacturing—sectors with high direct emission intensity. Carbon-exposed sectors (Tier 2, CPRS 4–6) include buildings, transportation, and agriculture, which face substantial indirect exposure through energy costs and supply chain links. Low-carbon sectors (Tier 3, CPRS 7–9) serve as the reference group.

Figure A3 displays the impulse responses and Table A9 reports full regression results. Energy-intensive sectors show the deepest two-year decline, with an insignificant -0.67 pp at impact, -1.28 pp at $h = 1$ ($p < 0.01$), peaking at -1.63 pp at $h = 2$ ($p < 0.05$). Carbon-exposed sectors follow a very similar trajectory: -0.44 pp at impact, -1.31 pp at $h = 1$ ($p < 0.01$), and -1.35 pp at $h = 2$ ($p < 0.05$). Low-carbon sectors exhibit the smallest point estimates but remain economically large: -0.51 pp at impact, -1.20 pp at $h = 1$ ($p < 0.01$), and -1.24 pp at $h = 2$ ($p < 0.05$). By year 3, all three groups show attenuated and insignificant effects.

The differential analysis, reported in Table A10, reveals modest and inconsistently signed differences relative to the low-carbon reference group. The energy-intensive-minus-low-carbon differential is approximately -0.17 pp at impact and becomes very small at $h = 1$, before reaching -0.39 pp at $h = 2$, suggesting that the timing—rather than the overall magnitude—of the response differs across tiers. Carbon-exposed-minus-low-carbon differentials are similarly small, ranging from near zero at impact ($+0.06$ pp) to approximately -0.11 pp at $h = 1$ and $h = 2$.

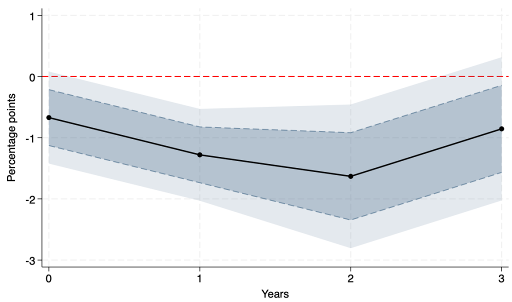
The lack of a strict, proportional relationship between carbon exposure and investment decline is an important finding in itself. It indicates that the mechanisms driving the investment response are not purely a function of sectoral carbon intensity. Instead, firm-specific characteristics—financial constraints, technological flexibility, and supply chain position—that vary within sectors appear to play a dominant role. This finding motivates the energy intensity and upstream exposure analyses in Section 6.2, which decompose the aggregate effect into direct energy cost and indirect supply chain components, and the financial constraints analysis in Section 6.3.

Taken together, the analysis of carbon exposure reveals a nuanced picture. The binary classification shows that low-carbon firms respond almost as strongly as high-carbon firms, indicating that carbon policy shocks spread widely through supply chains. The three-tier breakdown confirms this pattern: because there is no strict, proportional relationship between higher carbon intensity and steeper investment declines, it suggests that sectoral carbon intensity per se is less important than firm-specific vulnerability. These findings align with concerns about distributional inequities in carbon transitions (Känzig, 2023) and the need to monitor how climate-policy-induced costs ripple through production networks (Monasterolo and Battiston, 2020).

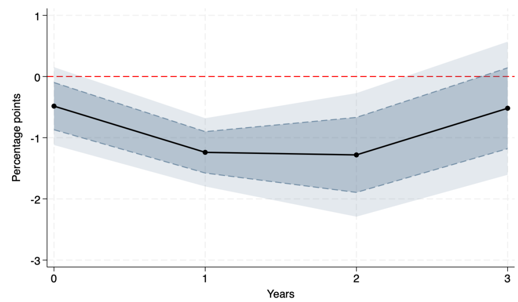
It is worth noting that the CPRS classification is an approximation of firms' actual carbon exposure: it assigns sectors to carbon-relevance tiers based on third-party assessments of emission intensity and regulatory vulnerability rather than on firm-level emissions data. This sector-wide grouping can mask significant differences between individual firms. For instance, a diversified manufacturer labeled as energy-intensive might actually produce very few direct emissions. Consequently, the lack of a clear, proportional trend across the tiers is partly due to the measurement limits inherent in these broad classifications. The energy intensity and upstream exposure analyses in Section 6.2 address this issue by using sector–country–year variation in energy intensity and supply chain composition, assigned to firms based on their NACE two-digit sector, country, and year, providing a more precise decomposition of the transmission channels.

Figure 4: The impact of carbon policy shocks on investment by carbon exposure

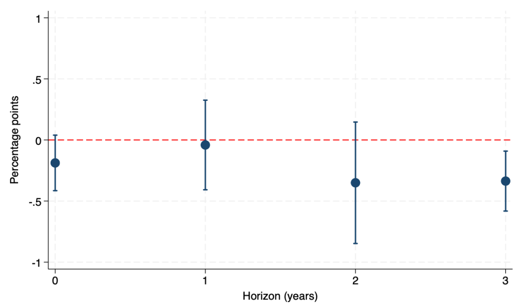
(a) *High carbon*



(b) *Low carbon*



(c) *Difference: High − Low*



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panel (c) shows the difference between high-carbon and low-carbon firms.

6.2 Direct and upstream energy-cost channels

This subsection investigates the specific channels through which carbon policy shocks propagate to firm investment decisions. Two mechanisms are distinguished: a direct cost channel proxied by sector-country-year energy intensity assigned to firms, and an indirect channel operating through supply chain linkages. This decomposition reveals that the aggregate investment response reflects not only the direct cost burden borne by energy-intensive firms but also the network propagation of policy-induced cost increases through input-output relationships.

6.2.1 Energy intensity

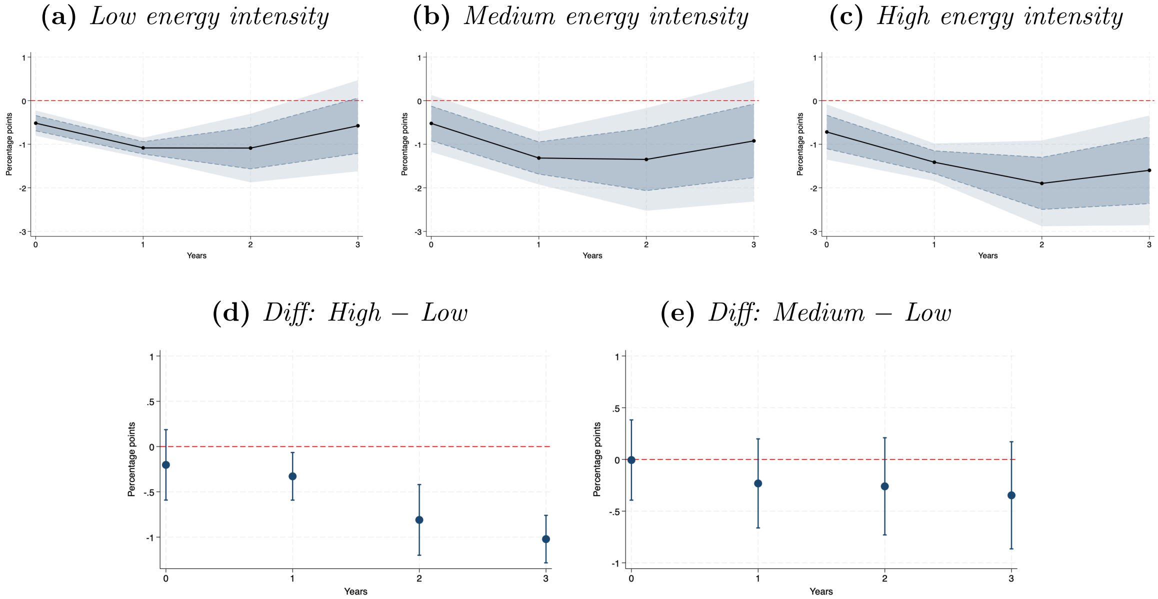
The direct cost channel operates when carbon policy increases the price of energy, raising production costs more in sectors with higher energy use relative to value added. To measure direct exposure, each firm is assigned the lagged energy intensity of its NACE two-digit sector in its country and year. This variable is constructed from Eurostat data as energy use in terajoules divided by gross value added in million euros and is merged to the firm panel at the sector-country-year level. Firms are then allocated into terciles based on this lagged assigned measure. This proxy does not observe firm-specific energy expenditure directly, but it captures systematic differences in exposure to energy-cost increases across sector-country-year cells. For brevity, the discussion below refers to firms in high- and low-energy-intensity terciles, although the classification is based on this assigned sector-country-year measure.[10]

Figure 5 presents the impulse response functions by energy intensity tercile. Full regression results are reported in Table A12 in the Appendix. The results reveal a clear and monotonic gradient. Low-energy-intensity firms respond by -0.52 pp at impact ($p < 0.01$), -1.08 pp at $h = 1$, and -1.09 pp at $h = 2$, with the effect attenuating by year 3. Medium-energy-intensity firms show intermediate effects, ranging from -0.52 pp at impact to approximately -1.35 pp at $h = 2$. High-energy-intensity firms display the strongest response: -0.72 pp contemporaneously ($p < 0.10$), deepening to -1.41 pp at $h = 1$ and -1.90 pp at $h = 2$ ($p < 0.01$), before moderating to -1.60 pp at $h = 3$ ($p < 0.05$).

The differential between high- and low-energy-intensity firms (Table A13) is economically significant: at the two-year horizon, high-energy firms reduce investment by approximately 0.8 percentage points more than low-energy firms, a 75 percent larger effect. Because energy intensity is measured at the sector-country-year level and assigned to firms, this monotonic, persistent gradient is best interpreted as evidence consistent with a direct cost channel rather than as direct evidence on firm-specific energy expenditure. The persistence of the effect through year 3 further suggests that firms do not immediately absorb increased energy costs; instead, the investment response reflects a gradual reassessment of project profitability and the return on capital, consistent with dynamic adjustment costs and firm learning about policy persistence.

[10] Because this measure is available only for the years covered by the Eurostat series and the terciles are based on its lagged value, the energy-intensity heterogeneity analysis is estimated on a later and smaller subsample than the full ORBIS panel.

Figure 5: The impact of carbon policy shocks on investment by energy intensity



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with low-energy-intensity firms as the reference group.

6.2.2 Upstream carbon-cost exposure

Supply chain propagation is a central transmission mechanism for carbon policy shocks: unlike the direct cost channel, it affects firms even if they do not themselves use energy-intensive inputs. The mechanism operates because carbon policy raises input prices industry-wide, and firms purchasing from carbon-intensive suppliers face higher intermediate input costs regardless of their own energy intensity.

To measure supply chain exposure, an *upstream carbon exposure* variable is constructed at the sector–country–year level that quantifies the carbon intensity of a sector's input suppliers. The construction follows standard input-output methodology, as outlined in Section 3.3. A direct requirements matrix $A_{s's,c,t}$ is extracted from Eurostat's FIGARO inter-country input-output tables (industry-by-industry), which provide transaction matrices for 27 EU countries at a 64-sector classification.[11] The FIGARO 64-industry classification uses codes that map to NACE Rev. 2 divisions.

[11] FIGARO tables are described in Dietzenbacher et al. (2020) and available at `https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/database`.

Most FIGARO codes correspond one-to-one with a single NACE 2-digit division (e.g., "C24" maps to NACE 24, basic metals). Where a FIGARO code bundles multiple NACE divisions (e.g., "C10T12" covers NACE 10, 11, and 12), the same upstream exposure value is assigned to all constituent divisions. Where a FIGARO code corresponds to a single NACE 2-digit division that is a subset of a broader NACE section (e.g., "M72" maps to NACE 72 alone), the mapping is direct. This concordance covers 56 FIGARO industry codes mapped to 88 NACE 2-digit divisions; the full mapping is reported in Table A4 in the Appendix. Each element $A_{s's,c,t}$ represents the share of sector s's intermediate inputs sourced from sector s' (Equation (2)). Sectoral energy intensity $\mathrm{EI}_{s,c,t}$ is constructed from Eurostat data as energy use in terajoules divided by gross value added in million euros. This sector-country-year measure is then combined with the FIGARO network structure to compute the upstream carbon exposure of sector s in country c at year t as the input-share-weighted average of supplier energy intensities (Equation (3)).

This variable captures total direct and indirect supply chain carbon content, naturally weighting supplying sectors by their importance in the production network and accounting for the amplification of cost shocks through successive production rounds. It focuses on domestic supplier links, a conservative choice appropriate for the European carbon market where firms predominantly source domestically (Antrás and de Gortari, 2020), and it varies over time, capturing shifts in supply chain composition. Each firm is assigned the upstream exposure value of its primary NACE two-digit sector in its country and year. Table A3 in the Appendix reports the top 20 sectors by time-invariant upstream exposure, allowing readers to identify which sectors occupy the most carbon-exposed positions in the production network.[12]

Figure 6 presents the results. Firms are sorted into terciles based on lagged upstream carbon exposure, and the impulse responses reveal a striking and statistically robust supply chain channel. Even low-upstream-exposure firms, whose suppliers are relatively carbon-efficient, reduce investment by -0.64 pp at impact ($p < 0.01$), -1.19 pp at $h = 1$, and -1.21 pp at $h = 2$—all significant at the 1 percent level. Medium-upstream-exposure firms experience moderate declines, ranging from -0.53 to -1.07 pp

[12]Because the FIGARO inter-country input-output tables only cover 2010–2021 and the upstream measure is assigned to firms at the sector-country-year level, the time-varying upstream specification is estimated on a smaller subsample than the baseline ORBIS panel; the time-invariant version, which averages exposure across all available FIGARO years, is used to extend coverage to the full sample period.

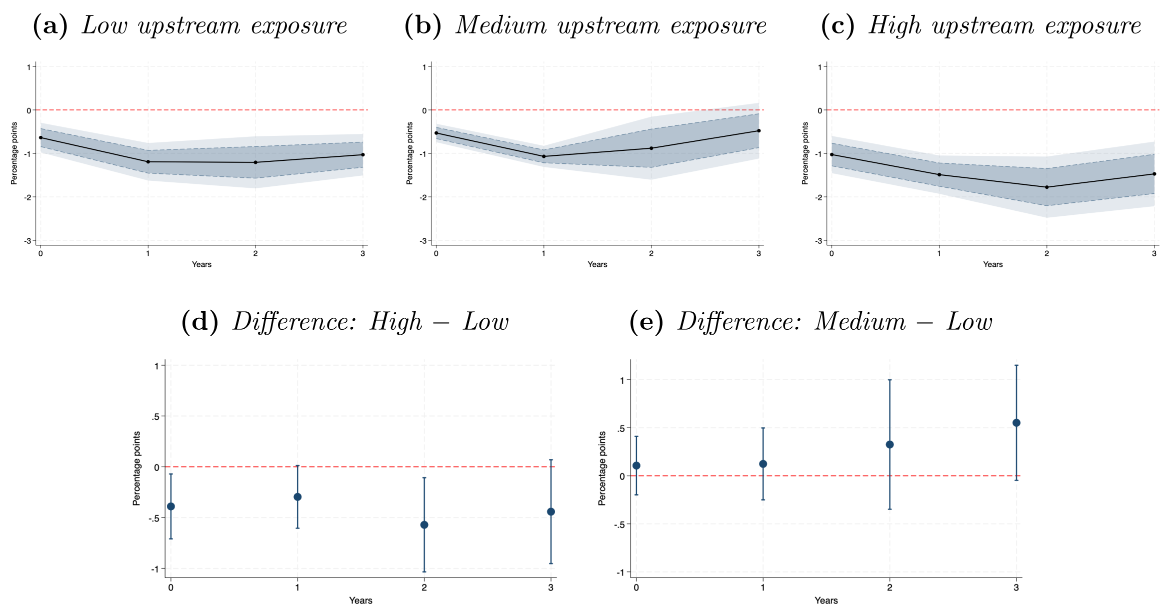
across the first two horizons. High-upstream-exposure firms experience the largest declines: -1.03 pp contemporaneously ($p < 0.01$), -1.49 pp at $h = 1$, and -1.78 pp at $h = 2$, with effects remaining highly significant at $h = 3$ (-1.47 pp, $p < 0.01$), indicating persistence of at least three years.

The differential between the top and bottom terciles (Table A15) is substantial and grows over time: -0.39 pp at impact, expanding to -0.57 pp at $h = 2$. At the two-year horizon, firms whose suppliers are carbon-intensive reduce investment by an additional 57 basis points relative to firms with carbon-efficient suppliers. Including both upstream exposure and terciles of the assigned sector-country-year energy-intensity measure jointly in the same regression (Table A16) confirms that the two channels are separately identifiable. The base effect for firms in the medium tercile of both dimensions is large and significant at short horizons (-0.58 pp at $h = 0$, -1.04 pp at $h = 1$), indicating a broad-based immediate investment response regardless of a firm's position in the exposure distribution. Differentiation by upstream exposure and assigned sector-country-year energy intensity emerges at longer horizons: high-upstream-exposure firms reduce investment by an additional -0.56 pp at $h = 2$ ($p < 0.01$) relative to the medium group, while high-energy-intensity firms show an additional -0.55 pp at $h = 2$ ($p < 0.01$) and -0.73 pp at $h = 3$ ($p < 0.01$). The delayed onset of both differential effects is consistent with gradual cost pass-through along supply chains and with the slow adjustment of capital-intensive production processes. Crucially, both channels remain economically and statistically significant when estimated jointly, confirming that upstream exposure captures a genuine supply chain mechanism distinct from the direct cost channel.

As a robustness check, the upstream specification is re-estimated using the time-invariant upstream exposure measure that averages across all available FIGARO years (2010–2021) and is therefore defined for the full sample period. The pattern is preserved: high-upstream-exposure firms decline by -1.61 pp at $h = 1$ ($p < 0.01$) and -1.97 pp at $h = 2$ ($p < 0.01$), tracking the time-varying baseline closely (see Table A17).

These findings carry three implications. First, the supply chain channel explains why the aggregate investment response is broad-based across sectors: even low-energy sectors experience substantial declines because they depend on carbon-intensive intermediate inputs such as electricity, chemicals, and primary metals. Second, the channel rationalizes the finding in Section 6.1 that low-carbon firms respond nearly as strongly as high-carbon firms: even firms in low-carbon sectors are exposed to cost pass-through from carbon-intensive manufacturers in their supply chains. Third, the persistence of upstream exposure effects through $h = 3$ indicates that supply chain adjustments occur gradually, consistent with frictions in supplier relationships including long-term contracts, switching costs, and information constraints (Boehm et al., 2019; Carvalho et al., 2021). The methodology aligns with the input-output approach to production network propagation developed by Acemoglu et al. (2012) and extended by Carvalho (2014) and Baqaee and Farhi (2019), with the FIGARO tables providing finer sectoral detail (64 industries) and consistent cross-country methodology compared with earlier studies.

Figure 6: The impact of carbon policy shocks on investment by upstream carbon-cost exposure



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) display difference-in-difference specifications using low upstream exposure as the reference group.

Full regression results are reported in Table A14 in the Appendix.

The results from the energy intensity and upstream exposure analyses jointly paint a picture of carbon policy transmission in which cost increases propagate through the economy via complementary channels. The direct channel affects firms more strongly when they operate in sector-country-year cells with higher energy intensity, generating the expected gradient in which firms assigned to high-energy-intensity cells experience the largest investment declines. The indirect supply chain channel broadens the policy impact well beyond directly affected firms, explaining why even those in low-carbon sectors reduce investment significantly when they purchase from carbon-intensive suppliers. Together, these two channels imply that carbon policy generates a broad, economy-wide investment contraction rather than targeted impacts on a narrow set of energy-intensive sectors. This pattern is consistent with the pervasive role of electricity, chemicals, and primary metals as intermediate inputs across the entire economy. The persistence of both channels through at least three years underscores the gradual and substantial nature of firm-level adjustment to carbon policy, carrying important implications for policy design: large, unexpected carbon price increases may generate significant macroeconomic disruption if they are not accompanied by transitional support measures or phased in gradually.

6.3 Financial constraints

A large literature has established that financial frictions amplify the investment response of constrained firms to aggregate shocks. Younger firms paying no dividends exhibit the largest investment declines (Cloyne et al., 2018); small manufacturing firms account for a disproportionate share of the aggregate contraction (Gertler and Gilchrist, 1994); and highly leveraged firms face tighter financing conditions that magnify adjustment costs (Fazzari et al., 1988; Kalemli-Ozcan et al., 2022). Whether the same channels operate for carbon policy is an open question, since carbon shocks differ in their sectoral incidence and the nature of the cost increase they impose. This subsection examines heterogeneity along three standard financial constraint proxies—firm age, size, and leverage—and assesses how each shapes the investment response to carbon policy.

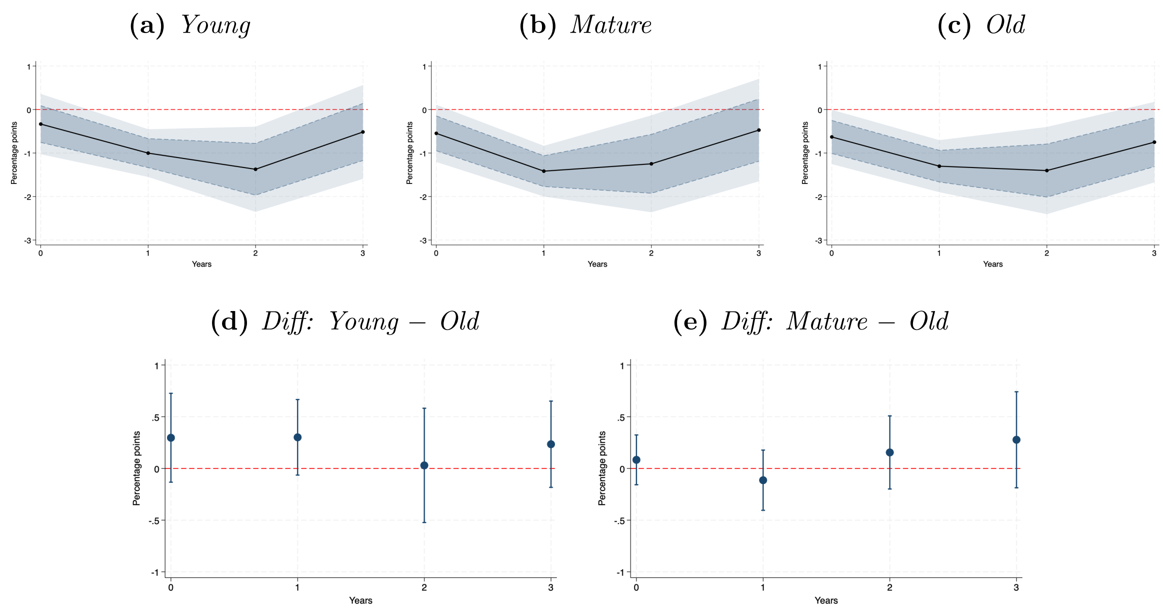
6.3.1 Firm age

Firms are classified into terciles of the age distribution: young (less than 10 years), mature (between 10 and 20 years), and old (more than 20 years). Figure 7 displays the impulse response functions for each group, with full regression results in Table A18 in the Appendix. All three groups show significant investment declines at the one- and two-year horizons. Old firms display the largest contemporaneous point estimate

(−0.63 pp, $p < 0.10$), while mature firms show the largest peak effect at $h = 1$ (−1.42 pp, $p < 0.01$). Importantly, the differences across age groups are modest and generally insignificant: the differential plots in panels (d)–(e) of Figure 7 and the regression results in Table A19 show no statistically significant gap between young and old or mature and old firms at any horizon.

This muted age gradient is noteworthy. A plausible explanation is that the age channel operates differently for carbon policy than for other aggregate shocks. While young firms face greater financial frictions (limited collateral, shorter credit histories), older firms have more established energy-intensive capital stocks that are costly to replace or retrofit. These opposing forces—tighter financial constraints for young firms versus larger physical adjustment costs for old firms—may offset each other, producing the muted age gradient observed in the data.

Figure 7: The impact of carbon policy shocks on investment by firm age



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with old firms as the reference group.

6.3.2 Firm size

The size analysis uses the European Commission's SME classification based on employee headcount (European Commission, 2003), which categorizes firms into four groups: micro (< 10 employees), small (10–49), medium (50–249), and large (≥ 250). This classification aligns with the policy-relevant thresholds used in EU industrial and competition policy and offers a more transparent definition of firm size than balance-sheet-based measures.[13]

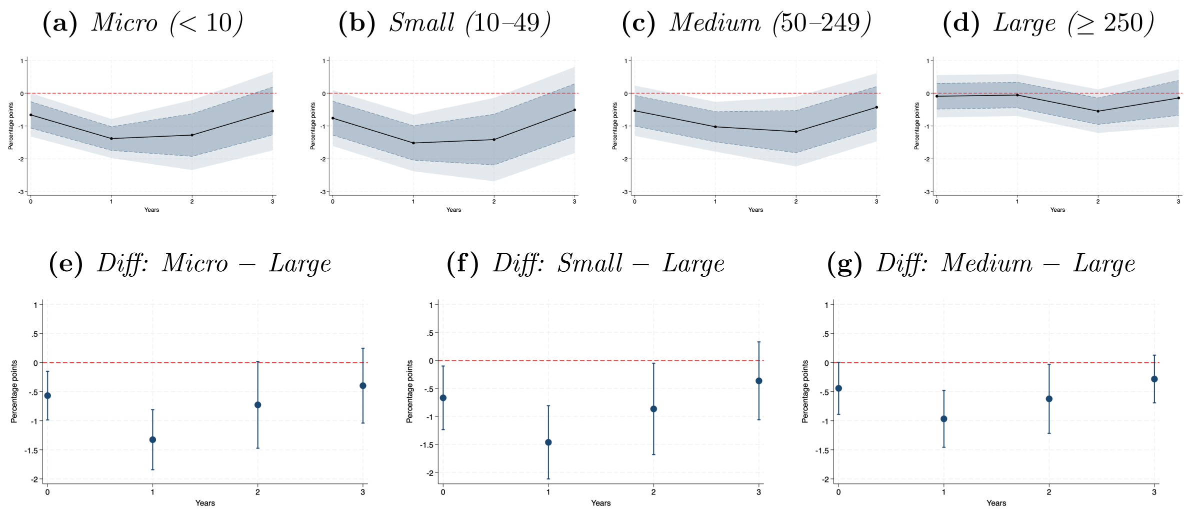
Figure 8 shows the results. The most striking finding is that large firms (≥ 250 employees) display *no* significant investment response at any horizon: point estimates are -0.09 ($h = 0$), -0.06 ($h = 1$), -0.55 ($h = 2$), and -0.15 ($h = 3$), all statistically insignificant. In stark contrast, micro and small firms respond strongly and significantly: at $h = 1$, micro firms decline by -1.38 pp ($p < 0.01$) and small firms by -1.52 pp ($p < 0.01$), while medium-sized firms respond by -1.02 pp ($p < 0.05$). The differential analysis in panels (e)–(g) of Figure 8 confirms that the micro-versus-large and small-versus-large differences are statistically significant at $h = 0$ ($p < 0.05$ and $p < 0.10$, respectively) and $h = 1$ ($p < 0.01$), while the medium-versus-large gap is significant at $h = 1$ ($p < 0.01$) and $h = 2$ ($p < 0.10$).

This sharp size gradient is consistent with several complementary mechanisms. Large firms possess deeper financial reserves and retained earnings that allow them to absorb temporary cost increases without curtailing investment. They also enjoy better access to external finance—both bank lending and capital markets—which provides a buffer against cash-flow shocks (Fazzari et al., 1988). Furthermore, large firms benefit from economies of scale in energy procurement and hedging, enabling them to negotiate more favorable energy contracts and to use financial derivatives to manage commodity price risk. Micro and small firms, lacking these advantages, must adjust their real investment plans when carbon policy raises operating costs. The lack of a statistically significant response among large firms is notable; it suggests that the cost channel through which carbon policy operates is more easily absorbed by firms with scale.

Full regression results are reported in Tables A20 and A21 in the Appendix.

[13]The employee-based classification is preferred to balance-sheet-based size proxies because it avoids the mechanical correlation between investment rates and total assets in the denominator.

Figure 8: The impact of carbon policy shocks on investment by firm size (EU SME classification)



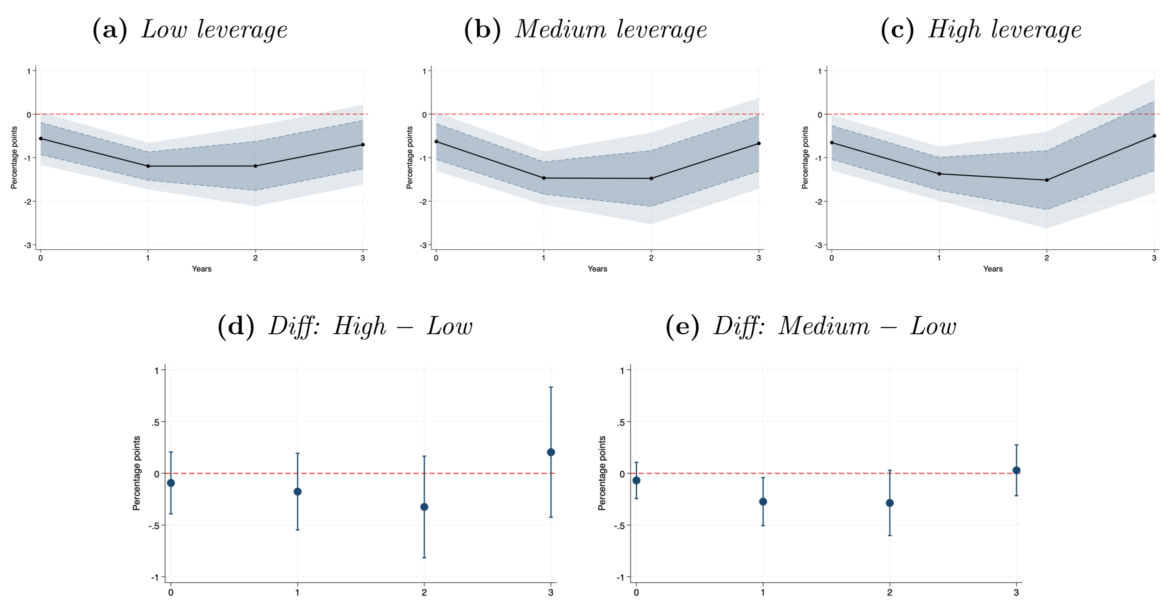
Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (e)–(g) show differences with large firms (≥ 250 employees) as the reference group.

6.3.3 Leverage

Firms are sorted into terciles based on lagged leverage (total debt to total assets). Figure 9 reports the impulse response functions, and full regression results appear in Tables A22 and A23 in the Appendix. Highly leveraged firms display the largest contemporaneous point estimate (-0.65 pp, $p < 0.10$), consistent with a credit channel: firms with higher debt burdens face tighter financing conditions and possess less internal liquidity to absorb unexpected cost increases. The larger point estimate of high-leverage firms is consistent with the "balance sheet channel," whereby rising costs erode net worth and tighten external finance constraints.

At the one-year horizon, medium-leverage firms respond most strongly (-1.47 pp, $p < 0.01$), followed by high-leverage (-1.37 pp) and low-leverage (-1.19 pp) firms. By $h = 2$, the ordering shifts toward the expected gradient: high-leverage firms decline by -1.52 pp, medium by -1.48 pp, and low by -1.19 pp. The differential analysis in Table A23 shows that the high-versus-low gap at $h = 2$ is economically meaningful (-0.33 pp), though not statistically significant. These results are consistent with the findings of Jeenas (2019), who documents that balance sheet vulnerability—rather than leverage per se—predicts investment sensitivity to aggregate shocks: the leverage channel operates most clearly on impact, when firms' ability to smooth cost shocks through borrowing is most constrained. The modest leverage gradient documented here stands in interesting tension with Ottonello and Winberry (2020), who find that firms with *low* default risk respond *more* to monetary policy shocks because they operate on the flatter portion of the marginal cost curve for external finance. The carbon policy context may differ from monetary policy for two reasons. First, carbon shocks raise production costs directly rather than operating through the interest rate channel; highly leveraged firms face a double squeeze (rising input costs and tighter borrowing conditions), which generates the expected positive gradient on impact. Second, the Ottonello and Winberry (2020)'s mechanism predicts that low-risk (low-leverage) firms are more *willing* to adjust, whereas the financial constraints channel predicts that high-leverage firms are more *forced* to adjust—and for carbon policy, the forcing effect appears to dominate at short horizons while the willingness effect may attenuate the gradient at longer horizons.

Figure 9: The impact of carbon policy shocks on investment by leverage



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with low-leverage firms as the reference group.

6.3.4 Liquidity and cash flow

To complete the financial-constraints picture, firms are also sorted into terciles of lagged liquidity (current assets to current liabilities) and lagged cash flow scaled by total assets. Figure A5 and Table A24 report the impulse responses by liquidity tercile, with the corresponding differential analysis in Table A25. The pattern is in line with an internal-finance interpretation: low-liquidity firms display somewhat larger investment declines than high-liquidity firms at the one- and two-year horizons, but the gradient is modest and largely insignificant in the differential test, consistent with the view that liquidity and cash flow operate as complementary rather than dominant amplifiers of the carbon policy shock.

The cash-flow tercile analysis (Figure A6, Table A26, and Table A27) tells a similar story. Low-cash-flow firms reduce investment slightly more than their high-cash-flow counterparts, and the differential is again economically small. Therefore, across both measures, liquidity and cash flow operate as complementary rather than dominant amplifiers of the carbon policy shock, while size and productivity remain the sharpest sources of heterogeneity in the financial-constraints story.

Taken together, the evidence on financial constraints reveals a clear hierarchy. Firm size produces the sharpest heterogeneity: large firms do not show a statistically significant response at any horizon, while micro, small, and medium firms all respond significantly, with the differential statistically confirmed. Leverage amplifies the contemporaneous response, consistent with a credit channel that tightens external finance precisely when firms need it most. The age channel, by contrast, is muted, suggesting that opposing forces (financial frictions for young firms versus physical adjustment costs for old firms) attenuate the age gradient for carbon policy. Liquidity and cash flow add a complementary but quantitatively secondary layer to this hierarchy, complementing rather than displacing the size and leverage findings. These findings indicate that financial constraints are an important amplifier of the carbon policy transmission mechanism, but they do not constitute the sole channel. The muted response of large firms, combined with the broad-based response across sectors documented in Section 6.1, points toward cost and supply chain propagation as the dominant transmission channels, with financial frictions determining which firms can absorb the resulting cost increases and which cannot. As a robustness check, Appendix B reports results using total fixed investment (combining tangible and intangible components) as the dependent variable; the patterns are qualitatively similar, with attenuated magnitudes consistent with partial offsetting by intangible investment (see Table A6 and Figure A2).

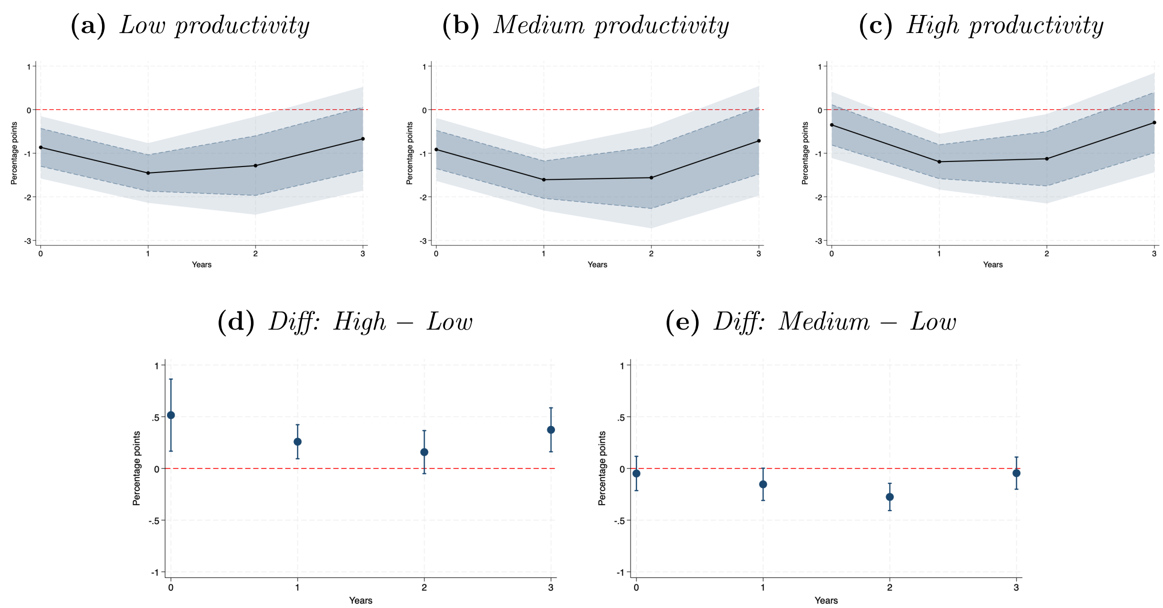
6.3.5 Productivity

Beyond the standard balance-sheet proxies for financial constraints (size, age, and leverage), firm-level productivity is a complementary indicator of capability and resilience. More productive firms generate higher cash flow per unit of input, which both relaxes internal financing constraints and lowers the cost of external finance (Midrigan and Xu, 2014). They also tend to operate with more efficient production technologies, allowing them to absorb input-cost shocks—such as those induced by carbon policy—without scaling back investment as sharply. This subsection examines whether firm-level productivity shapes the investment response to carbon policy shocks. Two complementary measures of labor productivity are used: real sales per employee, the standard ORBIS-friendly proxy for revenue labor productivity (Bartelsman and Doms, 2000; OECD, 2001), and real value added per employee, the theoretically preferred measure of factor productivity (Foster et al., 2008), which strips out intermediate inputs at the cost of sparser ORBIS coverage. The latter is reported as a robustness check.

Firms are sorted into terciles based on the lagged value of each productivity measure. Figure 10 displays the impulse response functions for the three productivity terciles based on sales per employee, with full regression results in Tables A28 and A29 in the Appendix. The results reveal a clear and economically meaningful productivity gradient. Low-productivity firms display a strong contemporaneous response (-0.86 pp, $p < 0.05$), which deepens to -1.45 pp at $h = 1$ ($p < 0.01$) and -1.28 pp at $h = 2$ ($p < 0.10$) before attenuating to -0.67 pp at $h = 3$. Medium-productivity firms exhibit a slightly larger decline: -0.91 pp at impact ($p < 0.05$), -1.61 pp at $h = 1$ ($p < 0.01$), and -1.56 pp at $h = 2$ ($p < 0.05$). High-productivity firms, by contrast, show a markedly weaker contemporaneous response: the impact effect is only -0.35 pp and statistically insignificant, indicating that the most productive firms in the sample show no statistically significant immediate investment response. At the one- and two-year horizons, high-productivity firms still adjust (-1.19 pp at $h = 1$, $p < 0.01$; -1.13 pp at $h = 2$, $p < 0.10$), but the magnitudes remain consistently smaller than for the lower terciles.

The differential analysis in Table A29 formalizes these comparisons against the low-productivity reference group. The high-minus-low differential is positive and statistically significant at impact (+0.52 pp, $p < 0.05$) and at $h = 1$ (+0.26 pp, $p < 0.05$), and remains positive and significant at $h = 3$ (+0.37 pp, $p < 0.01$), confirming that high-productivity firms reduce investment by substantially less than their low-productivity peers, particularly on impact and in the short run. The medium-minus-low differential is small and mostly insignificant (-0.05 pp at $h = 0$, -0.15 pp at $h = 1$), with the exception of $h = 2$ (-0.28 pp, $p < 0.01$), suggesting that the productivity gradient is not strictly monotonic but is driven primarily by the resilience of the top tercile. This pattern is consistent with two complementary mechanisms. First, more productive firms enjoy higher profit margins and stronger internal cash flow, which buffer the impact of carbon-induced input cost increases and reduce reliance on external finance. Second, productive firms tend to operate with more efficient capital and energy-using technologies, so a given carbon shock raises their marginal cost by less. Both forces predict a smaller investment cutback for high-productivity firms, in line with the evidence here.

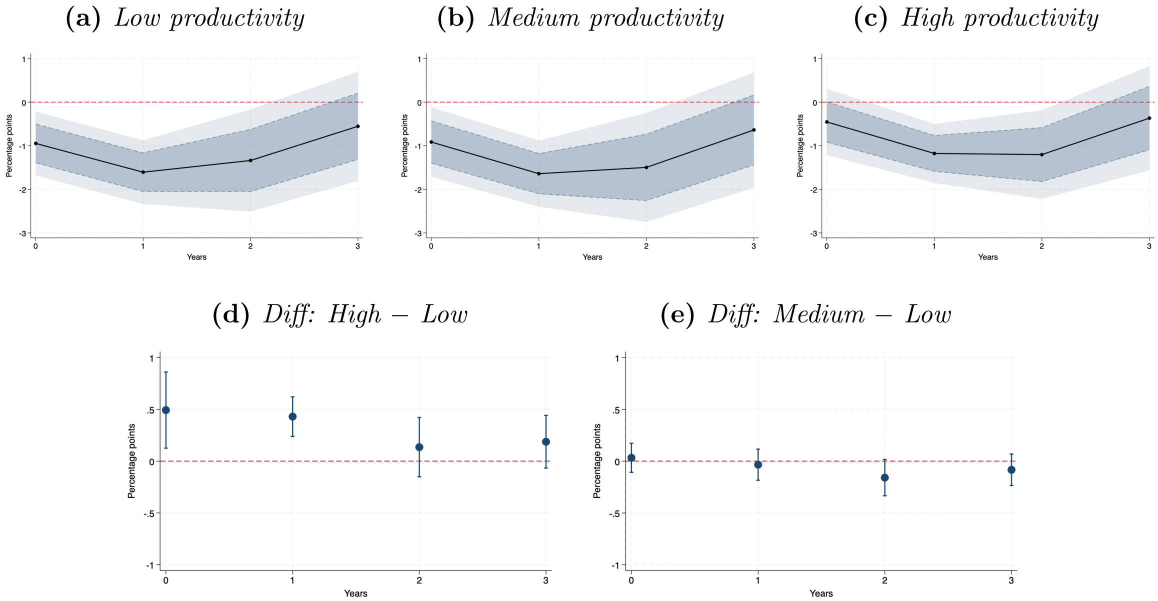
Figure 10: The impact of carbon policy shocks on investment by labor productivity (sales per employee)



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with low-productivity firms as the reference group.

A natural concern is that sales per employee captures revenue productivity rather than true factor productivity: differences in market power, product mix, or input prices may drive cross-firm variation in sales without reflecting underlying technological efficiency (Bartelsman and Doms, 2000). To address this, the analysis is replicated using value added per employee—defined as sales minus the cost of intermediate inputs, divided by employment—which strips out intermediate-input intensity and is closer to the welfare-relevant measure of factor productivity (Foster et al., 2008; OECD, 2001). Figure 11 reports the impulse responses, and the corresponding regression results are reported in Tables A30 and A31 in the Appendix. The qualitative pattern is preserved: low-productivity firms decline by -0.95 pp at impact ($p < 0.05$), -1.61 pp at $h = 1$ ($p < 0.01$), and -1.34 pp at $h = 2$ ($p < 0.10$); medium-productivity firms by -0.91 pp at impact ($p < 0.10$), -1.64 pp at $h = 1$ ($p < 0.01$), and -1.50 pp at $h = 2$ ($p < 0.10$); while high-productivity firms display the most muted response, with an insignificant -0.45 pp at impact, -1.18 pp at $h = 1$ ($p < 0.01$), and -1.20 pp at $h = 2$ ($p < 0.10$). The differential analysis confirms that high-productivity firms reduce investment by significantly less than low-productivity firms at impact ($+0.49$ pp, $p < 0.05$) and at $h = 1$ ($+0.43$ pp, $p < 0.01$). The convergence of results across the two productivity measures indicates that the muted response of high-productivity firms is not an artifact of the revenue-based metric, but reflects a robust feature of the data: firms with higher labor productivity—whether measured by sales or by value added per worker—are systematically less responsive to carbon policy shocks, particularly at short horizons.

Figure 11: The impact of carbon policy shocks on investment by labor productivity (value added per employee)



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with low-productivity firms as the reference group.

Taken together, the productivity evidence reinforces and refines the financial-constraints story. The absence of a contemporaneous response among high-productivity firms mirrors the analogous pattern for large firms documented in Section 6.3.2, suggesting that the two characteristics proxy for a common underlying margin: the capacity to absorb cost shocks without immediately cutting investment. Whereas size operates through scale—giving large firms diversified financing options and lower marginal cost of external funds—productivity operates through margins and technology—giving high-productivity firms greater internal cash flow and lower sensitivity to carbon-policy-induced cost increases. Both channels point in the same direction: firms with stronger fundamentals smooth investment in the face of climate-policy shocks, while less productive firms bear a disproportionate share of the adjustment burden.

Whether this asymmetric adjustment is beneficial is ambiguous, though the positive reading appears more compelling. A "Schumpeterian cleansing" interpretation (Caballero and Hammour, 1994) views the result as productivity-enhancing: by inducing the least efficient producers to scale back disproportionately, carbon policy frees up capital, labor, and material inputs for more productive uses, raising aggregate labor productivity through the reallocation channel documented in Foster et al. (2008). Because lower labor productivity is empirically correlated with higher emission intensity per unit of value added, this reallocation also reinforces the policy's environmental objective, generating a "double dividend" in productivity and emissions. A misallocation reading cannot be ruled out—revenue-based productivity measures confound true efficiency with markups, so some "low-productivity" firms may be financially constrained rather than technologically inefficient (Bartelsman and Doms, 2000; Midrigan and Xu, 2014)—but the robustness of the gradient under value added per employee, which strips out intermediate-input intensity, mitigates this concern. The evidence is best read as a stylized fact that is suggestive of efficiency-enhancing reallocation, and which motivates a richer structural analysis as a natural next step.

6.4 Sectoral analysis

The transmission channel analysis has shown that carbon policy shocks propagate through both direct energy costs and supply chain linkages. A natural question is whether these channels produce meaningfully different investment responses across broad sectors of the economy. This subsection examines heterogeneity across four macro sectors defined by NACE Rev. 2 sections: manufacturing (Section C), construction (Section F), services (Sections G, H, I, J, M, N), and primary industries & utilities (Sections A, B, D, E).

Figure 12 displays the impulse responses, and Table A32 in the Appendix reports the full regression results. All four sectors respond negatively and significantly at the one-year horizon, though the magnitude and timing of the response differ in informative ways. Manufacturing exhibits the largest and most persistent decline, with an insignificant -0.74 pp at impact that deepens sharply to -1.46 pp at $h = 1$ ($p < 0.01$) and peaks at -1.71 pp at $h = 2$ ($p < 0.05$). This pattern is consistent with manufacturing's direct exposure to energy and material cost increases, its high capital intensity, and the long lead times involved in adjusting physical investment plans. Construction follows a similar trajectory (-0.51 pp at impact, -1.43 pp at $h = 1$, $p < 0.01$, and -1.30 pp at $h = 2$, $p < 0.10$), reflecting the sector's dependence on energy-intensive inputs (cement, steel, glass) and its sensitivity to the economic cycle.

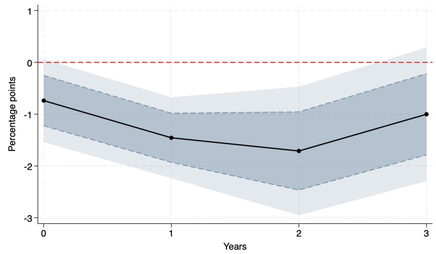
Services, the largest sector by firm count, responds with somewhat smaller but still highly significant declines: -0.44 pp at impact, -1.15 pp at $h = 1$ ($p < 0.01$), and -1.20 pp at $h = 2$ ($p < 0.05$). Although services firms have low direct energy intensity, they are exposed through multiple indirect channels: they purchase electricity and intermediate goods from carbon-intensive suppliers, their revenues depend on the spending of manufacturing and construction clients, and broad-based policy uncertainty may delay their investment decisions. Primary industries and utilities show an interesting temporal pattern: the impact and one-year effects are comparatively modest (-0.44 pp and -0.83 pp, respectively), but the two-year response is the second largest across sectors (-1.50 pp, $p < 0.01$), suggesting a delayed adjustment as these capital-intensive sectors gradually revise long-lived investment projects.

The differential analysis in panels (e)–(g) of Figure 12 and Table A33, with manufacturing as the reference group, confirms that the cross-sectoral differences are generally not statistically significant. The services-minus-manufacturing differential is positive at all horizons but reaches significance only at $h = 3$ ($+0.57$ pp, $p < 0.01$); the construction-minus-manufacturing and primary-minus-manufacturing differentials are likewise modest and mostly insignificant. The absence of large, persistent sectoral differentials is itself a central result: it implies that the adjustment burden of carbon policy is not confined to a narrow set of energy-intensive industries but is distributed broadly across the economy.

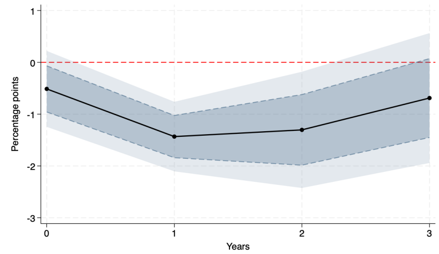
The cross-sectoral similarity is consistent with—though not uniquely predicted by—an indirect transmission channel operating through supply chains, as directly tested in Section 6.2. Carbon price increases in regulated upstream sectors are passed through to downstream purchasers via higher intermediate input prices. Because energy-intensive sectors—electricity, chemicals, primary metals—supply inputs to virtually all parts of the economy, the cost shock propagates along input-output linkages to construction, services, and primary industries alike. The result is an economy-wide investment contraction in which sector-specific direct exposure matters at the margin but does not dominate the aggregate pattern. However, similar cross-sectoral responses are also consistent with alternative explanations such as aggregate demand contraction, policy uncertainty, or credit tightening; the supply chain channel is more directly established by the upstream exposure analysis in Section 6.2.2. From a policy perspective, this finding implies that transition support measures should not be narrowly targeted at a few heavy-emitting sectors; instead, they should account for the broad diffusion of adjustment costs through production networks.

Figure 12: The impact of carbon policy shocks on investment by macro sector

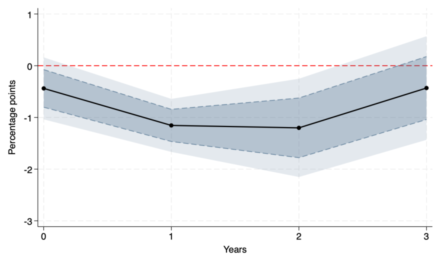
(a) *Manufacturing*



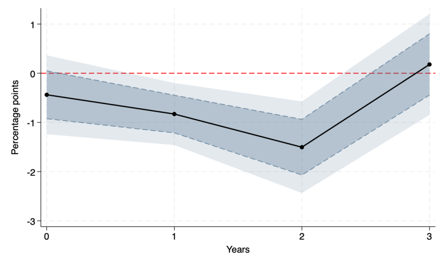
(b) *Construction*



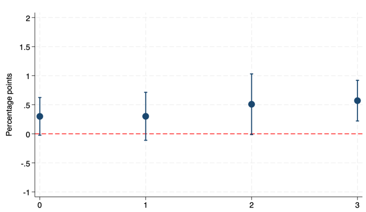
(c) *Services*



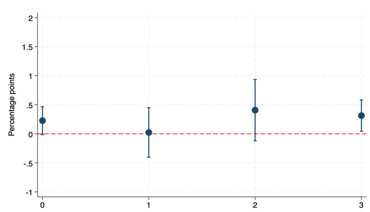
(d) *Primary & Utilities*



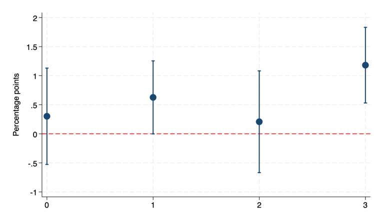
(e) *Diff: Services − Manuf.*



(f) *Diff: Constr. − Manuf.*



(g) *Diff: Primary − Manuf.*



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (e)–(g) show differences with manufacturing as the reference sector.

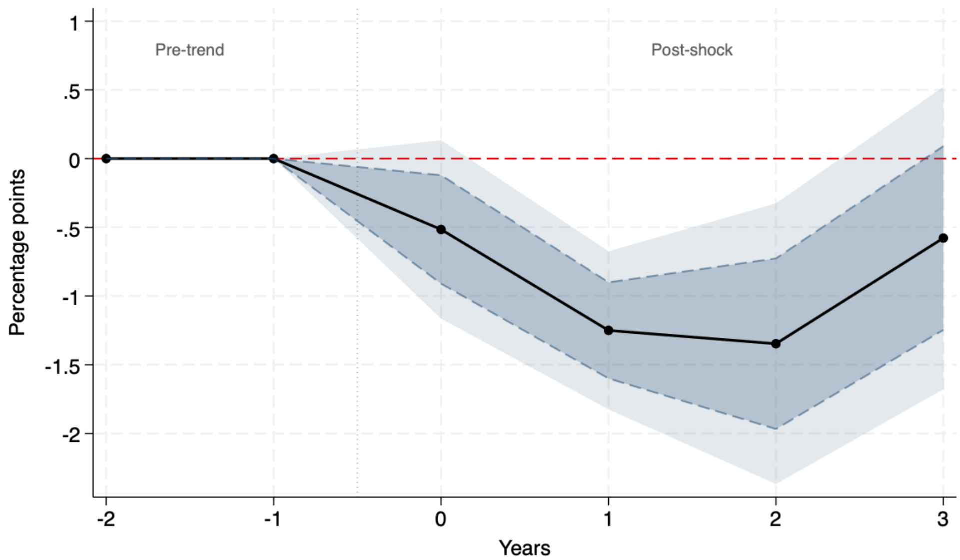
A finer disaggregation by NACE section, reported in Table A34 and Figure A7 in the Appendix, reinforces the broad-based nature of the investment response. Across 12 individual NACE sections, all exhibit significant investment declines at the one- or two-year horizon, with agriculture significant only at $h = 2$ ($p < 0.10$). The most responsive sectors are mining (-2.58 pp at $h = 1$, -4.05 pp at $h = 2$) and transportation (-2.32 pp at $h = 1$, -2.44 pp at $h = 2$), both of which are directly exposed to energy cost increases. Water and waste management (-1.88 pp at $h = 1$, -2.06 pp at $h = 2$) also responds strongly, reflecting the sector's energy-intensive operations. Among services subsectors, trade (-1.20 pp at $h = 1$), ICT (-0.88 pp at

$h = 1$, -1.09 pp at $h = 2$), professional services (-0.79 pp at $h = 1$, -1.23 pp at $h = 2$), and administrative services (-1.16 pp at $h = 1$) all show significant declines, confirming that the investment impact extends well beyond energy-intensive industries. Accommodation stands out for its persistent response (-0.72 pp at $h = 1$, -0.94 pp at $h = 2$, -0.71 pp at $h = 3$, all significant), suggesting that demand-side effects may complement the cost channel in consumer-facing sectors. This granular evidence further supports the conclusion that carbon policy shocks diffuse broadly through production networks and aggregate demand channels, rather than remaining confined to directly regulated sectors.

7 Robustness checks

This section examines the robustness of the baseline results. A first and fundamental check tests whether the local projection design satisfies the parallel trends assumption. If the carbon policy shock is truly exogenous to firm-level investment decisions, it should have no predictive power over *pre-treatment* changes in investment. To assess this, the baseline local projection is extended to include two pre-treatment horizons ($h = -2$ and $h = -1$), where the dependent variable measures the change in investment *before* the shock realization. Table 5 reports the results. The estimated coefficients at $h = -2$ and $h = -1$ are precisely zero, with negligible standard errors, confirming that carbon policy shocks do not predict prior investment dynamics. In contrast, the post-shock horizons reproduce the familiar hump-shaped pattern documented in Section 5, with the investment rate declining by -1.25 pp at $h = 1$ ($p < 0.01$) and -1.35 pp at $h = 2$ ($p < 0.05$). Figure 13 visualizes the full impulse response from $h = -2$ to $h = 3$: the response is flat at zero in the pre-trend window and drops sharply upon impact, providing strong graphical evidence that the estimated effects are not driven by pre-existing trends.

Figure 13: Pre-trend test and baseline impulse response ($h = -2$ to $h = 3$)



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. The pre-trend window ($h = -2$, $h = -1$) tests whether carbon policy shocks predict changes in investment prior to the shock realization. The sharp discontinuity at $h = 0$ supports the causal interpretation of the post-shock response.

Table 5: Pre-Trend and Baseline Impulse Response: Effect of Carbon Policy Shocks on Tangible Investment

	$\Delta I^*_{it,-2}$	$\Delta I^*_{it,-1}$	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.00	-0.00	-0.52	-1.25***	-1.35**	-0.58
	(0.00)	(0.00)	(0.39)	(0.35)	(0.62)	(0.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,909,607	7,909,607	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.

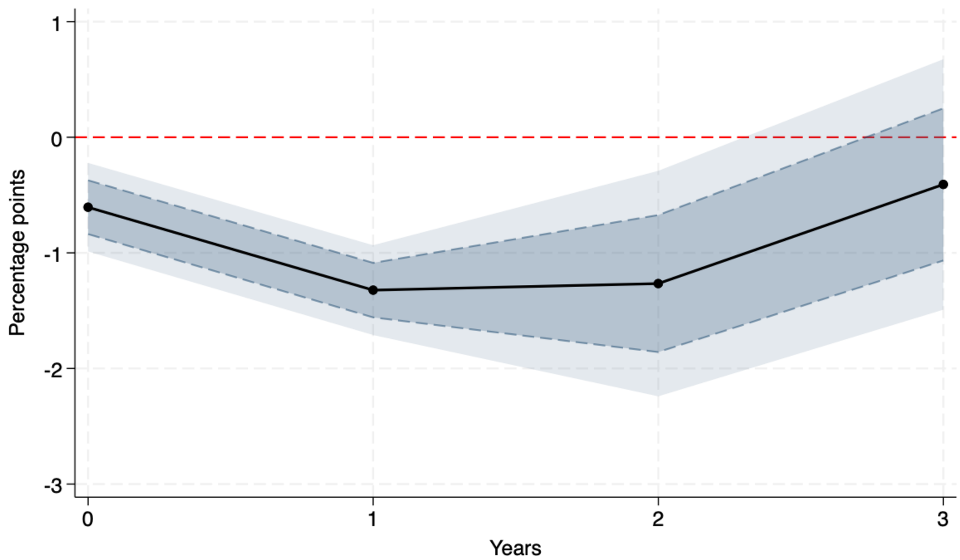
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns $h = -2$ and $h = -1$ test whether the current shock predicts pre-treatment investment changes.

A second concern is that the estimated investment response could be confounded by unrelated aggregate shocks hitting the European economy over the sample period. To address this, the baseline specification is re-estimated on a sub-sample that excludes the Global Financial Crisis and the immediately following recession years

(2008–2010). This period was characterized by large, non-carbon-related declines in investment across all European economies, and dropping it provides a direct test that the estimated response to carbon policy shocks is not driven by the crisis episode. Table 6 reports the resulting estimates, which remain negative and significant at the one- and two-year horizons, with magnitudes broadly in line with the baseline.

Figure 14: Robustness: Average effect excluding the Global Financial Crisis (2008–2010)



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. The specification replicates the baseline while dropping observations for fiscal years 2008, 2009, and 2010.

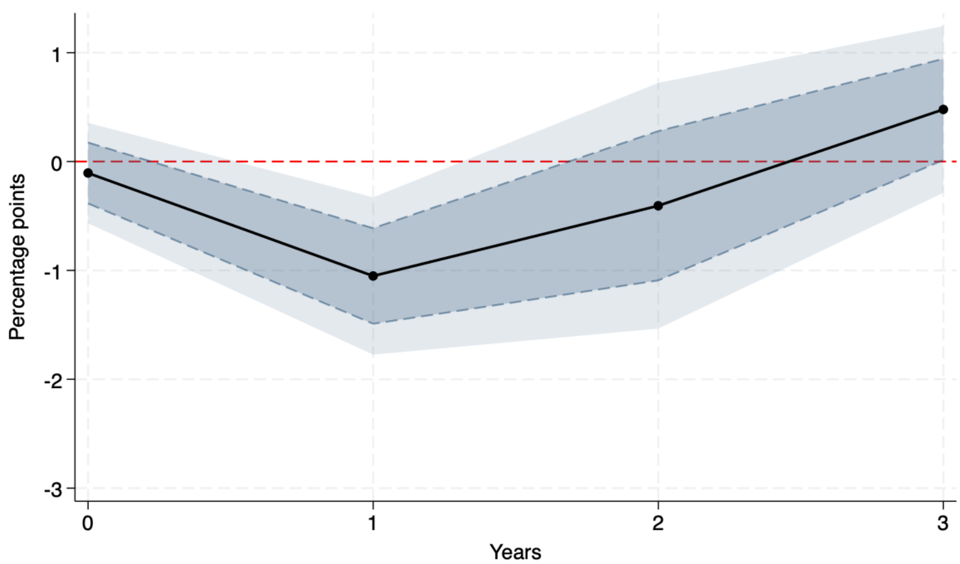
Table 6: Robustness: Average Effect Excluding the Global Financial Crisis (2008–2010)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.61**	-1.32***	-1.27**	-0.41
	(0.23)	(0.24)	(0.59)	(0.66)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Excludes 2008–2010	Yes	Yes	Yes	Yes
Observations	6,309,130	5,169,188	4,183,979	3,376,630

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a third check, the baseline specification is augmented with country-level macroeconomic controls—contemporaneous and lagged real GDP growth and HICP inflation—to absorb aggregate demand and price-level variation that may be correlated with the carbon policy shock. Table 7 reports the results. The carbon policy shock coefficient at horizon one remains negative and significant (-1.05 pp, $p < 0.05$), while the macro controls enter with expected signs: real GDP growth is positively associated with investment and HICP inflation negatively so. The attenuation at other horizons suggests that part of the baseline effect operates through aggregate demand channels, which is consistent with the transmission channel analysis in Section 6.2.

Figure 15: Robustness: Baseline with country-level macro controls



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. The specification adds contemporaneous and lagged real GDP growth and HICP inflation as additional controls.

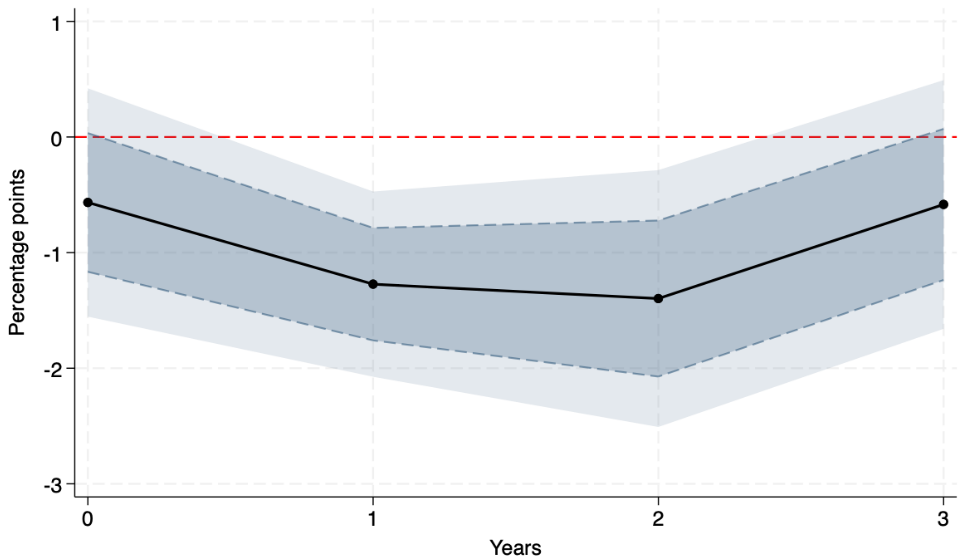
Table 7: Robustness: Baseline + Country-Level Macro Controls (Real GDP Growth, HICP Inflation)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.11	-1.05**	-0.41	0.48
	(0.28)	(0.44)	(0.69)	(0.47)
Real GDP growth$_t$	2.47***	1.92***	2.26**	1.56*
	(0.91)	(0.36)	(0.93)	(0.84)
Real GDP growth$_{t-1}$	0.43	0.27	0.43	1.10
	(0.30)	(0.65)	(0.70)	(0.70)
HICP inflation$_t$	-2.94**	-0.18	-3.94**	-3.17**
	(1.26)	(1.62)	(1.69)	(1.28)
HICP inflation$_{t-1}$	2.93**	-0.90	0.73	-1.14
	(1.36)	(1.52)	(1.63)	(1.42)
Firm-level controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a fourth check, the baseline is re-estimated on a balanced panel that restricts the sample to firms observed at all horizons $h = 0, \ldots, 3$. This addresses the concern that the 43 percent drop in observations between $h = 0$ and $h = 3$ could induce survivorship bias if firms most affected by carbon policy exit the sample at longer horizons. Table 8 reports the results. The impulse response retains its hump shape: the one-year effect is -1.27 pp ($p < 0.01$) and the two-year effect is -1.40 pp ($p < 0.05$), closely tracking the baseline magnitudes. The similarity of the balanced and unbalanced estimates suggests that the attenuation at $h = 3$ in the baseline reflects genuine dynamic adjustment rather than selective exit of the most affected firms.

Figure 16: Robustness: Average effect on a balanced panel



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. The sample is restricted to observations that are non-missing at all horizons $h = 0, \dots, 3$.

Table 8: Robustness: Average Effect on a Balanced Panel

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.57	-1.27***	-1.40**	-0.58
	(0.60)	(0.49)	(0.68)	(0.65)
ϵ_{it-1}	-1.21***	-1.06***	-0.16	-0.19
	(0.38)	(0.37)	(0.47)	(0.42)
ϵ_{it-2}	-0.62	0.52	0.42	1.05
	(0.65)	(0.72)	(0.77)	(0.68)
ΔI_{it-1}	-0.68***	-0.68***	-0.67***	-0.67***
	(0.02)	(0.01)	(0.01)	(0.01)
ΔI_{it-2}	-0.33***	-0.33***	-0.33***	-0.32***
	(0.02)	(0.01)	(0.01)	(0.01)
ΔSG_{it-1}	0.04***	0.04***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
ΔSG_{it-2}	0.04***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
ΔCF_{it-1}	0.35***	0.13***	0.05*	0.04
	(0.04)	(0.03)	(0.03)	(0.03)
ΔCF_{it-2}	0.24***	0.08***	0.03	0.02
	(0.03)	(0.02)	(0.02)	(0.02)
Observations	4,458,948	4,458,948	4,458,948	4,458,948

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Sample restricted to observations non-missing at all horizons $h = 0, \ldots, 3$.

A fifth robustness check examines whether the investment decline documented in Section 5 is accompanied by a contraction on the employment margin, or whether firms adjust capital while leaving labor broadly unchanged. Re-estimating the baseline specification with employment growth as the dependent variable yields a coefficient that is small and statistically insignificant at every horizon (Figure A10, Table A36). The same is true when the size dimension is allowed to vary: micro, small, medium, and large firms all show a near-zero employment response, both under the time-varying employee-based classification and under an initial-period (time-invariant) classification (Table A37). This indicates that the investment margin—rather than the employment margin—is the primary adjustment channel through which firms respond to carbon policy at the firm level, consistent with the standard view that investment is more elastic than employment to short-run cost shocks for European firms with stringent labor protections.

Finally, country-level heterogeneity analysis (Table A35, Figure A9) reveals that Italy and Spain drive the aggregate firm-level result, while Germany and France show insignificant effects. This pattern is consistent with the well-documented differences in ORBIS coverage across countries (Kalemli-Özcan et al., 2015): Germany contributes only 21,753 firms (1.8 percent of the sample) with mean log total assets of 21.34, compared with 436,143 firms for Spain with mean log total assets of 13.57. The German ORBIS sample is thus heavily skewed toward large firms. The insignificance of the German and French results therefore likely reflects the composition of the ORBIS sample in those countries rather than the absence of a true effect.

8 Concluding remarks

The preceding analysis has documented the heterogeneous effects of carbon policy shocks on firm-level investment across four major European economies. Using approximately 7.9 million firm-year observations and exogenous carbon policy shocks identified from EU ETS regulatory announcements, the analysis yields several key findings.

First, carbon policy shocks produce significant and persistent declines in tangible investment, peaking at 1.25–1.35 percentage points at the one- to two-year horizon. This hump-shaped response is consistent with the gradual pass-through of carbon costs into energy and input prices and the delayed adjustment of firm investment plans. Intangible investment shows a small positive but statistically insignificant response, so the response of total fixed investment is somewhat smaller than the tangible-only effect. Second, sectoral carbon exposure measured through the CPRS classification generates only modest cross-sectoral differences: high-carbon and low-carbon firms respond by similar magnitudes, indicating that the impact of carbon policy is far broader than the set of directly regulated sectors, and EU ETS-covered firms themselves display a comparatively muted response. Third, the direct energy cost channel is quantitatively important: the sector-country-year energy-intensity measure assigned to firms generates a clear and monotonic gradient, with firms in the top tercile reducing investment by 1.90 percentage points at the two-year horizon—approximately 75 percent more than firms in the bottom tercile—and the persistence of this differential through year three is consistent with gradual adjustment to higher energy-related production costs. Fourth, supply chain linkages constitute an independent transmission mechanism: firms with high upstream carbon exposure reduce investment substantially more than those with low exposure, and the energy cost and supply chain channels remain separately significant when included jointly in the same specification. Fifth, firm size matters sharply: using the EU SME classification, large firms ($\geq$ 250 employees) show no significant investment response at any horizon, while micro, small, and medium firms all reduce investment substantially. Leverage further amplifies the contemporaneous response, consistent with a financial constraints channel. Sixth, firm-level productivity shapes the response in a way that closely mirrors the size pattern: the investment cut is concentrated among less productive firms, while the most productive firms are largely unresponsive on impact and adjust by less at one- and two-year horizons, with the gradient robust to the move from sales per employee to value added per employee. Seventh, the investment response is qualitatively similar across broad sectors—manufacturing, construction, services, and primary industries—consistent with input-output linkages diffusing carbon cost increases throughout the economy.

These findings have direct policy implications. The observation that adjustment costs fall disproportionately on financially constrained, less productive, and supply-chain-exposed firms suggests that complementary policies should target the broader production network rather than the narrow set of regulated installations. Transition subsidies, green investment tax credits, and targeted lending facilities for small and highly leveraged firms could help mitigate the distributional costs of carbon pricing. Importantly, narrowly targeting support to EU ETS-covered sectors would miss a large share of the adjustment burden, which falls on non-regulated firms through supply chain cost propagation—a finding with direct relevance for the design of the EU's Carbon Border Adjustment Mechanism and the Social Climate Fund.

Several extensions of this work are possible. Incorporating firm-level data on patents, R&D expenditure, and technology adoption would permit analysis of whether carbon policy stimulates green innovation alongside the investment declines documented here. Extending the shock series beyond 2019 would capture the effects of the more recent and ambitious regulatory tightening under the European Green Deal, including the sharp rise in EU ETS prices after 2020. Finally, combining the firm-level evidence with structural general equilibrium models would enable quantification of the aggregate welfare implications of the heterogeneous adjustment costs documented in the present analysis.

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A Variable definitions and classifications

A.1 Variable definitions

Table A1: Description of variables

Variable	Description
$I_{i,t}$	Tangible net investment rate: (Tangible fixed assets$_t$ − Tangible fixed assets$_{t-1}$) / Tangible fixed assets$_{t-1}$ × 100
$I_{i,t}^{INT}$	Intangible net investment rate: (Intangible fixed assets$_t$ − Intangible fixed assets$_{t-1}$) / Intangible fixed assets$_{t-1}$ × 100
$I_{i,t}^{FIX}$	Total fixed net investment rate: (Total fixed assets$_t$ − Total fixed assets$_{t-1}$) / Total fixed assets$_{t-1}$ × 100
$\varepsilon_{i,t}$	12-month moving sum of the carbon policy shocks (percentage points)
$\Delta I_{i,t-k}$	k-th lag of the first difference in the tangible investment rate
$\Delta SG_{i,t-k}$	k-th lag of the first difference in sales growth (log sales$_t$ − log sales$_{t-1}$)
$\Delta CF_{i,t-k}$	k-th lag of the first difference in cash flow to total assets
Age	Years since incorporation
Size	Log of total assets in euros
Leverage	(Loans + Long-term debt) / Total assets × 100
Liquidity	Current assets / Current liabilities
Labor productivity	Real sales per employee (thousands of euros).
Value added per employee	Real value added per employee (thousands of euros).
Energy intensity	Sector-country-year energy intensity assigned to firms: energy use (TJ) / gross value added (million EUR) (from Eurostat, merged at NACE 2-digit × country × year)
Upstream carbon-cost exposure	Leontief-inverse-weighted sum of suppliers' energy intensity, $\text{Upstream}_{s,c,t} = \sum_{s'} L_{s's,c,t} \cdot \text{EI}_{s',c,t}$ where $L = (I - A)^{-1}$. Captures direct and indirect (through all production rounds) energy content embodied in a sector's inputs and proxies cost pass-through of a carbon-policy shock through the supply chain. Computed from Eurostat FIGARO inter-country input-output tables (industry-by-industry, 64 sectors) and Eurostat energy intensity data. Time-varying version covers 2010–2021; time-invariant version averages across all FIGARO years.
EU ETS	Indicator for firms matched to the JRC-EU-ETS-FIRMS dataset (European Commission, Joint Research Centre, 2022), which records installations directly regulated under the EU Emissions Trading System. Matched at the firm level using BvD identification numbers.

A.2 CPRS classification

Table A2: Climate Policy Relevant Sectors (CPRS) Main Classification

CPRS	Category	Description	Key NACE codes
1	Fossil fuels	Mining, quarrying, oil and gas extraction, fossil fuel-based electricity	05, 06, 08, 09, 46.71
2	Utilities	Electricity, gas, water production and distribution, waste management	35, 36, 37, 38, 39
3	Energy-intensive manufacturing	Mining-related processing, food/beverages, textiles, paper, chemicals, petroleum refining, metals, non-metallic minerals	07, 10–25 (selected)
4	Buildings & construction	Construction of buildings and civil engineering, real estate	41, 42, 43, 68
5	Transportation	Road, rail, water, and air transport; logistics and warehousing	29, 30, 49–53
6	Agriculture & forestry	Crop and animal production, forestry, fishing	01, 02, 03
7	Low-carbon services	Finance, IT, professional services, public administration	62, 64, 70, 72, 84
8	Remaining sectors	Accommodation, food service, personal services	55, 56, 96
9	R&D & advanced services	Pure R&D, design, specialized professional services	72 (selected)

Note: Classification based on Battiston et al. (2017). NACE codes refer to the Rev. 2 classification. "Selected" indicates that only specific subsectors within the listed NACE divisions are included. In the present analysis, CPRS 1–3 are grouped as *energy-intensive sectors*, CPRS 4–6 as *carbon-exposed sectors*, and CPRS 7–9 as *low-carbon sectors*. NACE 72 (Scientific R&D) is listed under both CPRS 7 and CPRS 9 because the assignment is made at the 4-digit NACE level: some sub-codes of division 72 are classified as low-carbon services (CPRS 7) and others as pure R&D (CPRS 9). Since both categories fall within the low-carbon tier, this does not affect the three-tier classification.

A.3 Upstream carbon-cost exposure by sector

Table A3: Top 20 Sectors by Upstream Carbon-Cost Exposure (Time-Invariant, Averaged over 2010–2021)

NACE	Sector	Upstream exposure
19	Coke & petroleum refining	86.47
50	Water transport	66.91
51	Air transport	62.24
20	Chemicals & chemical products	35.44
24	Basic metals	33.91
23	Non-metallic mineral products	23.23
17	Paper & paper products	21.89
3	Fishing & aquaculture	13.87
5–9	Mining & quarrying	13.84
16	Wood & wood products	13.67
35	Electricity, gas & steam	13.43
49	Land transport & pipelines	11.80
1	Crop & animal production	9.52
10–12	Food, beverages & tobacco	9.35
22	Rubber & plastic products	8.41
36	Water collection & supply	8.17
25	Fabricated metal products	7.05
37–39	Sewerage & waste management	6.62
18	Printing & reproduction	6.53
79	Travel agencies	5.95

Note: Upstream carbon-cost exposure is the input-share-weighted average of suppliers' energy intensity (TJ / GVA in M€), computed from Eurostat FIGARO inter-country input-output tables (industry-by-industry) and Eurostat energy intensity data. Higher values indicate greater pass-through of a carbon-policy shock through the supply chain. Values are averaged across all available FIGARO years (2010–2021) and across the four sample countries (DE, ES, FR, IT). Sectors sharing a FIGARO code are reported jointly. See Section 6.2.2 for details.

A.4 FIGARO to NACE concordance

Table A4: Concordance: FIGARO Industry Codes to NACE Rev. 2 Two-Digit Divisions

FIGARO code	NACE section	NACE 2-digit	Description
A01	A	01	Crop and animal production
A02	A	02	Forestry and logging
A03	A	03	Fishing and aquaculture
B	B	05–09	Mining and quarrying
C10_T12	C	10, 11, 12	Food, beverages, tobacco
C13_T15	C	13, 14, 15	Textiles, wearing apparel, leather
C16	C	16	Wood and wood products
C17	C	17	Paper and paper products
C18	C	18	Printing and reproduction
C19	C	19	Coke and refined petroleum products
C20	C	20	Chemicals and chemical products
C21	C	21	Pharmaceutical products
C22	C	22	Rubber and plastic products
C23	C	23	Non-metallic mineral products
C24	C	24	Basic metals
C25	C	25	Fabricated metal products
C26	C	26	Computer, electronic, optical products
C27	C	27	Electrical equipment
C28	C	28	Machinery and equipment n.e.c.
C29	C	29	Motor vehicles
C30	C	30	Other transport equipment
C31_32	C	31, 32	Furniture; other manufacturing
C33	C	33	Repair and installation of machinery
D35	D	35	Electricity, gas, steam
E36	E	36	Water collection and supply
E37_T39	E	37, 38, 39	Sewerage, waste management, remediation
F	F	41, 42, 43	Construction
G45	G	45	Wholesale and retail of motor vehicles
G46	G	46	Wholesale trade
G47	G	47	Retail trade
H49	H	49	Land transport and pipelines
H50	H	50	Water transport
H51	H	51	Air transport
H52	H	52	Warehousing and transport support

Continued on next page

Table A4 – *Continued from previous page*

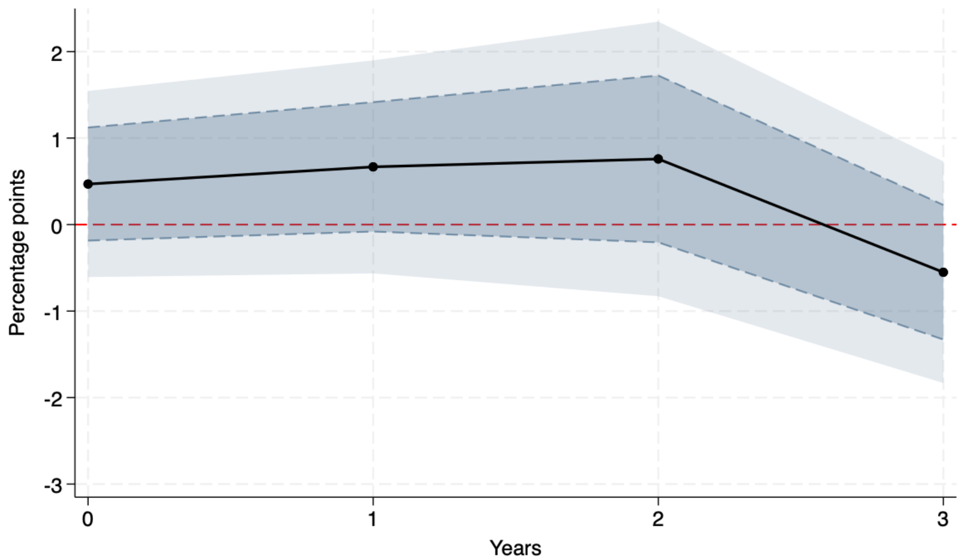
FIGARO code	NACE section	NACE 2-digit	Description
H53	H	53	Postal and courier activities
I	I	55, 56	Accommodation and food service
J58	J	58	Publishing activities
J59_60	J	59, 60	Film, TV, music; broadcasting
J61	J	61	Telecommunications
J62_63	J	62, 63	Computer programming; information services
K64	K	64	Financial services
K65	K	65	Insurance and pension funding
K66	K	66	Auxiliary financial services
L	L	68	Real estate activities
M69_70	M	69, 70	Legal, accounting; head offices, consulting
M71	M	71	Architecture and engineering
M72	M	72	Scientific research and development
M73	M	73	Advertising and market research
M74_75	M	74, 75	Other professional; veterinary activities
N77	N	77	Rental and leasing activities
N78	N	78	Employment activities
N79	N	79	Travel agencies and tour operators
N80_T82	N	80, 81, 82	Security; services to buildings; office support
O84	O	84	Public administration and defense
P85	P	85	Education
Q86	Q	86	Human health activities
Q87_88	Q	87, 88	Residential care; social work
R90_T92	R	90, 91, 92	Arts, entertainment; libraries, museums; gambling
R93	R	93	Sports and recreation
S94	S	94	Membership organizations
S95	S	95	Repair of computers and personal goods
S96	S	96	Other personal service activities
T	T	97, 98	Households as employers

Note: The table shows the mapping from FIGARO inter-country input-output table industry codes to NACE Rev. 2 two-digit divisions. One-to-one mappings (e.g., C24 → NACE 24) are shown on a single row. Bundled FIGARO codes covering multiple NACE divisions (e.g., C10T12 → NACE 10, 11, 12) assign the same upstream exposure value to all constituent divisions. The concordance covers 56 FIGARO codes mapped to 88 NACE 2-digit divisions. Source: Eurostat FIGARO documentation and author's mapping.

B Additional results

B.1 Intangible investment

Figure A1: The impact of carbon policy shocks on average firm-level intangible investment



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels.

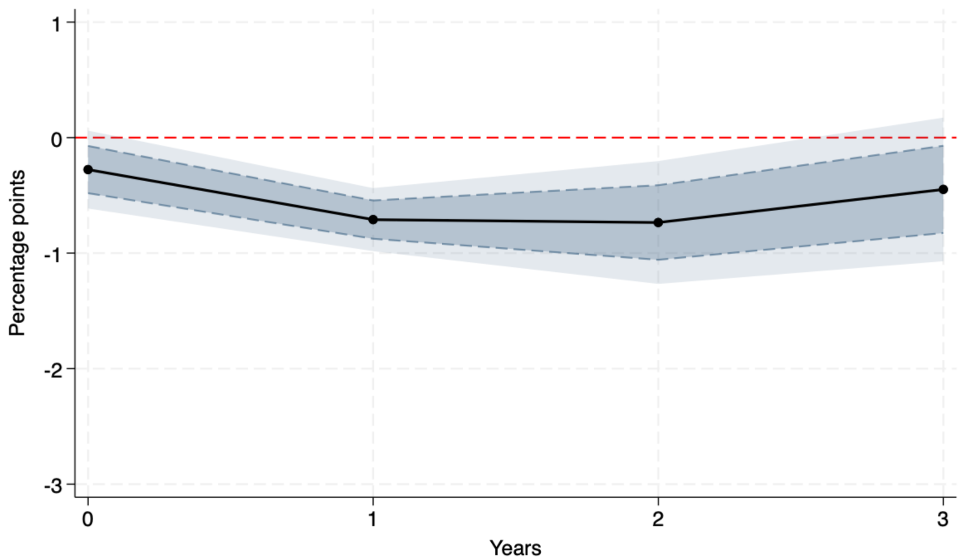
Table A5: Effect of Carbon Policy Shocks on Intangible Investment (Average)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	0.47	0.67	0.76	-0.55
	(0.65)	(0.75)	(0.96)	(0.78)
ϵ_{it-1}	-0.05	0.58	-0.26	-0.47
	(0.72)	(0.94)	(0.60)	(0.74)
ϵ_{it-2}	-0.07	-0.86	-0.63	-0.98
	(0.78)	(0.77)	(0.78)	(0.87)
ΔI_{it-1}	-0.22***	-0.25***	-0.28***	-0.34***
	(0.02)	(0.03)	(0.03)	(0.04)
ΔI_{it-2}	-0.12***	-0.12***	-0.16***	-0.17***
	(0.01)	(0.01)	(0.02)	(0.02)
ΔSG_{it-1}	-0.42***	-0.47***	-0.54***	-0.59***
	(0.06)	(0.07)	(0.08)	(0.10)
ΔSG_{it-2}	-0.16***	-0.19***	-0.19***	-0.22***
	(0.03)	(0.03)	(0.04)	(0.04)
ΔCF_{it-1}	0.59***	0.77***	0.85***	0.91***
	(0.14)	(0.18)	(0.18)	(0.25)
ΔCF_{it-2}	0.02	0.17	0.34*	0.08
	(0.11)	(0.17)	(0.19)	(0.24)
Observations	4,501,761	3,623,662	2,934,136	2,382,239

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Total fixed investment

Figure A2: The impact of carbon policy shocks on average firm-level total fixed investment



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels.

Table A6: Effect of Carbon Policy Shocks on Total Fixed Investment (Average)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.28	-0.71***	-0.73**	-0.45
	(0.20)	(0.17)	(0.32)	(0.38)
ϵ_{it-1}	-0.64***	-0.52***	-0.26	-0.21
	(0.15)	(0.19)	(0.27)	(0.26)
ϵ_{it-2}	-0.36	0.19	0.27	0.67
	(0.27)	(0.35)	(0.38)	(0.43)
ΔI_{it-1}	-0.38***	-0.38***	-0.38***	-0.38***
	(0.01)	(0.01)	(0.01)	(0.01)
ΔI_{it-2}	-0.19***	-0.19***	-0.19***	-0.18***
	(0.01)	(0.01)	(0.01)	(0.00)
ΔSG_{it-1}	-0.00	-0.01	-0.01	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
ΔSG_{it-2}	0.01*	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
ΔCF_{it-1}	0.47***	0.36***	0.31***	0.32***
	(0.02)	(0.02)	(0.02)	(0.02)
ΔCF_{it-2}	0.21***	0.12***	0.09***	0.10***
	(0.01)	(0.01)	(0.01)	(0.02)
Observations	7,909,607	6,624,883	5,504,598	4,551,185

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Carbon exposure and EU ETS

Table A7: Carbon Exposure Heterogeneity: High vs Low Carbon

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^h_{it}$	-0.67	-1.28***	-1.63**	-0.86
	(0.46)	(0.46)	(0.71)	(0.71)
$\epsilon_{it} D^l_{it}$	-0.48	-1.24***	-1.28**	-0.52
	(0.39)	(0.34)	(0.61)	(0.66)
Controls	Yes	Yes	Yes	Yes
Observations	7,682,806	6,407,555	5,309,797	4,380,973

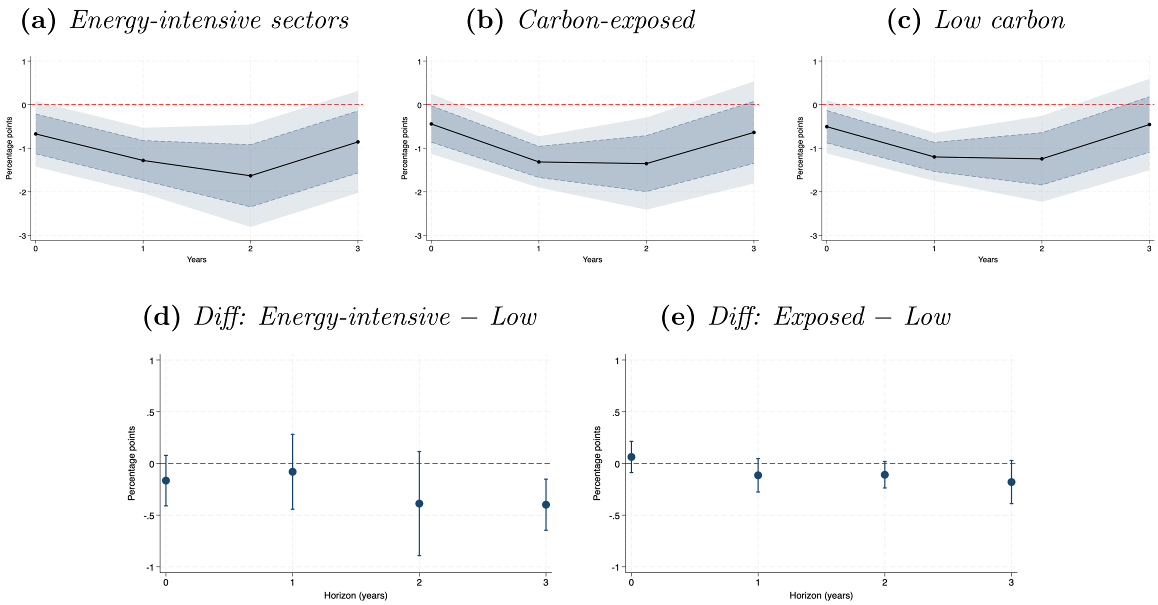
Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Differential Effect: High vs Low Carbon: Reference group = Low Carbon firms

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.48	-1.24***	-1.28**	-0.52
	(0.39)	(0.34)	(0.61)	(0.66)
$\epsilon_{it} D^h_{it}$	-0.19	-0.04	-0.35	-0.34**
	(0.14)	(0.22)	(0.30)	(0.15)
Controls	Yes	Yes	Yes	Yes
Observations	7,682,806	6,407,555	5,309,797	4,380,973

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A3: The impact of carbon policy shocks on investment by carbon group (3-tier)



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with low-carbon firms as the reference group.

Table A9: Carbon Exposure Heterogeneity: 3-Tier Classification

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^e_{it}$	-0.67	-1.28***	-1.63**	-0.85
	(0.46)	(0.46)	(0.71)	(0.71)
$\epsilon_{it} D^x_{it}$	-0.44	-1.31***	-1.35**	-0.64
	(0.42)	(0.36)	(0.64)	(0.71)
$\epsilon_{it} D^l_{it}$	-0.51	-1.20***	-1.24**	-0.46
	(0.37)	(0.33)	(0.60)	(0.64)
Controls	Yes	Yes	Yes	Yes
Observations	7,682,806	6,407,555	5,309,797	4,380,973

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Differential Effects: 3-Tier Carbon Groups: Reference group = Low Carbon firms

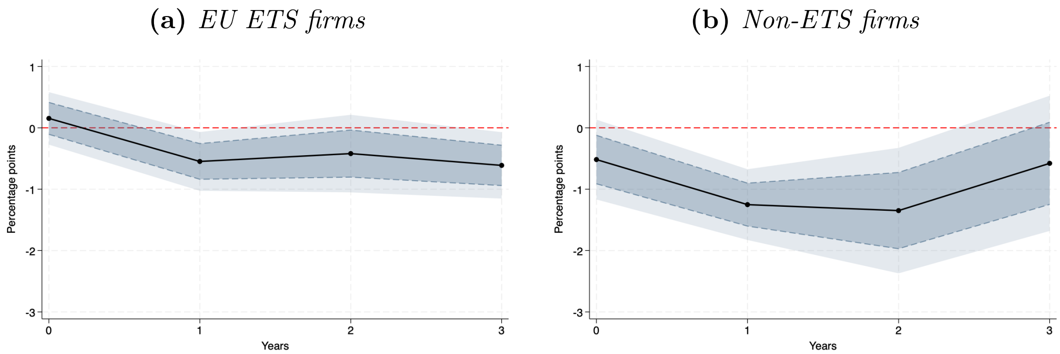
	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.51	-1.20***	-1.24**	-0.46
	(0.37)	(0.33)	(0.60)	(0.64)
$\epsilon_{it} D^e_{it}$	-0.17	-0.08	-0.39	-0.40***
	(0.15)	(0.22)	(0.31)	(0.15)
$\epsilon_{it} D^x_{it}$	0.06	-0.11	-0.11	-0.18
	(0.09)	(0.10)	(0.08)	(0.13)
Controls	Yes	Yes	Yes	Yes
Observations	7,682,806	6,407,555	5,309,797	4,380,973

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a further exploration, firms are classified as EU ETS-covered by matching the ORBIS firm-level data with the JRC-EU-ETS-FIRMS dataset (European Commission, Joint Research Centre, 2022). Figure A4 displays the results, with full regression output in Table A11. EU ETS-covered firms show a weaker and more delayed response, while non-ETS firms reproduce the aggregate pattern. However, EU ETS-matched firms account for only approximately 20,000 firm-year observations versus nearly 7.9 million for non-ETS firms, and the resulting low statistical power limits the ability to draw definitive conclusions.

The muted response of EU ETS-covered firms, while at first counterintuitive, is consistent with several mechanisms documented in the literature. First, during much of the sample period, ETS-covered installations received a substantial share of their allowances for free under the transitional allocation rules of Phases I and II (2005–2012) and through industry benchmarks in Phase III; free allocation effectively shields investment decisions from the marginal cost of carbon, even as the allowance price rises (Martin et al., 2014). Second, large emitters that are directly regulated under the EU ETS are overwhelmingly large firms—and the size analysis in Section 6.3.2 documents that large firms do not show a statistically significant response to carbon policy shocks at any horizon, likely due to deeper financial reserves, better access to external finance, and economies of scale in energy hedging. Third, ETS-covered firms in energy-intensive industries may pass through a significant fraction of carbon costs to downstream customers (Fabra and Reguant, 2014), preserving their own margins and hence investment capacity, while the cost burden materializes as indirect supply chain effects on non-ETS firms—precisely the pattern identified in the upstream exposure analysis (Section 6.2.2). Together, these mechanisms imply that the aggregate investment response to carbon policy operates primarily through indirect channels that affect the broader economy rather than through direct compliance costs borne by the regulated entities.

Figure A4: The impact of carbon policy shocks on investment by EU ETS status



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Full results in Table A11.

Table A11: Effect of Carbon Policy Shocks on Tangible Investment by EU ETS Status

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^{ETS}_{it}$	0.15	-0.55*	-0.42	-0.61*
	(0.26)	(0.29)	(0.38)	(0.33)
$\epsilon_{it} D^{non-ETS}_{it}$	-0.52	-1.25***	-1.35**	-0.58
	(0.40)	(0.35)	(0.62)	(0.67)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Direct and upstream energy-cost channels

Table A12: Effect of Carbon Policy Shocks on Tangible Investment by Energy Intensity

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^l_{it}$	-0.52***	-1.08***	-1.09**	-0.58
	(0.18)	(0.14)	(0.48)	(0.64)
$\epsilon_{it} D^m_{it}$	-0.52	-1.32***	-1.35*	-0.92
	(0.40)	(0.37)	(0.72)	(0.84)
$\epsilon_{it} D^h_{it}$	-0.72*	-1.41***	-1.90***	-1.60**
	(0.38)	(0.26)	(0.60)	(0.76)
D^m_{it}	-3.20	-2.68	-1.01	-10.08***
	(1.94)	(2.34)	(3.18)	(3.25)
D^h_{it}	-2.88	-3.62	-0.09	-9.03***
	(3.08)	(2.78)	(3.73)	(2.63)
Controls	Yes	Yes	Yes	Yes
Observations	3,668,569	2,875,604	2,194,525	1,624,563

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Differential Effects of Carbon Policy Shocks by Energy Intensity: Reference group = Low

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.52***	-1.08***	-1.09**	-0.58
	(0.18)	(0.14)	(0.48)	(0.64)
$\epsilon_{it} D^m_{it}$	-0.01	-0.23	-0.26	-0.35
	(0.24)	(0.26)	(0.29)	(0.31)
$\epsilon_{it} D^h_{it}$	-0.20	-0.33**	-0.81***	-1.02***
	(0.24)	(0.16)	(0.24)	(0.16)
D^m_{it}	-3.20	-2.68	-1.01	-10.08***
	(1.94)	(2.34)	(3.18)	(3.25)
D^h_{it}	-2.88	-3.62	-0.09	-9.03***
	(3.08)	(2.78)	(3.73)	(2.63)
Controls	Yes	Yes	Yes	Yes
Observations	3,668,569	2,875,604	2,194,525	1,624,563

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Effect of Carbon Policy Shocks on Tangible Investment by Upstream Carbon-Cost Exposure

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^l_{it}$	-0.64***	-1.19***	-1.21***	-1.03***
	(0.21)	(0.26)	(0.36)	(0.29)
$\epsilon_{it} D^m_{it}$	-0.53***	-1.07***	-0.88**	-0.48
	(0.13)	(0.15)	(0.44)	(0.39)
$\epsilon_{it} D^h_{it}$	-1.03***	-1.49***	-1.78***	-1.47***
	(0.26)	(0.27)	(0.43)	(0.45)
D^m_{it}	-3.08***	-5.45***	-5.83***	-4.08***
	(0.99)	(0.78)	(0.94)	(1.09)
D^h_{it}	-2.18**	-4.73***	-4.97***	-5.01***
	(1.05)	(0.83)	(0.95)	(0.82)
Controls	Yes	Yes	Yes	Yes
Observations	4,734,192	3,729,840	2,869,218	2,198,084

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Differential Effects of Carbon Policy Shocks by Upstream Carbon-Cost Exposure: Reference group = Low upstream carbon-cost exposure

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.64***	-1.19***	-1.21***	-1.03***
	(0.21)	(0.26)	(0.36)	(0.29)
$\epsilon_{it} D^m_{it}$	0.11	0.12	0.33	0.55
	(0.19)	(0.23)	(0.41)	(0.36)
$\epsilon_{it} D^h_{it}$	-0.39**	-0.30	-0.57**	-0.44
	(0.19)	(0.19)	(0.28)	(0.31)
D^m_{it}	-3.08***	-5.45***	-5.83***	-4.08***
	(0.99)	(0.78)	(0.94)	(1.09)
D^h_{it}	-2.18**	-4.73***	-4.97***	-5.01***
	(1.05)	(0.83)	(0.95)	(0.82)
Controls	Yes	Yes	Yes	Yes
Observations	4,734,192	3,729,840	2,869,218	2,198,084

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A16: Joint Specification: Upstream Carbon-Cost Exposure and Assigned Sector-Country-Year Energy Intensity

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.58***	-1.04***	-0.98**	-0.65
	(0.17)	(0.22)	(0.45)	(0.42)
$\epsilon_{it} D^{up,l}_{it}$	0.26	0.03	0.91***	0.11
	(0.21)	(0.21)	(0.31)	(0.52)
$\epsilon_{it} D^{up,h}_{it}$	-0.41*	-0.42	-0.56***	-0.47*
	(0.21)	(0.35)	(0.18)	(0.28)
$\epsilon_{it} D^{ei,l}_{it}$	-0.08	-0.09	-0.32	0.05
	(0.12)	(0.18)	(0.21)	(0.15)
$\epsilon_{it} D^{ei,h}_{it}$	-0.15	-0.10	-0.55***	-0.73***
	(0.11)	(0.14)	(0.20)	(0.20)
Controls	Yes	Yes	Yes	Yes
Observations	3,335,572	2,571,574	1,915,296	1,365,689

Reference group: medium upstream exposure and medium assigned sector-country-year energy intensity.

Standard errors in parentheses are two-way clustered at the firm and month-year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: Effect of Carbon Policy Shocks on Tangible Investment by Upstream Carbon-Cost Exposure (Time-Invariant)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^{l}_{it}$	-0.17	-0.74***	-0.82*	-0.32
	(0.35)	(0.27)	(0.45)	(0.48)
$\epsilon_{it} D^{m}_{it}$	-0.50	-1.23***	-1.02	-0.21
	(0.44)	(0.42)	(0.67)	(0.71)
$\epsilon_{it} D^{h}_{it}$	-0.78*	-1.61***	-1.97***	-1.02
	(0.45)	(0.44)	(0.72)	(0.76)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Financial constraints

Table A18: Effect of Carbon Policy Shocks on Tangible Investment by Firm Age

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^y_{it}$	-0.33	-1.00***	-1.37**	-0.52
	(0.42)	(0.33)	(0.59)	(0.66)
$\epsilon_{it} D^m_{it}$	-0.55	-1.42***	-1.25*	-0.47
	(0.40)	(0.35)	(0.68)	(0.72)
$\epsilon_{it} D^o_{it}$	-0.63*	-1.30***	-1.40**	-0.75
	(0.38)	(0.36)	(0.61)	(0.56)
D^y_{it}	-3.91	-4.79*	-6.24	-9.43*
	(2.39)	(2.51)	(4.41)	(5.06)
D^m_{it}	-0.77	-0.60	-1.01	-2.21
	(1.37)	(1.32)	(2.49)	(2.94)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A19: Differential Effects of Carbon Policy Shocks by Firm Age: Reference group = Old firms

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.63*	-1.30***	-1.40**	-0.75
	(0.38)	(0.36)	(0.61)	(0.56)
$\epsilon_{it}D^y_{it}$	0.30	0.30	0.03	0.23
	(0.26)	(0.22)	(0.34)	(0.25)
$\epsilon_{it}D^m_{it}$	0.08	-0.11	0.15	0.28
	(0.15)	(0.18)	(0.21)	(0.28)
D^y_{it}	-3.91	-4.79*	-6.24	-9.43*
	(2.39)	(2.51)	(4.41)	(5.06)
D^m_{it}	-0.77	-0.60	-1.01	-2.21
	(1.37)	(1.32)	(2.49)	(2.94)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A20: Effect of Carbon Policy Shocks on Tangible Investment by Firm Size (EU SME Definition)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^{mi}_{it}$	-0.66	-1.38***	-1.28*	-0.54
	(0.40)	(0.36)	(0.65)	(0.73)
$\epsilon_{it} D^{s}_{it}$	-0.76	-1.52***	-1.41*	-0.51
	(0.52)	(0.52)	(0.77)	(0.80)
$\epsilon_{it} D^{m}_{it}$	-0.54	-1.02**	-1.17*	-0.43
	(0.47)	(0.46)	(0.64)	(0.63)
$\epsilon_{it} D^{l}_{it}$	-0.09	-0.06	-0.55	-0.15
	(0.39)	(0.39)	(0.40)	(0.53)
D^{s}_{it}	-9.26***	-9.52***	-9.10***	-7.83***
	(0.79)	(0.73)	(0.65)	(0.52)
D^{m}_{it}	-19.68***	-19.71***	-18.49***	-16.11***
	(1.19)	(1.24)	(1.09)	(0.94)
D^{l}_{it}	-31.44***	-30.99***	-26.61***	-23.16***
	(2.08)	(1.83)	(1.85)	(1.80)
Controls	Yes	Yes	Yes	Yes
Observations	5,818,316	4,904,081	4,092,805	3,393,009

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A21: Differential Effects of Carbon Policy Shocks by Firm Size (EU SME): Reference group = Large firms

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.09	-0.06	-0.55	-0.15
	(0.39)	(0.39)	(0.40)	(0.53)
$\epsilon_{it} D^{mi}_{it}$	-0.57**	-1.33***	-0.73	-0.40
	(0.25)	(0.31)	(0.45)	(0.39)
$\epsilon_{it} D^{s}_{it}$	-0.67*	-1.46***	-0.87*	-0.36
	(0.34)	(0.40)	(0.50)	(0.42)
$\epsilon_{it} D^{m}_{it}$	-0.44	-0.97***	-0.62*	-0.28
	(0.27)	(0.30)	(0.36)	(0.25)
D^{mi}_{it}	31.44***	30.99***	26.61***	23.16***
	(2.08)	(1.83)	(1.85)	(1.80)
D^{s}_{it}	22.18***	21.47***	17.51***	15.32***
	(1.90)	(1.63)	(1.74)	(1.90)
D^{m}_{it}	11.76***	11.27***	8.11***	7.04***
	(1.53)	(1.28)	(1.32)	(1.62)
Controls	Yes	Yes	Yes	Yes
Observations	5,818,316	4,904,081	4,092,805	3,393,009

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A22: Effect of Carbon Policy Shocks on Tangible Investment by Leverage

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^l_{it}$	-0.56	-1.19***	-1.19**	-0.70
	(0.37)	(0.33)	(0.56)	(0.56)
$\epsilon_{it} D^m_{it}$	-0.63	-1.47***	-1.48**	-0.67
	(0.41)	(0.37)	(0.64)	(0.64)
$\epsilon_{it} D^h_{it}$	-0.65*	-1.37***	-1.52**	-0.50
	(0.39)	(0.38)	(0.68)	(0.80)
D^m_{it}	-18.69***	-14.55***	-11.92***	-10.58***
	(1.43)	(1.17)	(1.45)	(1.38)
D^h_{it}	-29.88***	-23.00***	-18.31***	-16.76***
	(2.75)	(2.40)	(2.93)	(2.80)
Controls	Yes	Yes	Yes	Yes
Observations	7,856,313	6,555,788	5,435,243	4,486,184

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

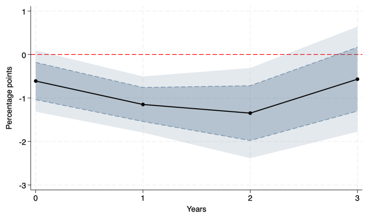
Table A23: Differential Effects of Carbon Policy Shocks by Leverage: Reference group = Low leverage

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.56	-1.19***	-1.19**	-0.70
	(0.37)	(0.33)	(0.56)	(0.56)
$\epsilon_{it} D^m_{it}$	-0.07	-0.27*	-0.29	0.03
	(0.11)	(0.14)	(0.19)	(0.15)
$\epsilon_{it} D^h_{it}$	-0.09	-0.18	-0.32	0.20
	(0.18)	(0.22)	(0.30)	(0.38)
D^m_{it}	-18.69***	-14.55***	-11.92***	-10.58***
	(1.43)	(1.17)	(1.45)	(1.38)
D^h_{it}	-29.88***	-23.00***	-18.31***	-16.76***
	(2.75)	(2.40)	(2.93)	(2.80)
Controls	Yes	Yes	Yes	Yes
Observations	7,856,313	6,555,788	5,435,243	4,486,184

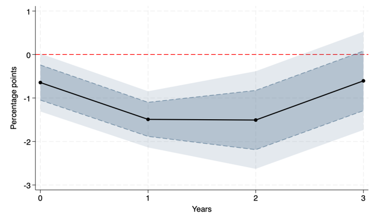
Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A5: The impact of carbon policy shocks on investment by firm liquidity

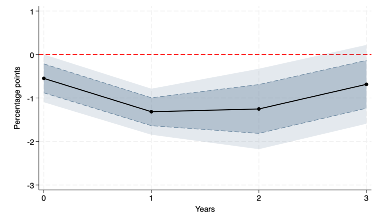
(a) *Low liquidity*



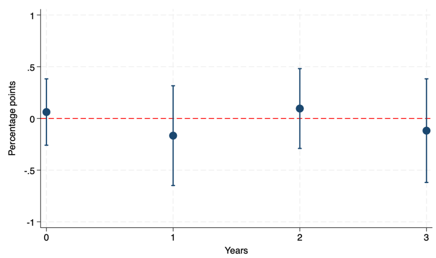
(b) *Medium liquidity*



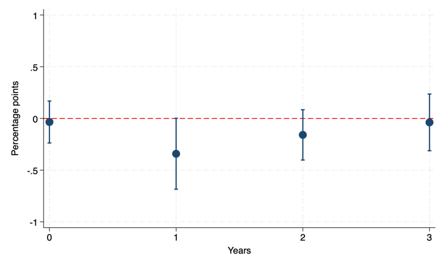
(c) *High liquidity*



(d) *Diff: High − Low*



(e) *Diff: Medium − Low*



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with low-liquidity firms as the reference group.

Table A24: Effect of Carbon Policy Shocks on Tangible Investment by Firm Liquidity

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^l_{it}$	-0.61	-1.15***	-1.35**	-0.57
	(0.43)	(0.39)	(0.63)	(0.73)
$\epsilon_{it} D^m_{it}$	-0.64	-1.49***	-1.51**	-0.61
	(0.40)	(0.39)	(0.68)	(0.69)
$\epsilon_{it} D^h_{it}$	-0.55	-1.32***	-1.25**	-0.69
	(0.33)	(0.32)	(0.56)	(0.55)
D^m_{it}	16.62***	11.43***	8.59***	7.04***
	(0.82)	(0.49)	(0.33)	(0.26)
D^h_{it}	35.71***	25.18***	19.94***	16.95***
	(0.79)	(0.58)	(0.77)	(0.82)
Controls	Yes	Yes	Yes	Yes
Observations	7,838,689	6,541,921	5,424,411	4,477,703

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A25: Differential Effects of Carbon Policy Shocks by Firm Liquidity: Reference group = Low liquidity

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.61	-1.15***	-1.35**	-0.57
	(0.43)	(0.39)	(0.63)	(0.73)
$\epsilon_{it} D^m_{it}$	-0.03	-0.34	-0.16	-0.04
	(0.12)	(0.21)	(0.15)	(0.17)
$\epsilon_{it} D^h_{it}$	0.06	-0.17	0.10	-0.12
	(0.20)	(0.29)	(0.23)	(0.30)
D^m_{it}	16.62***	11.43***	8.59***	7.04***
	(0.82)	(0.49)	(0.33)	(0.26)
D^h_{it}	35.71***	25.18***	19.94***	16.95***
	(0.79)	(0.58)	(0.77)	(0.82)
Controls	Yes	Yes	Yes	Yes
Observations	7,838,689	6,541,921	5,424,411	4,477,703

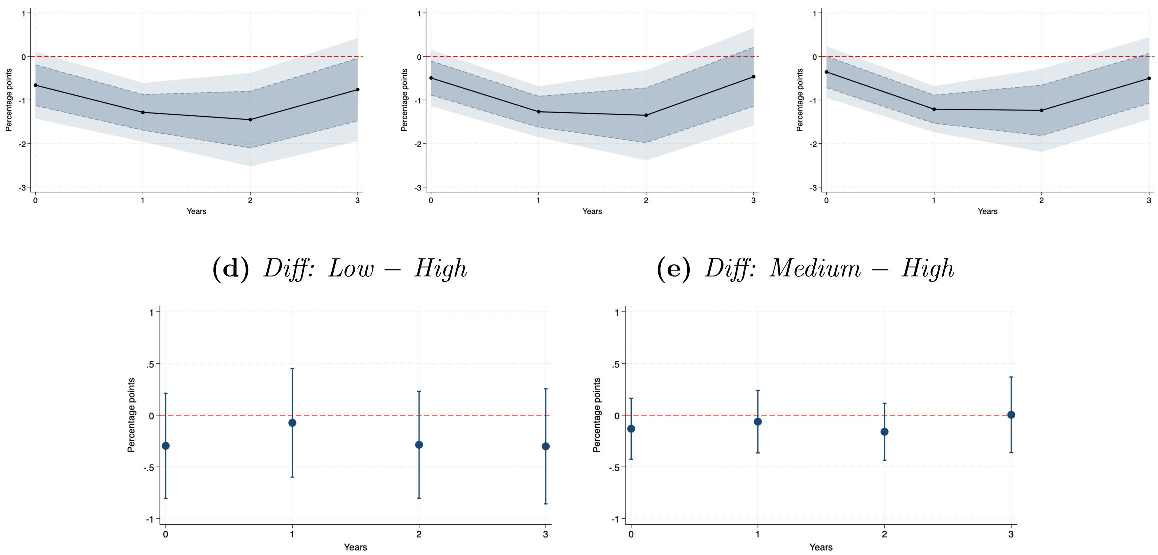
Standard errors in parentheses are two-way clustered at the firm and month-year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A6: The impact of carbon policy shocks on investment by cash flow strength

(a) *Low cash flow* **(b)** *Medium cash flow* **(c)** *High cash flow*

(d) *Diff: Low − High* **(e)** *Diff: Medium − High*



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels. Panels (d)–(e) show differences with high-cash-flow firms as the reference group.

Table A26: Effect of Carbon Policy Shocks on Tangible Investment by Cash Flow Strength

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^l_{it}$	-0.66	-1.28***	-1.45**	-0.76
	(0.47)	(0.41)	(0.65)	(0.72)
$\epsilon_{it} D^m_{it}$	-0.49	-1.27***	-1.35**	-0.47
	(0.39)	(0.36)	(0.63)	(0.68)
$\epsilon_{it} D^h_{it}$	-0.36	-1.21***	-1.24**	-0.50
	(0.36)	(0.32)	(0.58)	(0.57)
D^m_{it}	-3.08***	-3.95***	-4.13***	-3.45***
	(0.82)	(0.76)	(0.95)	(1.03)
D^h_{it}	1.73	-1.99	-3.47**	-2.92
	(1.45)	(1.41)	(1.70)	(1.90)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A27: Effect of Carbon Policy Shocks on Tangible Investment by Cash Flow Strength: Reference group = High CF

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.36	-1.20***	-1.19*	-0.47
	(0.35)	(0.33)	(0.61)	(0.59)
$\epsilon_{it}D^l_{it}$	-0.30	-0.07	-0.29	-0.30
	(0.31)	(0.32)	(0.31)	(0.34)
$\epsilon_{it}D^m_{it}$	-0.13	-0.06	-0.16	0.00
	(0.18)	(0.18)	(0.17)	(0.22)
D^m_{it}	-3.83***	-3.09***	-2.64***	-2.20***
	(0.31)	(0.25)	(0.28)	(0.28)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A28: Effect of Carbon Policy Shocks on Tangible Investment by Labor Productivity (Sales/Employees)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it}D^l_{it}$	-0.86**	-1.45***	-1.28*	-0.67
	(0.43)	(0.42)	(0.68)	(0.72)
$\epsilon_{it}D^m_{it}$	-0.91**	-1.61***	-1.56**	-0.71
	(0.44)	(0.43)	(0.71)	(0.76)
$\epsilon_{it}D^h_{it}$	-0.35	-1.19***	-1.13*	-0.30
	(0.46)	(0.39)	(0.62)	(0.69)
D^m_{it}	-3.09***	-4.54***	-5.78***	-5.36***
	(0.68)	(0.58)	(0.39)	(0.43)
D^h_{it}	-9.83***	-9.85***	-12.24***	-12.46***
	(2.93)	(1.30)	(0.91)	(0.88)
Controls	Yes	Yes	Yes	Yes
Observations	5,817,424	4,903,612	4,092,545	3,392,868

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A29: Differential Effects of Carbon Policy Shocks by Labor Productivity (Sales/Employees): Reference group = Low productivity

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.86**	-1.45***	-1.28*	-0.67
	(0.43)	(0.42)	(0.68)	(0.72)
$\epsilon_{it} D^m_{it}$	-0.05	-0.15	-0.28***	-0.05
	(0.10)	(0.09)	(0.08)	(0.09)
$\epsilon_{it} D^h_{it}$	0.52**	0.26**	0.16	0.37***
	(0.21)	(0.10)	(0.13)	(0.13)
D^m_{it}	-3.09***	-4.54***	-5.78***	-5.36***
	(0.68)	(0.58)	(0.39)	(0.43)
D^h_{it}	-9.83***	-9.85***	-12.24***	-12.46***
	(2.93)	(1.30)	(0.91)	(0.88)
Controls	Yes	Yes	Yes	Yes
Observations	5,817,424	4,903,612	4,092,545	3,392,868

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A30: Robustness: Effect of Carbon Policy Shocks on Tangible Investment by Value Added per Employee

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^l_{it}$	-0.95**	-1.61***	-1.34*	-0.55
	(0.44)	(0.44)	(0.71)	(0.76)
$\epsilon_{it} D^m_{it}$	-0.91*	-1.64***	-1.50*	-0.64
	(0.49)	(0.46)	(0.76)	(0.80)
$\epsilon_{it} D^h_{it}$	-0.45	-1.18***	-1.20*	-0.37
	(0.46)	(0.41)	(0.62)	(0.73)
D^m_{it}	-5.05***	-5.25***	-5.32***	-4.54***
	(0.38)	(0.41)	(0.35)	(0.41)
D^h_{it}	-11.78***	-12.02***	-12.50***	-11.32***
	(1.72)	(0.92)	(0.75)	(0.85)
Controls	Yes	Yes	Yes	Yes
Observations	5,330,969	4,510,463	3,778,822	3,148,330

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A31: Differential Effects of Carbon Policy Shocks by Value Added per Employee: Reference group = Low productivity

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.95**	-1.61***	-1.34*	-0.55
	(0.44)	(0.44)	(0.71)	(0.76)
$\epsilon_{it}D^m_{it}$	0.03	-0.03	-0.16	-0.08
	(0.09)	(0.09)	(0.11)	(0.09)
$\epsilon_{it}D^h_{it}$	0.49**	0.43***	0.13	0.19
	(0.22)	(0.12)	(0.17)	(0.15)
D^m_{it}	-5.05***	-5.25***	-5.32***	-4.54***
	(0.38)	(0.41)	(0.35)	(0.41)
D^h_{it}	-11.78***	-12.02***	-12.50***	-11.32***
	(1.72)	(0.92)	(0.75)	(0.85)
Controls	Yes	Yes	Yes	Yes
Observations	5,330,969	4,510,463	3,778,822	3,148,330

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.6 Sectoral analysis

Table A32: Effect of Carbon Policy Shocks on Tangible Investment by Macro Sector

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it}D^m_{it}$	-0.74	-1.46***	-1.71**	-1.00
	(0.49)	(0.47)	(0.75)	(0.78)
$\epsilon_{it}D^c_{it}$	-0.51	-1.43***	-1.30*	-0.69
	(0.45)	(0.41)	(0.68)	(0.76)
$\epsilon_{it}D^s_{it}$	-0.44	-1.15***	-1.20**	-0.43
	(0.36)	(0.31)	(0.58)	(0.61)
$\epsilon_{it}D^p_{it}$	-0.44	-0.83**	-1.50***	0.18
	(0.49)	(0.38)	(0.57)	(0.62)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A33: Effect of Carbon Policy Shocks on Tangible Investment by Macro Sector: Reference group = Manufacturing (NACE C)

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
ϵ_{it}	-0.74	-1.46***	-1.71**	-1.00
	(0.49)	(0.47)	(0.75)	(0.78)
$\epsilon_{it} D^c_{it}$	0.23	0.02	0.41	0.31*
	(0.15)	(0.26)	(0.32)	(0.16)
$\epsilon_{it} D^s_{it}$	0.30	0.30	0.51	0.57***
	(0.20)	(0.25)	(0.32)	(0.21)
$\epsilon_{it} D^p_{it}$	0.30	0.63	0.21	1.18***
	(0.50)	(0.38)	(0.53)	(0.40)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.6.1 Broad NACE sectoral analysis

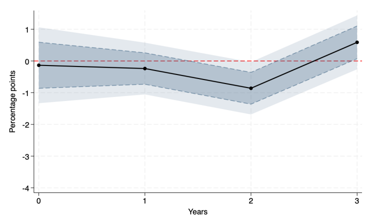
Table A34: Effect of Carbon Policy Shocks on Tangible Investment by NACE Section

	ΔI^*_{it0}	ΔI^*_{it1}	ΔI^*_{it2}	ΔI^*_{it3}
$\epsilon_{it} D^{agri}_{it}$	-0.13	-0.24	-0.86*	0.59
	(0.73)	(0.50)	(0.50)	(0.52)
$\epsilon_{it} D^{min}_{it}$	-2.19*	-2.58*	-4.05**	1.74
	(1.12)	(1.31)	(1.90)	(1.85)
$\epsilon_{it} D^{man}_{it}$	-0.74	-1.46***	-1.71**	-1.00
	(0.49)	(0.47)	(0.75)	(0.78)
$\epsilon_{it} D^{enrg}_{it}$	-0.39	-0.82**	-1.71***	-0.30
	(0.65)	(0.32)	(0.57)	(0.46)
$\epsilon_{it} D^{wtr}_{it}$	-0.62	-1.88***	-2.06**	-1.49
	(0.53)	(0.52)	(0.82)	(0.97)
$\epsilon_{it} D^{con}_{it}$	-0.51	-1.43***	-1.30*	-0.69
	(0.45)	(0.41)	(0.68)	(0.76)
$\epsilon_{it} D^{trd}_{it}$	-0.35	-1.20***	-1.06*	-0.26
	(0.39)	(0.32)	(0.60)	(0.60)
$\epsilon_{it} D^{trn}_{it}$	-1.08	-2.32***	-2.44**	-1.13
	(0.66)	(0.67)	(1.06)	(1.05)
$\epsilon_{it} D^{acc}_{it}$	-0.38*	-0.72***	-0.94***	-0.71**
	(0.21)	(0.19)	(0.31)	(0.32)
$\epsilon_{it} D^{ict}_{it}$	-0.24	-0.88***	-1.09**	-0.54
	(0.37)	(0.28)	(0.48)	(0.56)
$\epsilon_{it} D^{pro}_{it}$	-0.45	-0.79***	-1.23**	-0.57
	(0.33)	(0.28)	(0.49)	(0.59)
$\epsilon_{it} D^{adm}_{it}$	-0.58	-1.16***	-1.21*	-0.21
	(0.41)	(0.43)	(0.67)	(0.76)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

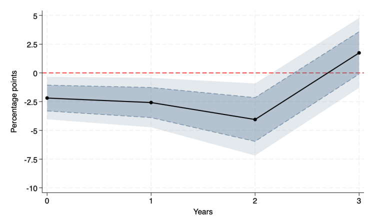
Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A7: The impact of carbon policy shocks on investment by NACE section

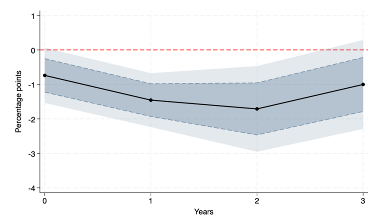
(a) *Agriculture*



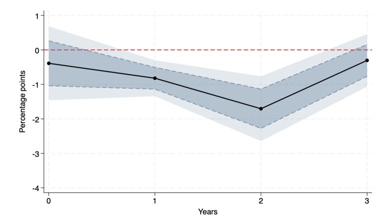
(b) *Mining*



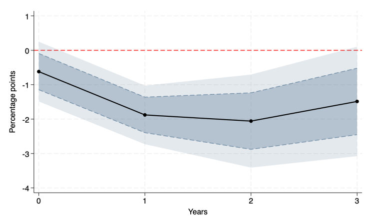
(c) *Manufacturing*



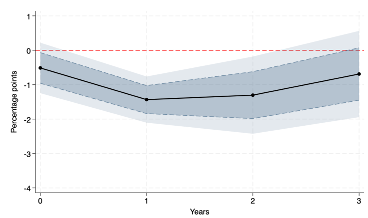
(d) *Energy*



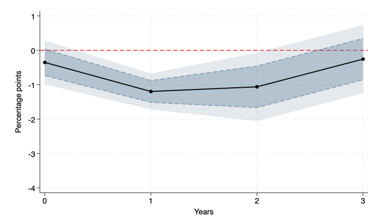
(e) *Water/Waste*



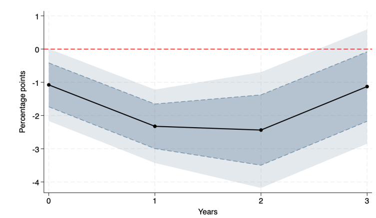
(f) *Construction*



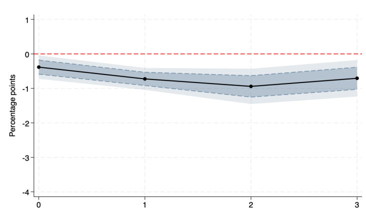
(g) *Trade*



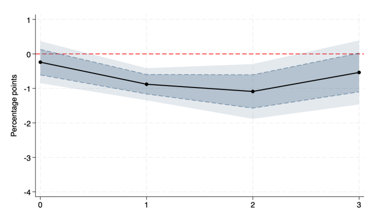
(h) *Transport*



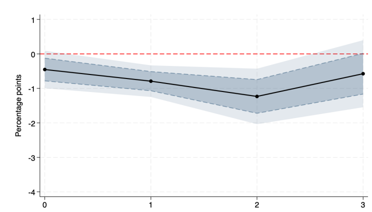
(i) *Accommodation*



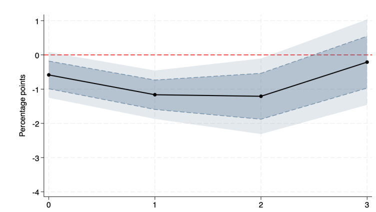
(j) *ICT*



(k) *Professional*



(l) *Administration*

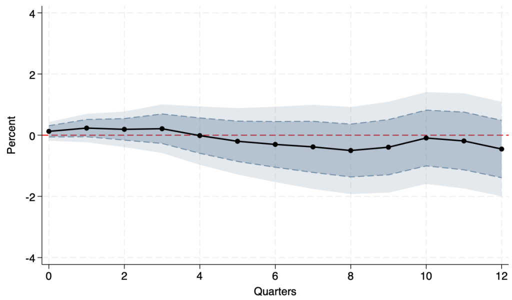


Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels.

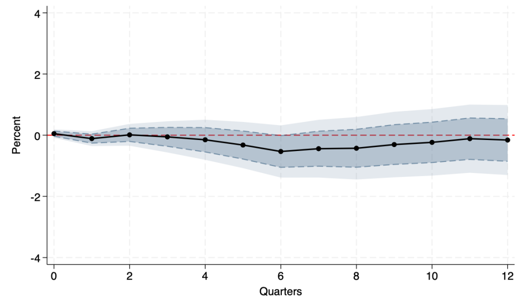
B.7 Country heterogeneity

Figure A8: The impact of carbon policy shocks on aggregate investment by country

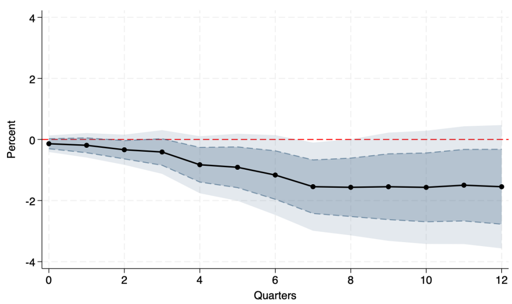
(a) *Germany*



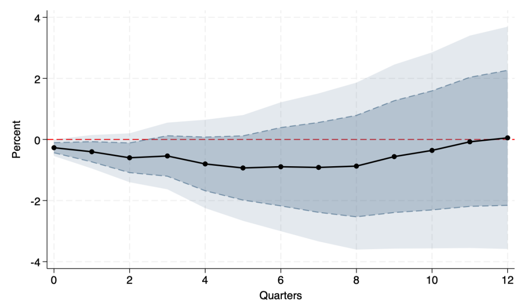
(b) *France*



(c) *Italy*

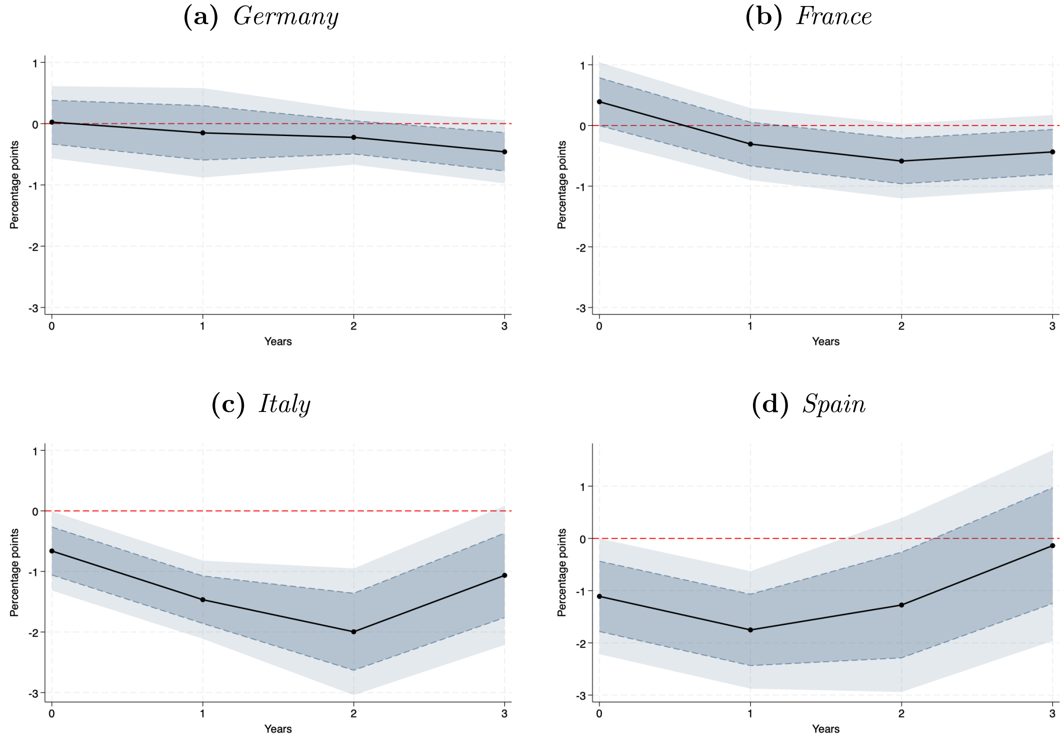


(d) *Spain*



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are heteroskedasticity-robust.

Figure A9: The impact of carbon policy shocks on firm-level investment by country



(a) *Germany* **(b)** *France* **(c)** *Italy* **(d)** *Spain*

Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels.

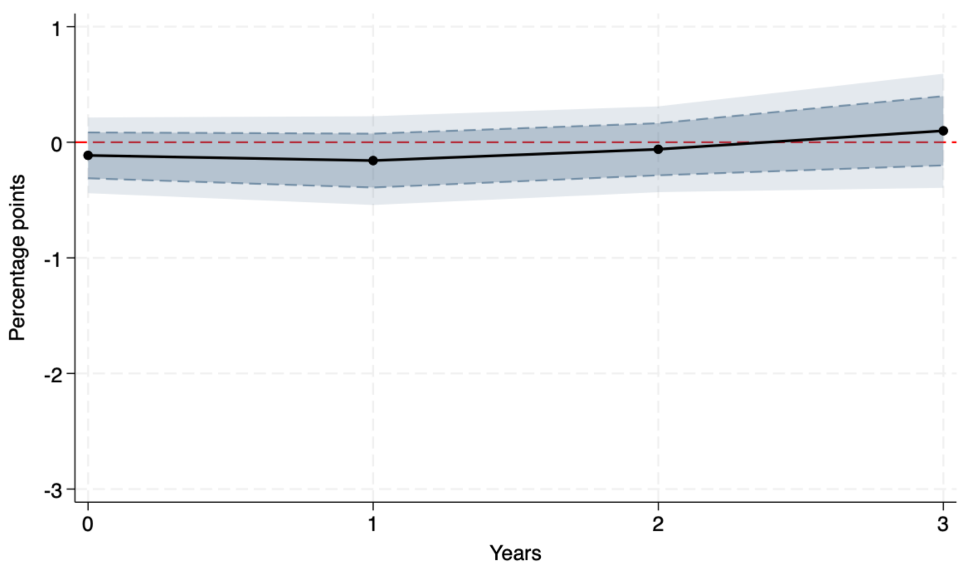
Table A35: Effect of Carbon Policy Shocks on Tangible Investment by Country

	ΔI^{*}_{it0}	ΔI^{*}_{it1}	ΔI^{*}_{it2}	ΔI^{*}_{it3}
$\epsilon_{it} D^{DE}_{it}$	0.02	-0.15	-0.22	-0.46
	(0.36)	(0.44)	(0.27)	(0.31)
$\epsilon_{it} D^{FR}_{it}$	0.39	-0.31	-0.59	-0.44
	(0.39)	(0.36)	(0.37)	(0.37)
$\epsilon_{it} D^{IT}_{it}$	-0.66*	-1.47***	-2.00***	-1.06
	(0.40)	(0.39)	(0.64)	(0.70)
$\epsilon_{it} D^{ES}_{it}$	-1.11	-1.75**	-1.28	-0.14
	(0.67)	(0.68)	(1.01)	(1.11)
Controls	Yes	Yes	Yes	Yes
Observations	7,860,972	6,560,315	5,439,659	4,490,620

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.8 Employment effects

Figure A10: The impact of carbon policy shocks on average employment growth



Note: 68 and 90 percent confidence intervals are displayed. Standard errors are two-way clustered at the firm and month-year levels.

Table A36: Effect of Carbon Policy Shocks on Employment Growth

	ΔEMP^*_{it0}	ΔEMP^*_{it1}	ΔEMP^*_{it2}	ΔEMP^*_{it3}
ϵ_{it}	-0.11	-0.16	-0.06	0.10
	(0.20)	(0.23)	(0.23)	(0.30)
Controls	Yes	Yes	Yes	Yes
Observations	5,029,898	4,038,752	3,308,190	2,718,541

Standard errors in parentheses are two-way clustered at the firm and month-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a robustness check on the employment size analysis, Table A37 re-estimates the specification using initial-period (time-invariant) size classification, where each firm is assigned to a size group based on its first-observed employment count in the sample. This addresses the concern that time-varying employee-based size groups may be endogenous to the carbon policy shock itself. The results confirm that employment growth does not respond significantly to carbon policy shocks in any size group when size is defined at the initial period, reinforcing the baseline finding that the investment margin—rather than the employment margin—is the primary adjustment channel for carbon policy at the firm level.

Table A37: Effect of Carbon Policy Shocks on Employment Growth by Initial-Period Size

	ΔEMP^*_{it0}	ΔEMP^*_{it1}	ΔEMP^*_{it2}	ΔEMP^*_{it3}
$\epsilon_{it} D_i^{mi,0}$	-0.07	-0.11	-0.02	0.22
	(0.19)	(0.23)	(0.25)	(0.32)
$\epsilon_{it} D_i^{s,0}$	0.03	-0.10	0.12	0.29
	(0.20)	(0.25)	(0.27)	(0.29)
$\epsilon_{it} D_i^{m,0}$	-0.02	0.04	0.10	0.17
	(0.15)	(0.16)	(0.15)	(0.19)
$\epsilon_{it} D_i^{l,0}$	0.11	0.23^{**}	0.14	0.03
	(0.12)	(0.12)	(0.17)	(0.16)
Controls	Yes	Yes	Yes	Yes
Observations	3,926,985	3,164,577	2,598,337	2,146,181

Standard errors in parentheses are two-way clustered at the firm and month-year level.
Size groups defined by first-observed employment in sample (time-invariant).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$