Taxing carbon across borders: Trade, pass-through, and *green* technology adoption*

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Abstract

Climate policies in advanced economies increasingly condition market access on the carbon content of production abroad. Foreign suppliers can respond by adopting cleaner technologies, contracting, or redirecting exports to less regulated destinations. I study these responses and their implications for global emissions and welfare in the context of the EU's *Carbon Border Adjustment Mechanism (CBAM)*. To do so, I merge firm-to-firm customs records with administrative and capital-investment data for Indian firms exporting to the EU. Subsequently, I develop a novel taxonomy of green, transitional, and vintage technologies by industry, which I use to classify a database of 60,000 investment projects with a Large Language Model. Firms with more at stake in the EU market expand their stock of green capital projects to preserve access, replacing polluting production processes, and substituting grid electricity for on-site fossil-fuel generation. Less exposed firms divert trade to other destinations. To quantify the aggregate effects, I develop a general equilibrium model of trade and technology adoption among heterogeneous suppliers. CBAM reduces global emissions in the covered industries by 1.9%, at USD 11 per tonne avoided, well below standard estimates of the social cost of carbon. Most of the reduction comes from plant-wide adoption, which also lowers emissions on goods sold outside the EU. If firms could instead clean only their EU-bound production, global emissions reductions would be a third smaller and emissions from sales outside the EU would barely fall.

JEL Classification: F18, H23, Q56, Q58

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1 Introduction

Climate change is a global issue, however the policies designed to address it are often introduced on a national level. Richer economies have acted faster, regulating the environmental footprint of domestic production and decoupling emissions from economic growth. However, much of the developing world, with older technology and more relaxed regulation, has not managed to do so (Intergovernmental Panel on Climate Change, 2022; Freire-González et al., 2024). This gap in regulatory stringency creates a familiar problem at the intersection of environmental policy and trade, whereby firms facing pollution-related costs may shift production and sourcing toward less regulated regions. This phenomenon, known as *carbon leakage*, can undermine the effectiveness of unilateral climate policy, while placing domestic producers at a competitive disadvantage relative to foreign suppliers (Copeland and Taylor, 2004; Cherniwchan et al., 2017; Shapiro and Walker, 2018; Tanaka et al., 2022). In response, policymakers in developed countries increasingly turn to cross-border regulations that extend environmental requirements to production abroad.

The effectiveness of these policies ultimately depends on how foreign suppliers respond. Faced with new environmental costs in an important export market, firms may invest in cleaner technologies, absorb the additional costs, or redirect sales toward markets without such requirements. These responses have very different implications for emissions, trade, and welfare, yet evidence on how suppliers adjust remains scarce. In this paper, I study whether conditioning access to a major market on the environmental impact of production can discipline supplier behavior abroad. More specifically, I ask how foreign suppliers adjust their investment, production, and trade decisions and what are the aggregate implications for emissions and welfare.

I study these questions in the context of the most prominent such regulation, the EU's *Carbon Border Adjustment Mechanism (CBAM)*, introduced in 2023. The policy seeks to equalize carbon costs faced by EU producers under the *EU Emissions Trading System (EU ETS)* and foreign suppliers selling into the EU. By imposing a charge based on the emissions embodied in imported goods, CBAM prevents carbon leakage and protects the competitiveness of EU producers, while creating incentives for foreign suppliers to adopt cleaner production technologies. The reach of the policy is substantial, covering approximately 4.5% of the EU's imports, worth around $110 billion as of 2021, while exposing foreign suppliers to carbon costs they may not face in their home markets (Dolphin and Ferrucci, 2026; World Bank, 2025).[1]

My empirical analysis focuses on India, a major developing-country exporter of CBAM-covered products with substantial exposure to the EU market. As of 2024, the EU was India's largest trading partner, accounting for approximately 11.5% of its total trade, while India accounted for roughly 6.2% of EU imports of CBAM goods. The importance of this relationship has already prompted policy responses, including a recently announced $2.2 billion Indian government investment in carbon capture and related decarbonization technologies aimed at preserving export competitiveness (De Luna, 2026). Existing evidence also shows that market-based environmental regulation can effectively influence firm behavior in India (Greenstone et al., 2025). Beyond its economic relevance, India offers unusually detailed firm-level data, allowing me to construct precise measures of exposure to the policy and estimate the effects using within-firm variation over time.

To do so, I combine three sources of microdata. The first is a proprietary customs dataset of firm-to-firm trade linkages on the shipment level, from *S&P Global*. This dataset identifies Indian exporters and their foreign buyers, together with traded products, quantities, and unit prices. I link these transactions to

[1] Similar approaches are emerging elsewhere, including the United Kingdom's planned carbon border adjustment and sourcing requirements attached to electric-vehicle tax credits under the United States' *Inflation Reduction Act* (Buffie, 2024).

administrative firm-level data from the *Center for Monitoring the Indian Economy*, using tax identifiers, firm names, and geographic proximity. This allows me to identify firms exporting CBAM-covered products to the EU, measure their exposure before the regulation, and follow their subsequent investment, production, and trade decisions. I then merge a detailed dataset of 60,000 firm-level capital investment projects, containing project descriptions, investment values, outputs, and locations. To distinguish which of these projects reduce emissions, I develop a novel taxonomy of 547 production technologies across 23 emissions-intensive industries from sectoral decarbonization roadmaps. Each technology is categorized as green (eliminating process emissions), transitional (reducing emissions without eliminating them), or vintage (not contributing to emissions reductions). I then use a Large Language Model (LLM) to match each investment project to the technologies it embodies. The classification also separates investments that replace a plant's core production process from cross-cutting ones such as renewable electricity installations and carbon capture.

My empirical strategy exploits the timing of CBAM's introduction together with cross-sectional variation in firm exposure. I define firms as exposed if they exported CBAM-covered products to the EU during the 2021–2022 baseline, and measure exposure intensity using the share of baseline exports accounted for by EU-bound covered goods. To study green investment, production decisions, and firm performance, I estimate a difference-in-differences design comparing exposed firms with similar, unexposed firms before and after the policy's introduction. To study trade responses, I move to the firm-product-quarter level, using the continuous measure of baseline exposure and examining EU-bound and non-EU shipments separately. In both designs, exposure is fixed at its pre-regulation level, and identification rests on conditional parallel trends and the absence of spillovers to firms in the comparison group.

The results show that exposed Indian firms adjust along the margins of technology adoption and trade. First, they increase investment in cleaner technologies, expanding their stock of green capital projects by 18% relative to comparable firms and roughly doubling pollution-control spending as a share of operating expenses. Second, this investment largely takes the form of upgrading existing production processes, without installing renewable generation capacity. It is concentrated among firms starting from dirtier asset bases, suggesting that the policy induces technological catch-up by more polluting firms. Third, exposed firms substitute on-site fossil-fuel generation with purchased grid electricity, reducing the fossil share of their energy bill by 18 p.p., while increasing grid electricity purchases by 23 p.p., with total energy spending remaining flat. Finally, firms relocate trade away from the EU, discontinuing some EU export lines and entering new markets elsewhere. This diversion offsets only about one fifth of the contraction in EU-bound exports, while export prices measured at the Indian border remain flat during the period of interest.

Among exposed firms, responses differ with how much they have at stake in the EU market. Firms with greater exposure invest more in cleaner technologies, substitute energy inputs, and are more likely to remain in the EU market. These patterns hold whether exposure is measured by export size, the share of EU sales covered by CBAM, or expected carbon liability, and are particularly pronounced among larger, domestically owned, and more export-oriented firms. Export diversion follows the opposite pattern. Firms with relatively little covered trade are more likely to redirect sales toward other destinations, while the most exposed barely divert at all. Hence, firms with the most at stake in the EU market invest in cleaner production to preserve market access, whereas those with less at stake adjust by selling elsewhere.

The reduced-form evidence shows how exposed Indian suppliers respond to the border charge, but not what those responses imply for global emissions or welfare. These broader effects depend on how India's competitors respond, how production shifts across markets, and whether cleaner production extends beyond exports to the EU. To quantify these effects and compare the charge with alternative policies, I build a model

of trade and technology adoption across four markets, the EU, India, India's main competitors, and the rest of the world, following Melitz (2003) and Bustos (2011). The model builds on the mechanisms identified in the reduced-form analysis; firms differ in productivity and decide whether to serve the EU market and whether to adopt a cleaner technology at a fixed cost. Following Almunia et al. (2021), each plant has a fixed capacity, such that its marginal cost rises with total output and a firm that loses sales in the EU can expand elsewhere. The border charge depends on each exporter's embedded carbon emissions, hence the incentive to adopt is strongest for firms with larger EU sales. Adoption changes production throughout the plant, therefore adopters produce more cleanly both for the EU and for other markets. India's foreign competitors face the same decisions.

I estimate the model to match observed market shares, export participation, and the technology adoption response of exposed firms following the announcement of the charge. The model reproduces the trade responses, although they are not targeted in the estimation. I then use the estimated model to assess the aggregate effects of CBAM and run counterfactual exercises.[2]

The model yields four main findings. First, CBAM reduces global emissions in the covered industries by 1.9%, with the entire reduction occurring outside the EU, at an implied cost of USD 11 per tonne of carbon, well below standard estimates of the Social Cost of Carbon (SCC). Second, the reduction is driven primarily by changes in how foreign suppliers produce, not by how much they sell. By inducing firms to adopt cleaner technologies that affect production throughout the plant, CBAM also reduces emissions from goods sold in markets not subject to the charge, reversing the conventional pattern of carbon leakage. When I restrict technology adoption to production destined for the EU, global emissions reductions are smaller by one third, and emissions outside the EU barely fall. Third, the incentive to adopt cleaner technologies distinguishes CBAM from conventional tariffs. A conventional EU tariff raising the same revenue achieves only a quarter of CBAM's emissions reduction, because it raises the cost of exporting without rewarding cleaner production. Fourth, CBAM imposes economic costs on India primarily through the loss of market share in the EU, which cleaner technology adoption mitigates. A domestic Indian carbon price would be more costly, as it would apply to all production regardless of destination. In contrast, making clean technology more efficient would both reduce emissions further and increase India's income.

With this paper, I contribute to the economic literature in three main ways. First, I provide novel firm-level causal evidence that exposure to a carbon border charge induces cleaner technology adoption among foreign suppliers. A large literature on domestic carbon pricing documents reductions in emissions and induced innovation with limited effects on output and trade competitiveness (Martin et al., 2014; Calel and Dechezleprêtre, 2016; Calel, 2020; Naegele and Zaklan, 2019; Dechezleprêtre et al., 2022, 2023; Colmer et al., 2024). In these settings, firms face a carbon price on domestic production, irrespective of where their output is sold. Carbon border charges create a different incentive, as the cost depends on both the carbon intensity of production and the destination of sales. Emerging evidence on CBAM focuses on trade responses (Aytun et al., 2026; Vriz et al., 2026), the aggregate incidence on lower-income exporters (Clausing et al., 2025), and the responses of exposed EU buyers (Shi et al., 2025), leaving the technological response of foreign suppliers largely unexplored.

My paper also relates to work on the transmission of environmental and social standards through global

[2] This requires accounting for another important change in EU climate policy. Under the EU Emissions Trading System, producers must hold allowances for the carbon they emit, but many of these allowances have historically been provided for free. As the border charge is introduced, these free allowances are gradually being withdrawn, requiring EU producers to pay for a larger share of their emissions. This can make production within the EU more costly and shift some production and emissions abroad. To isolate what the border charge itself adds, I compare the joint implementation of both policies with a counterfactual in which free allowances are phased out but no border charge is imposed.

value chains, where suppliers respond to buyer pressure, certification requirements, and due diligence obligations (Podhorsky, 2015; Meemken, 2020; Boudreau et al., 2023; Alfaro-Ureña et al., 2022; Macchiavello et al., 2026; Bermejo et al., 2025; Keilbach et al., 2026). Unlike these settings, I study a statutory charge linked directly to each supplier's embedded carbon emissions. I directly measure cleaner technology adoption rather than inferring it from patents or aggregate emission intensities, documenting upgrading among exposed exporters.

Second, I contribute to the literature on carbon leakage by showing how endogenous, plant-wide technology adoption changes the aggregate effects of carbon border regulation. Existing quantitative studies evaluate border carbon adjustments through changes in trade, production, and emissions, typically treating foreign abatement as fixed, homogeneous across firms, or specific to production destined for the regulated market (Kortum and Weisbach, 2017; Larch and Wanner, 2017; Dechezleprêtre et al., 2025; Farrokhi and Lashkaripour, 2021; Clausing et al., 2025; Casey et al., 2026). Related empirical work documents leakage through the relocation of production and the diversion of trade toward less-regulated markets (Aichele and Felbermayr, 2015; Fowlie et al., 2016; Tanaka et al., 2022; Bartram et al., 2022). I introduce heterogeneous foreign suppliers that choose whether to adopt cleaner technologies at a fixed cost, with adoption affecting production across all destinations, and whose markets are linked through rising marginal costs, so that output displaced from the EU is diverted elsewhere. As a result, a charge imposed only on exports to the EU can reduce emissions from output sold in markets where no carbon price applies. I also distinguish the effects of CBAM from those of the simultaneous phaseout of free emission allowances under the EU ETS, separating the effect of the border charge from the leakage caused by removing these allowances.

Third, I contribute to the literature on trade policy and firm-level technology upgrading by showing how carbon tariffs differ from conventional ones in the incentives they create. Existing research shows that trade liberalization can encourage technology adoption by increasing the returns to fixed investments, particularly among larger and more productive exporters (Lileeva and Trefler, 2010; Bustos, 2011; Atkin et al., 2017), while policy announcements can induce firms to adjust before implementation (Handley and Limão, 2017). Conventional import tariffs reduce the returns to serving foreign markets, with evidence of substantial pass-through into import prices and export diversion toward alternative destinations (Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021; Bown and Crowley, 2007; Fajgelbaum et al., 2024). A carbon border charge differs because its effective rate depends on the exporter's own emissions intensity (Delipalla and Keen, 1992; Weyl and Fabinger, 2013). Firms can therefore lower the cost of exporting by adopting cleaner technologies, making market access and technology upgrading complementary decisions. Carbon border charges can therefore induce technological change that conventional trade restrictions do not, allowing them to reduce emissions with less disruption to trade.

The remainder of this paper is structured as follows: Section 2 outlines the institutional setting, the timeline of the introduction of CBAM, as well as the margins of adjustment available to foreign suppliers. Section 3 describes the data sources, the creation of firm-to-firm trade linkages, the classification of *green* technologies and their evolution over time. Section 4 presents the empirical strategy and reduced-form evidence. Section 5 presents the theoretical framework. Section 6 presents the model estimation and counterfactual exercises. Finally, Section 7 concludes.

2 Institutional setting and conceptual framework

The EU prices the carbon emissions of its domestic heavy industry through the *Emissions Trading System (ETS)*, under which firms must hold an allowance for each tonne of CO_2 they emit and allowances trade at a market price. Firms outside the EU do not pay this price, therefore there is a risk that production of carbon intensive goods moves abroad. To prevent this, the EU has so far provided exposed industries with most of their allowances for free. It is now phasing out these free allowances and replacing them with CBAM, which charges EU importers for the carbon embedded in the goods they buy from abroad at a price linked to the *ETS* (European Union, 2023b). Under the two frameworks, imported and EU-made goods face a similar carbon cost, a setting that also protects EU producers from foreign competitors that do not pay for their emissions.[3]

CBAM covers cement, iron and steel, aluminum, fertilizers, hydrogen, and electricity. It applies to basic products such as aluminum ingots and sheets, while goods made from them, such as car parts, are not yet covered. The European Commission has proposed extending coverage to some downstream products from 2028 onwards, while the emissions that count towards the charge differ by sector. For iron, steel, aluminum, and hydrogen, only direct emissions released at the plant are charged, whereas for cement and fertilizers the emissions from the electricity the plant uses are charged as well.

The EU importer pays the charge by buying certificates priced at the *ETS* level. The emissions based on which the charge is computed are either the exporter's own verified emissions or a default value that the European Commission sets for each product (European Commission, DG TAXUD, 2023). Default values include a mark-up that rises from 2026 onward, therefore exporters that are cleaner than the default have a reason to verify their emissions. When they do so, the charge depends on their own, firm-level carbon intensity.

Two deductions lower the total cost induced by CBAM. First, importers pay only on the share of emissions that EU producers no longer receive as free allowances, a share that rises from 2.5% in 2026 to 100% in 2034. Second, any carbon price already paid in the exporting country is subtracted (Nehrkorn and Elkerbout, 2026). A country that prices its own emissions can therefore collect that revenue at home, and the deduction is meant to encourage trading partners to adopt carbon pricing of their own (Clausing et al., 2024). Appendix A.1 outlines the CBAM charge formula in more detail.

The EU reached a political agreement on CBAM in December 2022, and the regulation entered into force in May 2023. A *transitional phase* followed from October 2023 to December 2025, during which importers had to report embedded emissions without financial liability. The *definitive phase* began in January 2026, when the charge started to apply. A 2025 simplification, the "Omnibus" package, exempted importers of less than 50 tonnes a year, removing most small importers while keeping most covered emissions in scope. The same amendment delayed the sale of certificates to February 2027 (Kulesza, 2025).

India's exposure. The EU is India's largest trading partner and accounts for 11.5% of its trade. India in turn supplies 6.2% of the EU's imports of CBAM goods, mostly iron, steel, and aluminum. The EU-India free-trade agreement, concluded in January 2026, does not exempt Indian goods from CBAM. The EU did commit to give India any flexibility it grants other partners under CBAM, and to cooperate on recognizing Indian carbon pricing (Abnett, 2026). India is also building its own *Carbon Credit Trading Scheme*, which

[3] CBAM is one of several recent EU measures that tie access to the single market to how goods are produced abroad. The Corporate Sustainability Due Diligence Directive requires large firms to identify and address environmental and human-rights harms in their supply chains (European Union, 2024), and the Deforestation Regulation requires firms to show that key commodities are deforestation-free before selling them in the EU (European Union, 2023a). I focus on CBAM because it is a price on specific products, so its cost to each exporter can be measured.

sets emission-intensity targets for heavy industry (Bureau of Energy Efficiency, Government of India, 2012; Ministry of Power, Government of India, 2023). Steel and fertilizers do not have targets yet, and it is unclear whether an intensity-based scheme would count as a carbon price that can be deducted under CBAM.[4]

No Indian exporter was subject to a CBAM charge before 2026. Even so, the responses I estimate begin in 2023. This is consistent with Vriz et al. (2026), who find that high-emission Indian steel exporters reduced their EU sales relative to cleaner firms during the transitional phase.

Conceptual framework. For each tonne shipped to the EU, the importer pays the *ETS* price τ times the tonne's chargeable emissions. The total cost therefore rises with the exporter's carbon intensity and with how much it sells to the EU. Although EU importers are responsible for paying the charge, it raises the cost of purchasing from carbon-intensive foreign suppliers. Depending on how the burden is shared, these suppliers may face lower prices, reduced demand, or both. They therefore have an incentive to change how they produce or where they sell.

The first option they have is *green upgrading*. The firm can pay a fixed cost F to switch from a dirty to a green technology, lowering its carbon intensity from ε_D to ε_G. Most of these technologies are specific to a sector.[5] Ignoring changes in operating costs, the firm upgrades when the charge it saves exceeds the cost of the investment.

The saving grows with EU sales q_{EU}, so large firms that sell a lot to the EU are the most likely to upgrade. In the data, 94% of firms that export to several destinations do so from a single plant. Therefore, in the model a new technology cleans a firm's total output, including what it sells outside the EU.

The charge counts only for part of the emissions, therefore the reductions in total cost and emissions can differ. In steel and aluminum, electricity bought from the grid is not charged. A plant that replaces its own fossil generation with grid power lowers its cost by the full amount of the emissions it moves to the grid. However, its total emissions fall only if the grid is cleaner than the power it replaces. This matters for reading the shift in energy use in Section 4. It also explains why the charge bites differently across sectors. In aluminum, most emissions come from electricity and are not charged. In cement, most emissions come from the production process itself and are charged in full.

The second margin of adjustment is to keep the technology intact and change where or how much the firm sells. The firm can ship less to the EU, or stop selling there altogether (*trade contraction*), or choose to ship part of its exports to other markets (*trade diversion*).

Together, these choices change global emissions through three terms:

$$\Delta E = \underbrace{\text{Green upgrading}}_{\leq 0} + \underbrace{\text{Trade contraction}}_{\gtrless 0} + \underbrace{\text{Trade diversion}}_{\gtrless 0} \tag{1}$$

Green upgrading lowers emissions on every tonne the firm produces. Trade contraction lowers emissions only if the suppliers that replace Indian goods in the EU are cleaner. Trade diversion can also cause carbon leakage. It raises emissions if the diverted tonnes are dirtier than the supply they replace in other markets.

The overall effect on emissions depends on which firms upgrade and on how clean the replacement suppliers are. Section 4 estimates each response for Indian exporters. The model in Section 5 accounts for the

[4] The scheme is part of India's wider push toward its 2070 net-zero target. This includes large-scale renewable deployment, subsidies for solar manufacturing, and the *National Green Hydrogen Mission*, which funds green hydrogen for uses such as steel and fertilizers (Ministry of Environment, Forest and Climate Change, Government of India, 2022; IRENA and ILO, 2023; JMK Research and IEEFA, 2023; Ministry of New and Renewable Energy, Government of India, 2023). These programs affect which clean technologies Indian firms can access.

[5] Examples include an electric arc furnace or gas-based direct reduction in steel, and lower-clinker blends in cement. Section 3 describes the taxonomy of technologies I build to classify investment projects.

behavior of competitors and estimates the aggregate effect of the three channels.

3 Data, sample construction, and stylized facts

3.A Data sources

S&P Global Panjiva Supply Chain Intelligence Dataset. First, I utilize a proprietary customs dataset of firm-to-firm trade linkages on the shipment level, obtained through *S&P Global*. The data is available for 21 countries and is sourced through official customs import-export records (S&P Global Market Intelligence, 2025). Specifically for India, I observe the universe of export shipments over the period between 2016 and 2026. Each raw record is a shipment linking an Indian exporter (the *shipper*) to a foreign buyer (the *consignee*), and reports the product shipped at the six-digit Harmonized System level (HS6), the destination country, the date, the customs value in U.S. Dollars, and the physical quantity. Exporters are the nodes on the Indian side of the network and consignees the nodes on the foreign side. A shipment is a link between them, indexed by product and time. Units of measurement are reported inconsistently across shipments, therefore I harmonize quantities to a common weight basis, imputing a conversion ratio for the subset of HS6 codes whose dominant reported unit is not a weight (This process is described in more detail in Appendix D.2.1).

CMIE ProwessDx. Furthermore, I utilize firm-level data from the *Center for Monitoring the Indian Economy (CMIE)*, an independent think tank that compiles data on private companies in India and provides it to academic institutions and researchers through a subscription-based model. The *ProwessDx* subscription provides access to the *Prowess* database, a proprietary dataset put together by *CMIE* that monitors the performance of firms based on annual reports, stock exchange filings, and regulatory filings. It contains information for more than 50,000 firms annually, since the 1990s. Relevant information includes the turnover, size, and exact location of firms, along with granular information on capital expenditures, labor spending, spending on inputs, consulting and auditing fees, as well as spending on pollution prevention and corporate social responsibility (Centre for Monitoring Indian Economy, 2025b).

CMIE CapexDx. I complement *Prowess* with *CMIE*'s *CapexDx* service, which provides access to a database tracking investment projects over time for companies in India, both those included in *Prowess* and additional ones. Drawing on various sources of data and on direct contact with firms, the database tracks more than 60,000 projects, of which roughly 35,000 have been tracked to completion, with the remainder in progress. For each project, it reports a short description, the exact location, the industry, the details of the parent firm, periodic updates on the project status by year, and the firm's total spending on it, again at an annual level (Centre for Monitoring Indian Economy, 2025a).

S&P Global Capital IQ. To distinguish shipments to unrelated foreign buyers from shipments to affiliates of EU-headquartered groups, I link the consignees in *Panjiva* to *Capital IQ*, a database of company records that covers listed and private firms worldwide and records, for each company, its headquarters country and its position in a corporate hierarchy. The link uses *Capital IQ*'s own cross-reference table, which lists the *Panjiva* identifier among the external identifiers attached to a company record. Ownership is taken from *Capital IQ*'s point-in-time ultimate-parent history, where for each company it records the ultimate parent and the dates over which that ownership link held.

3.B Mapping firm-to-firm trade linkages and policy exposure

I aggregate the shipment-level *Panjiva* data to the shipper × HS6 × quarter level. Each row records the value, quantity and weighted unit price the firm ships in that quarter, broken down by destination (the EU-27, non-EU Europe, and the other world regions). For other regions, I further split by whether the buyer is an affiliate of an EU-headquartered group.

The measure of exposure. CBAM places a carbon charge on imports of specific goods into the EU. Its transitional phase began in October 2023, requiring importers to report embedded emissions. I take the set of covered products from Annex I of the Regulation and map it to the HS6 codes in my data. A firm's exposure is then measured from its export structure in the two years before the transitional phase. Let A_{iq} be the value of CBAM-covered goods Indian exporter i ships to the EU in quarter q and let X_{iq} be its total export value to all destinations in that quarter, with a firm that ships nothing in a quarter counted as zero on both. The continuous exposure measure is the share of the firm's baseline exports accounted for by EU-bound covered goods, given by:

$$S_i = \frac{1}{8} \sum_{q \in B} \frac{A_{iq}}{X_{iq}}, \qquad B = \{2021Q1, \ldots, 2022Q4\} \tag{2}$$

and the corresponding indicator is $I_i = \mathbb{1}\{S_i > 0\}$, equal to one if the firm shipped any covered product to the EU during the baseline window. In the trade regressions S_i enters scaled by ten, so that a coefficient is the effect of ten percentage points of covered share. The baseline covariates that enter the time-varying controls are the firm's averages over the same period.

Linking exporters to firm administrative data. *Panjiva* identifies shippers by a proprietary shipper name and numeric code, whereas *ProwessDx* identifies firms by company code and by Corporate Identification Number (CIN), the registration identifier assigned by *India's Ministry of Corporate Affairs*. The two systems share no common key, so merging the *CMIE* databases to trade exposure requires a crosswalk, which I build in two steps.

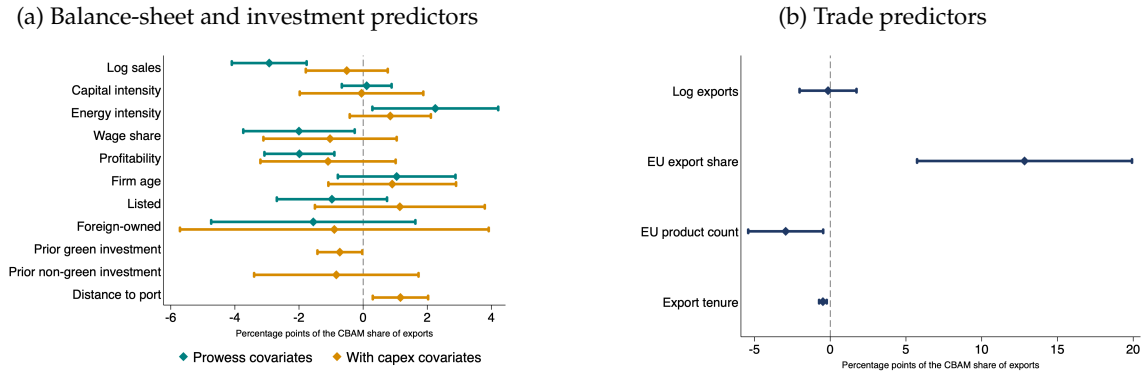
I first recover CINs for the universe of unique Indian exporters in *Panjiva* by querying their names against the public corporate registry (*Quickcompany.in*), and match the recovered CINs exactly to the CINs in *ProwessDx* and *CapexDx*. This exact match links 15.1% of *CapexDx* firms and 15.7% of *ProwessDx* firms to a *Panjiva* exporter (as reported in Appendix Table D.14). The process of recovering CINs is described in more detail in Appendices D.1.2 and D.2.2.

For the exporters left unmatched, I add a second stage that combines name and geographic proximity. I normalize firm names (harmonizing legal-form suffixes and stripping punctuation), geocode *Panjiva* exporters, *CapexDx* project sites, and *ProwessDx* firm addresses, restrict candidate matches to firms within ten kilometers of an exporter, score the remaining name pairs with a distance-penalized fuzzy criterion, and retain a match only if the paired locations lie within five kilometers of each other. The geolocation process is described in Appendices D.1.1, D.1.4, and D.2.1, while the merging process is described in Appendix D.2.2.

I consolidate the two stages into a single exporter-to-firm crosswalk, giving priority to exact CIN matches over fuzzy matches wherever both exist. Given that a single firm can ship under several *Panjiva* identifiers, I aggregate exposure from the shipper to the firm level. More specifically, a firm's CBAM exposure sums the EU-bound CBAM product and total export values of all *Panjiva* exporters associated with the firm, and its extensive-margin indicator equals the maximum across them. The result is a firm-level dataset linking each matched *ProwessDx* and *CapexDx* firm to its pre-period CBAM exposure, which I merge onto the panels used in my analysis.

Estimation samples and exposure summary. The crosswalk yields three estimation panels that share a common treatment definition. The investment panel pairs each matched firm's *CapexDx* projects with its CBAM exposure at annual frequency, the financials panel does the same for *ProwessDx* firms, and the trade panel retains the shipper × HS6 × quarter structure. Within the firm-level panels, I distinguish four groups of firms, namely (a) CBAM-affected exporters, which ship covered products to the EU in the baseline window, (b) exporters who ship non-covered products in the baseline window, (c) exporters who ship CBAM-affected products to non-EU destinations, and (d) non-exporters, which are not matched to any *Panjiva* shipper. Among the 5,099 Indian exporters that ship covered goods to the EU during the period 2021-22, the median firm earns 2 percent of its export revenue from those sales, three quarters earn under 11 percent, and fewer than one in ten earn more than half. Among the firms that can be linked to balance sheets in *ProwessDx*, the median is 0.2 percent.

Figure 1: Predictors of exposure to the legislation



Notes: Both panels regress the measure of exposure, the 2021-22 share of CBAM-covered exports to the EU in total exports in percentage points, on pre-period characteristics among treated firms, conditioning on non-zero pre-period covered exports to the EU. Panel (a) uses FY2022 annual statements for treated firms in the *ProwessDx* estimation sample, with two-digit industry and state fixed effects. The second series adds the stock of *green* and non-*green* investment and distance to the nearest port for the firms also present in *CapexDx*. Wage share stands for total wage bill divided by sales, while capital intensity for plant property and equipment divided by sales. Panel (b) uses 2021-22 customs records for treated exporters in the *Panjiva* universe, with four-digit ISIC industry and state fixed effects. Continuous characteristics are winsorised at the 1st and 99th percentiles and standardized, so a coefficient is the change in exposure corresponding to one standard deviation. Indicator variables are not standardized. Standard errors are clustered by industry, while the 95% confidence intervals are shown. *Source*: Own rendering based on data from *CapexDx*, *ProwessDx*, and *Panjiva* databases.

Figure 1 regresses the measure of exposure on pre-period characteristics within the treated group. In Panel 1(a), a one standard deviation increase in log sales is associated with a 2.9 p.p. reduction in exposure. A similar increase in profitability and in the wage share is associated with a 2 p.p. reduction each, while a one standard deviation increase in energy intensity is associated with a 2.3 p.p. higher exposure. Capital intensity, age, public listing status and ownership, on the other hand, are not significant predictors. When adding the covariates from *CapexDx*, lower *green* investment and distance to the nearest port become the only significant predictors, with treatment being associated with dirtier firms.

In the exporter universe, exposure rises with the EU share of exports and falls with the number of products shipped and with export tenure. The charge thus affects smaller, less profitable, more energy-intensive firms with lower stocks of *green* investment, that are newer to exporting and have narrower product portfolios. Appendix A.2 provides more information on the distribution and predictors of the measure of exposure.

Additionally, Table 1 summarizes Indian export flows over the 2021-2022 baseline window by CBAM coverage and destination, with values expressed as annual averages. CBAM-covered products account

for a small share of the export basket (fewer than 300 HS6 codes against four to five thousand non-CBAM products), yet a substantial set of firms participates in them. Specifically, 5,099 Indian exporters ship at least one CBAM-covered product to the EU in at least one year of the window, while 34,288 ship CBAM products to other destinations. The EU is consistently the smaller destination in both segments, with roughly five to seven times as many Indian exporters selling outside the EU as into it. Average annual per-exporter values are of the same order across the two CBAM cells, at 0.6 and 0.9 million dollars respectively, and largest in the non-CBAM exports to destinations outside the EU, at 1.6 million.

Table 1: Indian exports by CBAM coverage and destination, annual average 2021–2022 (2020 USD)

Type	Unique Exporters	Number of Products	Mean Value (2020 USD '000)
CBAM, EU	5,099	254	599.3
CBAM, Elsewhere	34,288	282	876.0
Non-CBAM, EU	39,459	4,174	624.5
Non-CBAM, Elsewhere	198,971	5,158	1,564.0

Notes: Each row reports descriptive statistics across Indian exporters over 2021-2022, where each exporter's value is its annual average of export flows within the cell defined by CBAM-product coverage and destination (EU vs. elsewhere), in constant 2020 US dollars. Exporter and HS6-product counts are unique within each row, counting any exporter or product with positive value in the cell in at least one year of the window, but overlap across rows. Firms and products that diversify across destinations or product types appear in multiple rows. *Source: Panjiva* dataset.

3.C *Green* upgrading

To measure the adoption of *green* technologies, I utilize *CapexDx*, where I can observe capacity expansion capital investments. These can be thought of as large investments that enhance the productive capacity of firms, their ability to produce energy (through various sources), or their research and development capabilities. However, *CapexDx* is not limited to *green* investments, therefore I follow a classification process in order to assign *green* indicators to each entry of the database.

Capital investment classification. To categorize investment projects in *CapexDx*, I label each project based on a taxonomy of 547 sector-specific and cross-cutting technologies, spanning 23 emissions-intensive sectors, which I compile from sectoral technology road maps provided by the *International Energy Agency (IEA)*, the EU, and sector-specific sources, reported in Appendix D.1.3. Each technology is assigned a tier, namely *green*, transition, or baseline (vintage, high-emission). Projects are first assigned to candidate sectors using the firm's industry and the project's product mix, and then matched to specific technologies through the use of a Large Language Model (*Claude Opus* 4.7). For each project, the model returns the matched technologies, their tier, and a confidence score, while it flags cases where the technology mapping cannot be resolved from the structured records alone (for example, whether a sponge-iron plant uses coal- or hydrogen-based reduction).

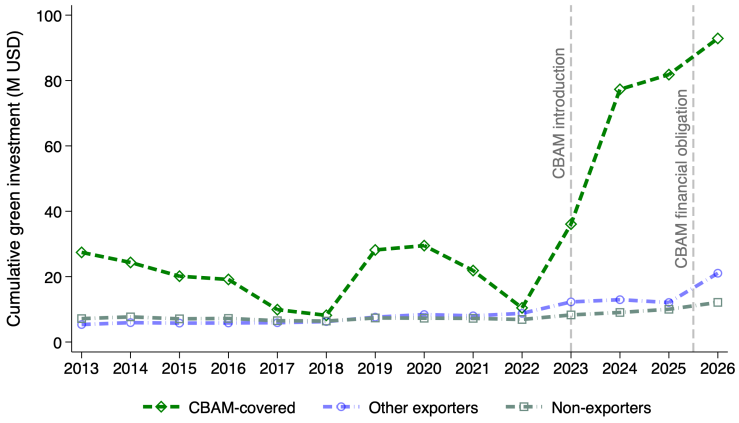
In cases where ambiguity arises, I carry out an online web search using the projects' details and location, I retrieve the text of the top results and re-classify them with this additional context. I then manually validate a random sample. Section D.1.3 of the Appendix describes the classification and validation process in more detail, outlining every step along with descriptive statistics. An example of a *green* investment project in my database is the newly commissioned *green* hydrogen plant by *Hygenco Green Energies*. This facility produces renewable hydrogen onsite using electrolysis powered by clean electricity, directly substituting fossil-based hydrogen in an export-oriented industrial production process. In the context of my data, this project is captured as a *green* capacity-expansion investment in renewable energy (H2 View, 2025).

Table A.3 summarizes the classified investment universe. Around one fifth of relevant projects announced over 2013-2025 are coded *green*. The measure includes projects that map to transitional technologies, that

is lower-carbon production methods that reduce but do not eliminate process emissions. Panel A shows the breakdown by technology type, with projects allowed to map simultaneously to *green*, transitional and vintage technologies. Most *green* firms undertake roughly one project per active year, with investment heavily right-skewed.

Panel B splits *green* and transitional projects by relevance to CBAM specifically. Over half of *green* and transitional projects fall in industries within CBAM's scope, but three quarters of that group is electricity. These are projects in captive and utility-scale renewable generation, transmission and distribution, and cleaner conventional generation. Electricity is an Annex I good that India does not export to the EU, so these projects reflect domestic decarbonization. In the goods CBAM taxes at the border, steel and sponge iron as well as cement constitute the bulk of low-carbon manufacturing investment and nearly all of the transitional projects. Firms in CBAM-affected industries invest less per firm-year on average than the overall pool (USD 91 million against 124 million). Industry rows reflect the firm's *CMIE* industry, which is coarser than CBAM's product-level scope, so the CBAM-affected grouping is indicative of the exposure measured in the trade data.

Figure 2: Cumulative *green* investment over time by type of firm



Notes: The figure presents the mean cumulative *green* capital investment per firm, in constant million 2020 USD, by group and year, for firms exporting CBAM-covered products to the EU, other exporters, and non-exporters. Firm-years in the top and bottom percentile of announced *green* investment are excluded. The vertical lines mark the start of the CBAM transitional period in 2023 and of the financial obligation in 2026. *Source*: Own rendering based on data from *CapexDx* and *Panjiva* databases.

Adoption of *green* technologies over time. Figure 2 plots the mean stock of *green* capital investment per firm over time for three groups, namely exporters of CBAM-covered products to the EU, and, as comparison groups, other exporters and non-exporters. The stock adds up *green* projects from the capital-expenditure database. Through most of the 2010s, *green* capital is low for all three groups, while there is a substantial increase for affected firms around the time CBAM enters the policy debate. Covered exporters' stock rises from about 10 million dollars per firm in 2022 to nearly 80 million dollars per firm in 2025, and keeps rising through 2026. Other exporters and non-exporters increase their *green* investment stock up from 10 to between 10 and 20 million over the same years.

3.D Emissions intensity and anticipated costs

India has no mandatory firm-level greenhouse gas reporting, and *ProwessDx* contains no direct measure of CO_2 emissions. To obtain measures of both actual emissions intensity and predicted costs induced by the regulation, I follow existing literature to impute emissions.

Imputed emissions. For the subset of manufacturing firms that disclose energy use, I impute annual CO_2 emissions from *ProwessDx* fuel consumption records, following Barrows and Ollivier (2018), Barrows and Ollivier (2021) and Semrau (2026). *ProwessDx* reports the physical quantity of each fuel a firm consumes per year (coal, diesel, furnace oil, natural gas, purchased electricity, etc.). I multiply each fuel's quantity by a source-specific CO_2 emission factor and sum across fuels, separating Scope 1 (direct combustion) from Scope 2 (purchased electricity). The emission factors are the *U.S. EPA Climate Registry* default factors used by Barrows and Ollivier (2021). Purchased electricity is valued at the average Indian grid factor. I map *ProwessDx* fuel labels to *EPA* energy sources, standardize units, and, following existing work, I drop records whose units cannot be reconciled. Self-generated electricity is excluded to avoid double-counting the fuel that produced it. The full set of emission factors and units is reported in Appendix Table D.18. Energy disclosure is effectively a manufacturing requirement, therefore emissions are defined for the 5,688 firms that report fuel use. Non-manufacturing firms (services, trade, construction, finance) do not report energy and are left missing.

One limitation of imputing emissions from fuel use is that it captures only combustion. Technologies that reduce a firm's emissions by substituting cleaner energy show up as lower fuel and electricity use and are therefore already reflected in the measure, whereas end-of-pipe carbon capture and storage (CCS) removes CO_2 after combustion without changing fuel use and would not be picked up. In principle one could net out captured CO_2 using the capture installations identified in *CapexDx* in the process described in Section 3.C. In practice, however, this margin is negligible in India over my period of interest. Across the entire *CapexDx* universe I find only two genuine CCS projects, namely *Indian Oil*'s CO_2 transport and storage investment at the Koyali refinery and *Tata Steel*'s demonstrative post-combustion capture plant at Jamshedpur. A significant amount of projects that carry a capture and utilization label are in fact *green* hydrogen and *green* ammonia electrolysis plants, which decarbonize through the electricity channel already embedded in the imputation rather than through carbon capture. I therefore proceed without making any capture adjustment to the imputed data.

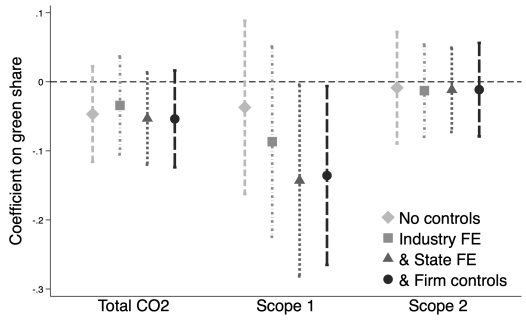
To assess the fuel-based imputation, I compare it against externally reported emissions for the firms I can match. Reported emissions come from two sources harmonized into a single firm-year Scope-1 series, namely Net-Zero Data Public Utility (2026), which compiles firms' self-reported greenhouse-gas emissions (Scopes 1-3), and Climate TRACE (2026), which provides facility-level CO_2 estimates from activity and remote-sensing data that I aggregate to the firm level through reported ownership. I match these to *ProwessDx* firms on normalized company names and align them to the imputed series by company and year, comparing like for like, i.e. reported Scope 1 against the imputed Scope 1 emissions. The two measures line up well, with the correlation between imputed and reported Scope 1 emissions being 0.69, as can be seen in Figure D.8.

Emissions intensity and *green* investment. Figure 3 relates realized carbon intensity to *green* investment in two ways. Panel 3(a) is a cross-section, plotting the coefficient of the *green* share of a firm's cumulative investment on CO_2 per ton of output for 2022 for total, Scope 1, and Scope 2 emissions, sequentially adding industry fixed effects, state fixed effects, and firm controls. As expected, the negative relationship is apparent for Scope 1 emissions. A ten percentage point increase in *green* share is associated with roughly 14 percent lower on-site intensity, once industry and state are absorbed, while purchased-electricity intensity is flat.

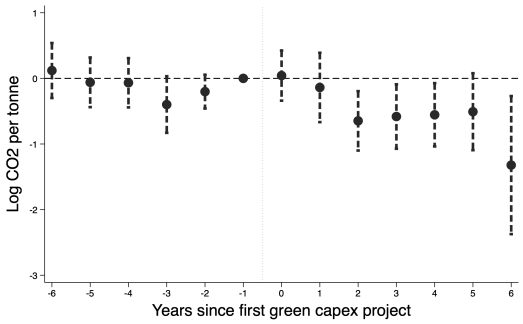
Panel 3(b) estimates the impact of the first *green* investment over time on CO_2 per tonne shipped, within firm. It compares CBAM-sector firms, against CBAM-sector firms that never announce one. Intensity is flat in the five years before the project, falls from the second year after it, and stays lower through the end of the window.

Figure 3: Emissions intensity and *green* investment

(a) *Green* share of investment and intensity



(b) Intensity following the first *green* investment



Notes: Panel (a) reports the coefficient of the *green* share of cumulative started investment, in units of ten percentage points, on log CO_2 per ton of output in 2022, for total, Scope 1, and Scope 2 emissions, under four specifications: no controls, industry fixed effects, industry and state fixed effects, and firm-level controls, the latter including log sales, log assets and capital intensity. Standard errors are clustered by industry, while bars are 95 percent confidence intervals. Panel (b) plots event-time coefficients for log CO_2 per tonne shipped around the first confirmed *green* capital project of CBAM-sector firms, relative to the year before the project, with firm and year fixed effects, standard errors clustered by industry, and projects started after 2022 excluded. Controls are CBAM-sector firms with no confirmed *green* project. Emissions are computed from reported fuel quantities. *Source:* Own rendering based on data from *CapexDx* and *ProwessDx* databases.

Ex-ante liability induced by the regulation. To quantify the differential incidence of CBAM across exposed Indian firms, I construct firm-level measures of the carbon cost implied by a firm's baseline shipments to the EU. I first build a crosswalk between each CBAM-covered HS6 code and the default embedded emission intensity, in tCO_2e per tonne of goods and covering direct and indirect emissions, published in the European Commission's *Default Values for the Transitional Period of the CBAM* (European Commission, DG TAXUD, 2023).[6] I merge these intensities onto the quarterly shipment panel. For HS6 codes whose shipments are reported by weight, the bulk of CBAM goods, tonnes are obtained by direct conversion. For the residual codes reported in other units, I impute tonnes from shipment value using a within-HS6 price per kilogram estimated from the weight-reported shipments of the same code. The embedded emissions of firm i in quarter q are then given by:

$$\text{tCO}_2\text{e}_{iq}^{\text{EU}} = \sum_{p \in \text{CBAM}} e_p \cdot Q_{ipq}^{\text{EU,tonnes}} \tag{3}$$

where e_p is the HS6 default intensity net of the benchmark, and $Q_{ipq}^{\text{EU,tonnes}}$ is firm i's quantity of product p shipped to the EU in quarter q. Embedded emissions are priced at the *EU ETS* price prevailing over the baseline, $p_{\text{base}} = \text{EUR}\,85$ per tCO_2e, giving the expected liability:

$$L_{iq} = \text{tCO}_2\text{e}_{iq}^{\text{EU}} \cdot p_{\text{base}} \tag{4}$$

That is the charge the firm's baseline EU shipments would attract once CBAM is fully phased in. The

[6] For HS6 codes that aggregate several CN8 lines with distinct defaults I take the mean. For codes covered only at the heading level I assign the heading value. Electricity carries no per-tonne default and receives zero, however no Indian firm in the sample ships it to the EU.

charge actually payable follows the phase-out of free allocation in the *EU ETS*, whereby 97.5 percent of the benchmark intensity is subtracted in 2026 and the full amount is applied from 2034 onwards. I therefore also report the expected liability at the 2026 factor, which is the charge a firm could expect to face in the first year of the *definitive period*. Both are averaged over the 2021Q1-2022Q4 baseline and normalized by the firm's baseline EU export value.

Figure A.4 describes the ex-ante liability across the exposed firms for which a cost could be measured. Panel A.4(a) shows its distribution in euros per baseline quarter, at full phase-in and at the 2026 factor. At full phase-in the mean is 39,000 and driven by a handful of large exporters. Figure A.4(b) shows where the aggregate liability sits in the size distribution of exposed firms. Ranking them by their baseline EU exports and dividing them into deciles, the largest tenth accounts for 94 percent of the expected CBAM liability at full phase-in and for 90 percent of the group's EU export value. The ninth decile carries 3.1 percent of the liability and 5.8 percent of EU sales, and the bottom half of exposed firms together carry less than one percent of either. Therefore, the charge is, in aggregate, a charge on a few hundred large exporters and any statement about the total cost of CBAM to Indian industry is a statement about the top decile of firms based on EU sales.[7]

3.E Trade relationships

Characteristics of the trade network. Table 2 describes the bilateral network behind the trade flows, over the pre-regulation window 2016-2022, which is sparse on both sides. As can be seen in Panel A, in a given year the median Indian exporter sells to two foreign buyers, in two HS6 products and two destination countries, and the ninetieth percentile exporter serves seventeen buyers. On the other hand, the median foreign buyer sources from a single Indian supplier and the ninetieth percentile from three.

Panel B shows that exporter-years with at least two buyers are two thirds of all exporter-years but carry 98 percent of export value, and those with at least five buyers, a third of exporter-years, carry 92 percent. On the buyer side the multi-supplier minority, 23 percent of buyer-years, accounts for two thirds of value. The typical link is therefore a small firm with one partner, while the bulk of value is concentrated in a firm with several ones. As seen in Panel C, of the 316,203 exporters and 2.4 million buyers that appear over the window, fewer than five million pairs are ever observed trading.

Table A.4 looks at the nature of those relationships over time. Classifying each exporter-buyer pair by the number of years in which it is observed trading, 73 percent of pairs appear in a single year and only 11 percent in three or more. The median relationship lasts one year and the ninetieth percentile three. However, the one-year pairs carry 23 percent of export value, and the one in ten pairs observed in three or more years carry 56 percent, with the 2.5 percent observed in five or more years alone accounting for 29 percent. Therefore, most links are one-off transactions, while most trade flows happen through a small set of established relationships.

[7] This is the liability at full pass-through, that is it prices every tonne of embedded emissions to the exporter, as if the EU importer shifted the entire certificate cost back onto the Indian supplier. How much of the charge is actually borne by exporters, as opposed to importers or EU consumers, is ambiguous and cannot be assumed in constructing the treatment. Therefore, the main treatment variable is the covered share of exports defined above, which depends on none of the intensity, imputation, price or incidence assumptions. The cost measure is used for heterogeneity analysis.

Table 2: The trade network

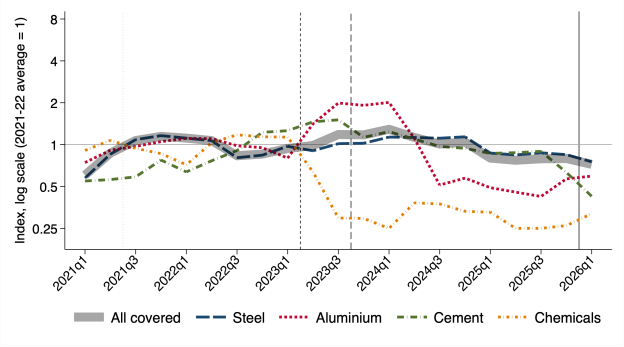
	Indian exporter		Foreign buyer	
Panel A: Per-year degree distribution				
	Median	p90	Median	p90
Distinct partners per year	2.0	17.0	1.0	3.0
Distinct HS6 products per year	2.0	16.0	1.0	7.0
Distinct destination countries per year	2.0	7.0	-	-
Panel B: Multiple partners				
	Share of cells (%)	Share of value (%)	Share of cells (%)	Share of value (%)
$\geq$ 2 partners	65.5	98.1	22.6	67.7
$\geq$ 5 partners	32.8	92.3	4.9	40.5
Panel C: Network totals				
	Count		Count	
Unique firms	316,203		2,430,102	
Realised exporter-buyer pairs	4,968,002			

Notes: Summary statistics over the *Panjiva* exporter-consignee-HS6 panel, 2016-2022, pooled across years and HS6 codes. Shipments with non-positive value are dropped. Panel A: medians and 90th percentiles across exporter-year cells (left) and buyer-year cells (right). Panel B: share of those cells with at least the stated number of partners, and the share of total export value they carry. Panel C: unique exporters and buyers, and distinct exporter-buyer pairs observed at least once. *Source: Panjiva* database.

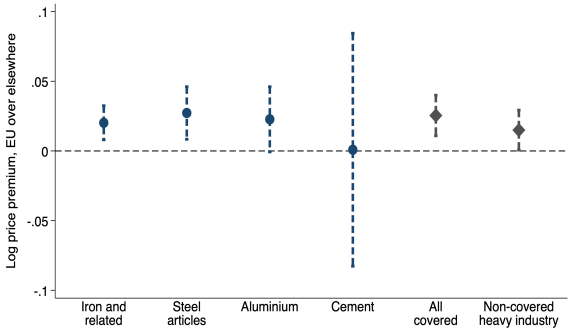
Trade with the EU. Figure 4(a) presents the affected firms' covered exports to the EU by product family from the first quarter of 2021 to the first of 2026, each series a four-quarter moving average of quarterly value indexed to its own 2021-22 mean.

Figure 4: Trade relationships with the EU

(a) Sales by covered shippers over time



(b) EU price premium



Notes: Panel (a) shows quarterly export value to the EU for CBAM-covered goods by the affected firms, i.e. the baseline EU exporters of covered goods. This is summed within product family, smoothed as a four-quarter moving average and indexed to the family's 2021-22 average, on a log scale. The shaded band represents all covered goods. Panel (b) plots the coefficients from an EU indicator in a regression of the log unit price on firm-by-product-by-quarter fixed effects, estimated on firm, HS6 line and quarter cells in which the affected firms, the baseline EU exporters of covered goods, sold the same line both to the EU and to other destinations during the period 2017Q1-2022Q4. Unit prices are *Panjiva*'s declared item prices in the harmonized base unit, trimmed at the 1st and 99th percentiles within HS6. "All covered" pools Annex I codes. "Non-covered heavy industry" are products in the mineral, chemical, plastics, paper, glass, ceramics and base-metal chapters. Bars are 95 percent confidence intervals clustered by industry. *Source*: Own rendering based on data from the *Panjiva* database.

The shaded band is the total, while the dashed lines are steel, aluminum, cement, and chemicals. The total value shipped to the EU seems more or less constant over time, slightly declining from 2025 onwards to about 0.8 by the end of the sample. However, there is significant heterogeneity in the evolution of trade

flows for different product families.

The family that drives the total is steel, moving from 0.6 in early 2021 to a plateau near 1.1 across 2023 and 2024 and settling at 0.8 in 2025. Aluminum doubles between the adoption of the regulation and the first quarter of 2024 and then halves, dropping to 0.6 by the end of the period. Chemicals, a small family for these firms, fall to a third of baseline in the second half of 2023 and stay there. Cement rises through 2023 and returns to baseline in 2024, while dropping to less than 0.5 in the first quarter of 2026. On a log scale these are movements of the same order as the total's entire range, and they are concentrated in the two years around the start of the transitional phase, which is when reporting obligations began but no payment was due. The aluminum spike in particular is consistent with front-loading ahead of an expected charge.

Additionally, Figure 4(b) documents the margin that firms gained by exporting to the EU market in the first place, that is the *EU premium*. For every affected firm, product line and quarter in which the same HS6 line was sold both to the *EU* and elsewhere, it compares the unit price in the two markets, so that the firm, the product, and the timing are all held fixed and only the destination varies. Over the six years before the regulation was adopted, the affected firms charged the *EU* about 2.5 percent more than other destinations for the same covered good in the same quarter. The premium is essentially the same across the three metal groups, 2 percent for primary iron and steel, 2.7 percent for steel articles, and 2.3 percent for aluminum, and it is zero and noisy for cement, given that only 35 firms serve both markets. The same firms earned a premium of 1.5 percent on their non-covered heavy-industry lines, chemicals, plastics, glass, paper and the base metals outside the regulation's scope, so the covered goods are at the upper end of that premium.

4 Reduced-form evidence

4.A Empirical approach

***Green* upgrading, production process, and firm performance.** I estimate the effect of exposure to CBAM on *green* investment, the production process and performance of Indian firms with a difference-in-differences design that compares CBAM-exposed and unexposed firms before and after the policy. A firm is exposed if it exported CBAM-covered goods to the EU during the 2021Q1-2022Q4 baseline window. I denote this time-invariant indicator by I_i. The CBAM *transitional phase* began in October 2023, so $t = 2022$ is the last fully pre-treatment year and serves as the reference period. The main specification is:

$$Y_{it} \;=\; \alpha_i + \lambda_t + \sum_{k \neq 2022} \beta_k \, I_i \times \mathbf{1}\{t = k\} + \gamma_{g(i),t} + \delta_{s(i),t} + X_i \lambda_t + \varepsilon_{it} \tag{5}$$

where Y_{it} is the outcome in logs and in 2020 USD, α_i are firm fixed effects, λ_t year fixed effects, $\gamma_{g(i),t}$ and $\delta_{s(i),t}$ industry-by-year and state-by-year fixed effects, and X_i a vector of baseline controls, baseline export value and distance to the nearest port, interacted with the year effects. The firm fixed effects absorb the level of I_i, so only the interactions are identified, and the coefficients of interest are the $\{\beta_k\}$. Standard errors are clustered by industry. I estimate Equation (5) on three samples that differ in the counterfactual: (a) all firms, (b) only exporters, and (c) only CBAM-covered product manufacturers irrespective of destination.

The estimand is the effect of CBAM exposure under conditional parallel trends. Absent the policy, exposed and unexposed firms would have followed parallel paths once firm and year effects, industry-by-year and state-by-year effects, and the baseline controls are netted out. The industry-by-year effects absorb any shock common to a sector in a year, so the concern that CBAM-intensive sectors such as steel

and aluminum were on distinct de-carbonization paths is addressed without imposing a functional form on those paths. The state-by-year effects do the same for location, and the baseline controls allow large and small exporters, and firms near and far from a port, to trend differently. Identification requires that unexposed firms are not themselves affected by the policy. There are two main channels that could violate this assumption. First, a domestic competitor of an exposed firm may gain sales or lose input suppliers as the exposed firm reallocates, and second, an unexposed firm in the same industry may anticipate an extension of the regulation to its own products. Both would make the comparison group move in the same direction as the exposed group and bias β_k towards zero, so the estimates are conservative for the effect on the exposed firm. I carry out several placebo exercises to test both issues, outlined below.

International trade. To estimate the effect of CBAM on Indian export flows I use a difference-in-differences design at the firm $\times$ HS6 product $\times$ quarter level, comparing the product lines of more and less exposed firms before and after the policy. Exposure is the continuous share S_i defined above, the share of the firm's 2021Q1-2022Q4 exports that were covered goods shipped to the EU, entered so that a coefficient is per ten percentage points. Let ip index a "line", firm i shipping product p. The main specification is:

$$Y_{ipq} \;=\; \alpha_{ip} + \mu_{p,q} + \sum_{k \neq 2022Q4} \beta_k \, S_i \times \mathbf{1}\{q = k\} + \theta_{g(i),q} + \gamma_{s(i),q} + X_i \lambda_q + \varepsilon_{ipq} \tag{6}$$

where Y_{ipq} is, in turn, the inverse hyperbolic sine of the quantity the line ships to a destination group in the quarter, in the product's own harmonised unit, an indicator for a positive shipment, the inverse hyperbolic sine of the value, and the log unit price. The panel runs from 2021Q1 to 2026Q1 and 2022Q4, the last quarter before the political agreement on the regulation, is the reference quarter. α_{ip} are firm-by-product fixed effects, so every comparison is within a line over time, $\mu_{p,q}$ are product-by-quarter fixed effects, which absorb world demand and price shocks to each HS6 product, $\theta_{g(i),q}$ and $\gamma_{s(i),q}$ are industry-by-quarter and state-by-quarter effects, and X_i, the same vector as before, is interacted with the quarter effects. Standard errors are clustered by industry. I estimate Equation (6) on three samples: (a) all firms, (b) firms whose exported products all belong to one product family, and (c) firms with positive EU exports at baseline, for which the EU outcome is not identically zero before the policy.

The coefficients $\{\beta_k\}$ are identified from the comparison of a line's shipments with those of lines in the same product, quarter, industry and state belonging to firms with a lower covered share. The identifying assumption is conditional parallel trends at the line level. More specifically, absent the policy, the lines of more and less exposed firms would have evolved in parallel once the fixed effects and controls are netted out. Exposure is a firm characteristic, therefore firm-by-quarter effects cannot be included. What the design does instead is compare lines within product-quarter cells, so that a shock to steel prices or to EU demand for a product is differenced out and only the differential response of the more exposed firm's line remains. The price outcome is estimated on the lines with a positive shipment and a price, and is therefore conditional on continued trade. The quantity and participation outcomes treat a quarter without a shipment as a zero and are not.

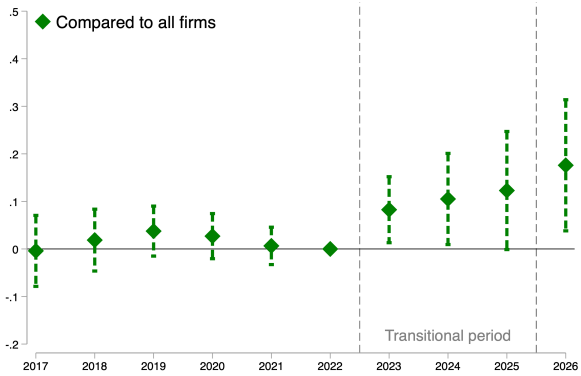
There are two potential violations of the Stable Unit Treatment Value Assumption (SUTVA), which I discuss in more detail when presenting the results. The first one is within affected firms. Specifically, a covered line and an uncovered line of the same exposed firm share management, capacity and EU customers, so the response to the charge is not necessarily confined to the covered line. The specification does not require that it does, since all of the firm's lines carry the firm's exposure, and a placebo exercise on the exposed firms' non-covered lines reports how far the response extends beyond the covered goods. The

second one is across firms. Shipments that exposed firms redirect away from the EU compete with those of unexposed Indian exporters in third markets, and EU buyers who reduce purchases from exposed firms may turn to unexposed Indian suppliers of substitute goods. I test this with a placebo exercise on firms that shipped covered goods only outside the EU.

4.B Firm-level *green* upgrading

Intensive margin adjustment. Affected firms respond by undertaking *green* investments. This section explores the size and type of *green* investment undertaken, overall and according to baseline firm-level characteristics. Figure 5 shows that exposed firms expand their stock of *green* capital projects by 18.1% relative to comparable firms, and this response appears almost immediately once the policy is announced. Building new *green* capacity is a discrete, forward-looking decision, and the announcement of CBAM is itself the relevant signal. A firm that anticipates a future carbon cost on its EU-bound shipments has an incentive to begin *greening* capacity now, to mitigate the expected costs.

Figure 5: Effects on cumulative *green* investment



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the log of cumulative *green* investment and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *CapexDx* database.

This pattern is robust to using alternative control groups. Figure A.5 of the Appendix presents the same estimates, comparing affected firms (a) only to other exporting firms and (b) only to other firms manufacturing products covered by the legislation, irrespective of exporter status. The results are near identical in magnitude. This matters because the two comparison groups guard against different confounders. Contrasting exposed firms with other exporters nets out shocks common to internationally oriented firms, such as exchange rates, global demand, or trade policy more broadly. Contrasting them with other manufacturers of similar products nets out specific shocks to the demand for such products more broadly. The fact that the estimates coincide across the two benchmarks indicates the response is not an artifact of exporter-specific trends or of the chosen counterfactual, but reflects a genuine reorientation of investment among the firms whose products are affected.

Figure A.6 also presents the effects on the flow of investment, that is the annual spending, as opposed to the stock of investment presented in Figure 5. Panel A.6(a) presents the results for *green* investment flow, indicating that firms respond both right after the beginning of the transitional period and right after the

beginning of the definitive one. To verify that my results are not reflecting broader investment activities undertaken by affected firms, Panel A.6(b) presents the same results for non-*green* investments, showing no equivalent response after 2022.

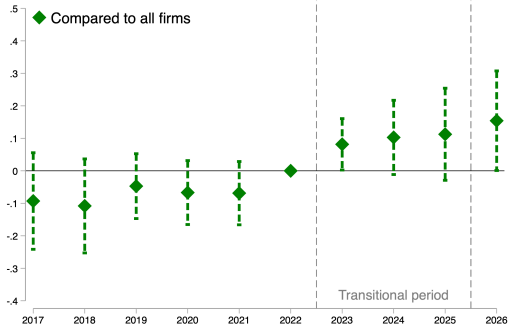
The results are also robust to alternative specifications. Table A.5 of the Appendix presents coefficients estimated based on the static version of Equation 5, progressively controlling for industry and state interacted with year fixed effects, as well as baseline export size and distance to the nearest port interacted with year fixed effects. Column (5) shows an 18.1% increase in the stock of *green* investment, and an average increase of 7% in the annual spending on *green* investment (flow), while showing no significant effect on non-*green* investment. Represented as a share, this corresponds to a 1.9 p.p. increase in the share of spending going towards *green* upgrading, or a 1.5 p.p. increase in the share of the number of *green* projects undertaken by affected firms.

Extensive margin adjustment. The intensive margin estimates capture how much exposed firms invest, but not whether CBAM draws new firms into *green* investment. Re-estimating the design with binary outcomes, an indicator for any *green* investment and one for a firm's first *green* project yields modest effects, as shown in Appendix Table A.6. Exposed firms are 1.8 p.p. more likely to undertake *green* investment, against a baseline rate of 2 percent, and 1.3 p.p. more likely to begin their first *green* project. The latter is insignificant with firm and year effects alone but stabilizes once industry-by-year effects are included and survives the full set of controls. CBAM therefore operates on the extensive margin as well as the intensive one, drawing firms into *green* investment.

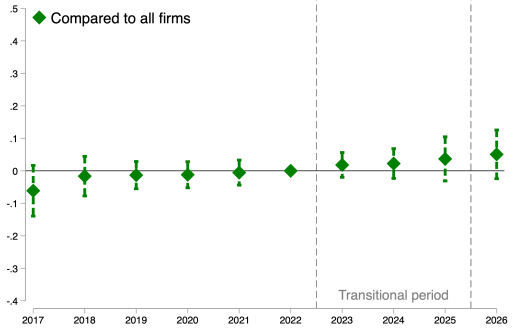
Response by type of technology. The classification method outlined above allows me to classify *green* technologies into sector-specific and cross-cutting ones. While cross-cutting technologies are those that can be easily adopted regardless of the economic activity of the firm (and as such are dominated by renewable electricity generation), sector-specific ones are technologies allowing firms to produce the same output through a less polluting production process. One example would be the replacement of a coal-based furnace with an electric one.

Figure 6: Effects on cumulative *green* investment by type of technology

(a) Sector-specific technologies



(b) Cross-cutting technologies



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the log of cumulative *green* investment by type and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown.
Source: Estimates based on data from the *CapexDx* database.

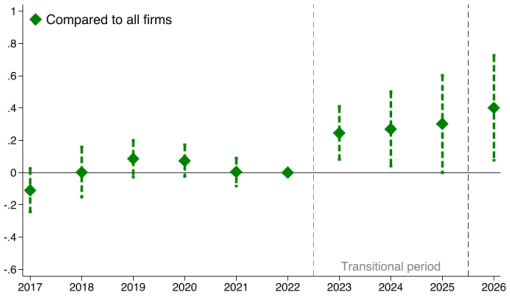
Figure 6 shows the response by type of technology, demonstrating that the effect is primarily driven by sector-specific technologies, i.e. that firms upgrade their production processes as a response to CBAM.

Figure A.7 splits the cumulative investment stock into purely *green* and *transitional* categories, against the all-firms comparison. In the example of a furnace, a natural-gas based one would fall into the transitional category. Averaged over 2023-2026 the *green* response is the larger of the two, albeit not statistically distinguishable. The pattern is, therefore, only suggestive of CBAM shifting investment toward *green* rather than *transitional* capital over time.

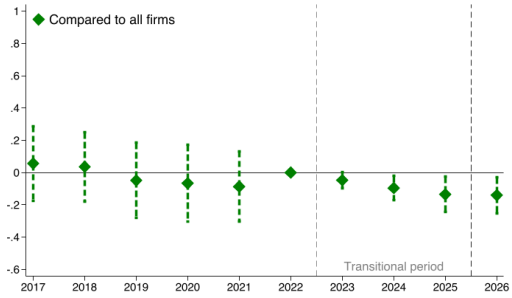
Response by firm characteristics. The response is heterogeneous, with firms of different positions in the supply chain, industry, and ownership behaving differently. Figure 7 presents the effects on the stock of *green* investment, separately for upstream and downstream firms.

Figure 7: Effects on cumulative *green* investment by position in the supply-chain

(a) Upstream firms



(b) Downstream firms



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the log of cumulative *green* investment by position in the supply-chain and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *CapexDx* database.

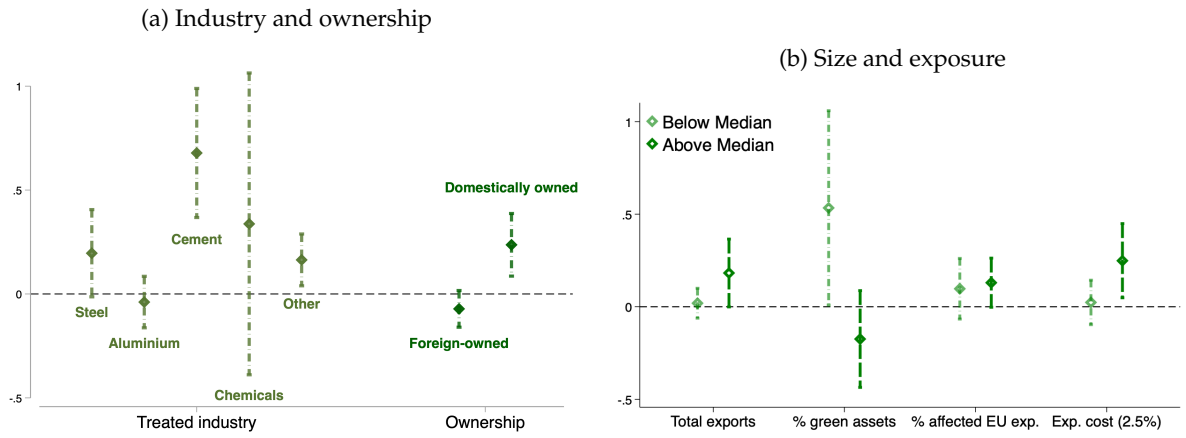
Here, downstream firms are CBAM-covered firms, that is firms shipping covered products to the EU over the baseline, but whose main industry is not in manufacturing those covered products. Upstream industries include cement, inorganic chemicals, copper & copper products, minerals, renewable electricity, and refinery sectors, which produce primary materials or energy inputs. Downstream industries include passenger vehicles, commercial vehicles, other automobile ancillaries, other transport equipment & ancillaries, agricultural machinery, diversified machinery, general purpose machinery, other electronics, wires & cables, glass & glassware, and road transport infrastructure services. Those industries ship covered products but also potentially use these materials as intermediate inputs in the production of downstream manufactured goods. As can be seen, the effects are driven by upstream firms, in line with the rationale and coverage of CBAM.

Furthermore, Figure 8(a) estimates the static specification separately by treated industry and by ownership. The response is concentrated in cement, and is positive but imprecise for steel. Aluminum is indistinguishable from zero and for chemicals, though large in magnitude, is noisily estimated. This pattern is in line with the aggregate trends of sales to the EU presented in Figure 4(a). When estimating the effect by ownership status, domestically-owned treated firms account for essentially the entire effect, while foreign-owned treated firms show a small negative coefficient centered close to zero. Foreign-owned firms plausibly already operate at the emissions standards CBAM makes binding, or can meet EU requirements through group-level capacity abroad, so the margin for new domestic *green* investment is narrower for them.

Figure 8(b) splits treated firms at their median on four baseline margins. Firm size seems to matter, as above-median exporters invest about 0.24 more while below-median exporters are flat at zero, consistent

with the fixed costs of *green* capacity expansion. Heterogeneity by the baseline share of *green* assets, shows that the effect is driven by dirtier firms. Specifically, treated firms with below-median *green* asset shares raise investment by roughly 0.55. CBAM therefore appears to prompt catch-up among firms starting from a dirty asset base. Lastly, firms with higher expected cost by the legislation respond more strongly.

Figure 8: Heterogeneity in *green* capacity expansion by firm characteristics



Notes: This figure reports coefficients of a static difference-in-differences regression based on Equation 5, where the dependent variable is the log of cumulative *green* investment by firm characteristics and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *CapexDx* database.

Placebo exercises. If the estimated effect reflects CBAM exposure, then designs that mimic the treatment without the mechanism should yield no effects. Appendix Table A.7 reports four such designs across the same set of specifications. The first assigns placebo treatment to EU exporters of carbon-intensive goods that CBAM does not cover (mineral fuels and oils, including petroleum products, coal, coke, and bituminous substances, ceramic products, including bricks and tiles, as well as glass and glassware). This tests whether the result reflects the behavior of carbon intensive industries more generally rather than regulatory coverage in particular. The second exercise assigns placebo treatment to firms exporting CBAM goods exclusively outside the EU, testing whether it is about producing covered goods or about exporting to the EU. The third exercise retains the true treatment but shifts the event to 2019 on the pre-2022 sample. Lastly, the fourth replaces the outcome with domestic-facing *green* investment in real estate, construction, transport, and logistics, i.e. categories with no channel to CBAM liability. None of those exercises yields a significant effect once industry-by-year effects are included. The single significant estimate, is negative at -8.2% for uncovered carbon-intensive exporters under firm and year effects alone, falling to -1.3% in specification (2) and remaining indistinguishable from zero thereafter. The remaining three are small and insignificant throughout, and the domestic-facing outcome in particular is flat at roughly 3% across every specification.

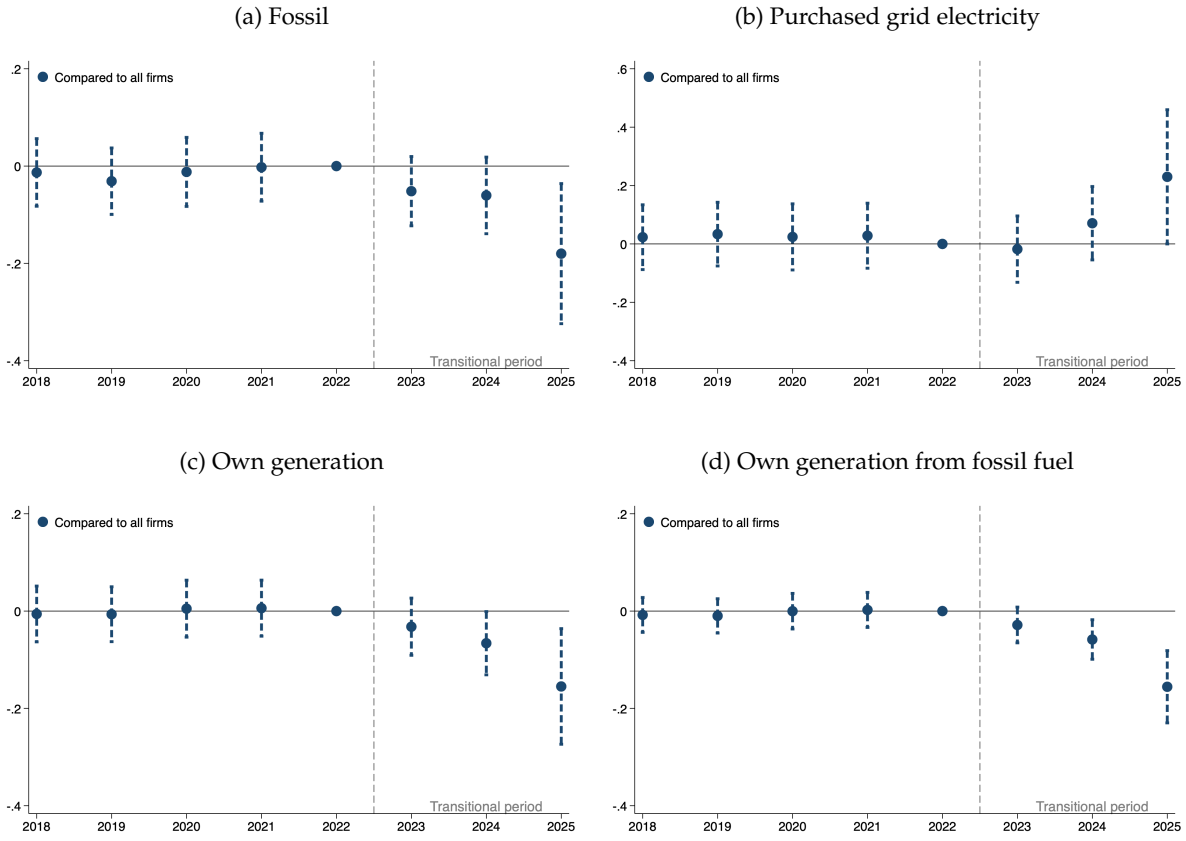
4.C Production process and firm performance

Subsequently, I proceed to study how firms reorganize their production processes as a response to the policy. Given the results presented above, it is expected that the investments undertaken by affected firms could have consequences for the production process, including firm inputs and costs, as well as for financial performance more broadly.

Energy mix. Figure 9 shows the effects on the composition of treated firms' energy bill through the *transitional period*. Each panel is an event study on one source's share of total power-and-fuel expenditure, estimated on the subset of firms that file *Prowess*'s detailed energy schedule.

The fossil share falls after 2022, showing a reduction of 18 p.p. below its 2022 level by 2025. The fall is concentrated in own generation, with the share of electricity generated on site dropping 16 p.p. by 2025, and the same magnitude appearing when own generation is restricted to lines that name a fossil fuel. The grid share moves the other way, rising by 23 p.p. in 2025. Appendix Figure A.8 breaks down fossil fuel input into its components, showing that gas drives the decline while coal and oil do not move, and renewables are flat and negligible throughout. Hence, purchased grid power replaces electricity that treated firms previously generated themselves from fossil fuel.

Figure 9: Effect on fuel use as a share of power and fuel expenditure

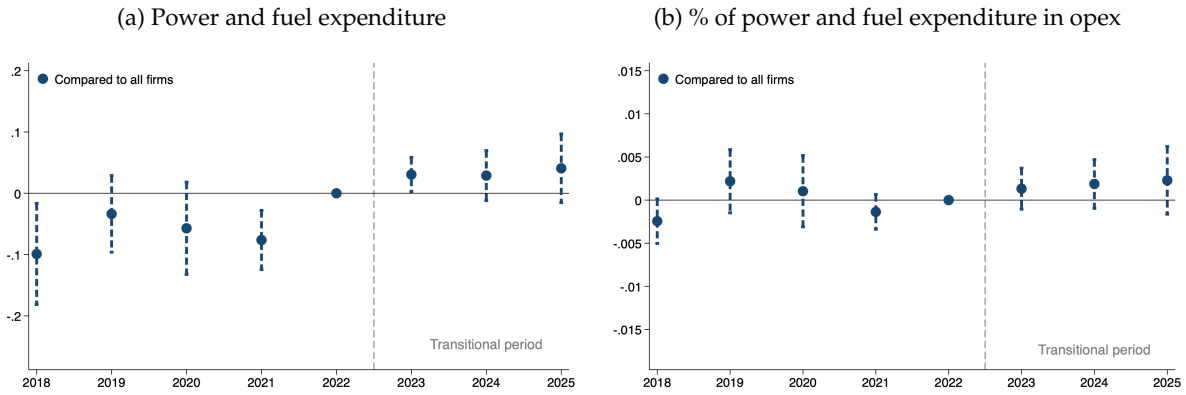


Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the share of fuel to the total power and fuel expenditure winsorised at the 1st and 99th percentiles and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *ProwessDx* database.

Figure 10 moves from the composition of the energy bill to its size. Figure 10(a) demonstrates that treated firms show a modest increase following 2022, although there are pre-trends. Figure 10(b) presents the estimates for power and fuel as a share of total operating expenses and the result is flat throughout. The two panels rule out the reading that treated firms cut energy use. The energy bill shows a modest increase within the firm, its weight in costs does not change, and the adjustment documented in Figure 9 is a reallocation

inside that bill, away from on-site fossil generation and toward purchased power from the grid.

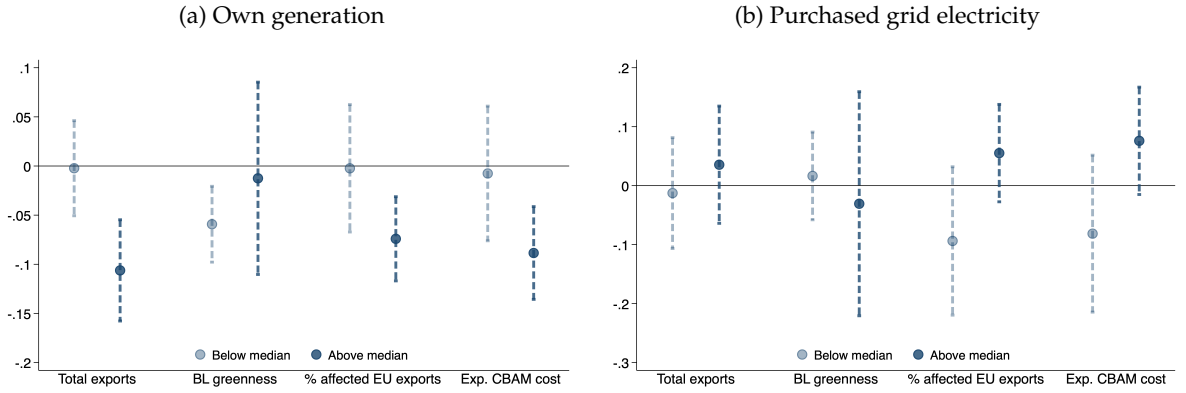
Figure 10: Effect on the energy bill



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the log of total power and fuel expenditure or the share of that expenditure in total operating expenditures, and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *ProwessDx* database.

Figure 11 splits own generation from fossil fuel and purchased grid electricity by four baseline characteristics of the treated firms, namely total export value, baseline *greenness*, the CBAM-covered share of EU exports, and the ex-ante expected CBAM liability at the 2026 phase-in factor of 2.5 percent.

Figure 11: Heterogeneity in fuel switching



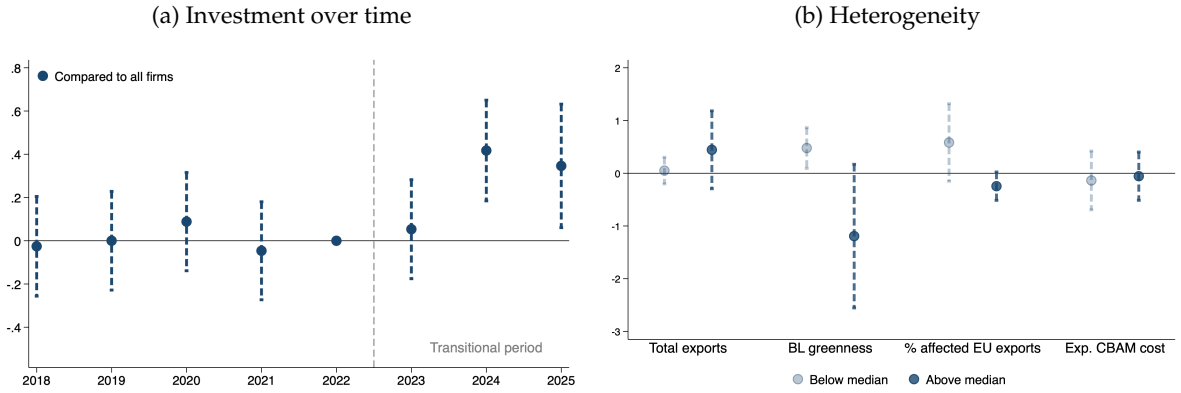
Notes: This figure reports coefficients of a static difference-in-differences regression based on Equation 5, where the dependent variable is the type of energy as a share of total power and fuel expenditure by bin of heterogeneity, and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *ProwessDx* database.

Each pair splits the treated firms at their median and re-estimates the static difference-in-differences on that half against the full control group, so the counterfactual is the same in every cell. The decline in own generation is concentrated in firms above the median on exports, on the affected share of EU exports, and on expected cost, where the share falls by 7 to 9%. Additionally, dirtier firms at baseline reduced own generation. This is in line with where the effect on *green* upgrading was observed in Figure 8. The grid panel in 11(b) is the mirror image, albeit noisily estimated. The grid share rises in above-median share of affected

EU exports, as well as in above median expected CBAM cost. Combined with the results presented in Figure 11(a) and Figure 8, more exposed, larger firms that invested in *greener* production processes, managed to substitute from own fossil-fuel based generation to purchasing electricity from the grid.

Pollution prevention. Figure 12(a) plots environmental and pollution-control spend as a share of operating expenses. As outlined in *ProwessDx*, "pollution control means the control of emissions and effluents into environment. It constitutes the use of materials, processes, or practices to reduce, minimize, or eliminate the creation of pollutants or wastes." While it is not clear whether such investment is dedicated to reducing CO_2 emissions or other types of pollutants, it is one margin along which firms would be expected to respond. The share rises by 0.4 p.p. in 2024 and 0.35 in 2025, roughly doubling the baseline level. Figure 12(b) also shows heterogeneity, with dirtier firms at baseline responding differentially, suggesting that this type of investment might either overlap with or be a complement of *green* upgrading investment undertaken.

Figure 12: Effects on pollution prevention as a share of operating expenses



Notes: This figure reports coefficients of a dynamic or static difference-in-differences regression based on Equation 5, where the dependent variable is the share of pollution prevention expenditure in total operating expenditures, and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *ProwessDx* database.

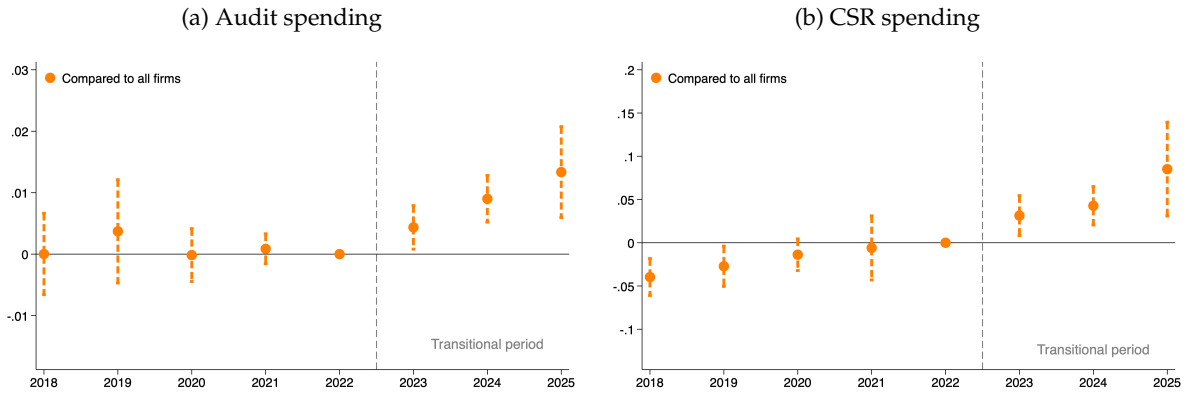
Output, profitability, and cost structure. Table A.8 reports static difference-in-differences estimates for output, export orientation, profitability, and the size of the cost base, starting from firm and year effects in column (1) and progressively adding controls, such that the full specification contains industry, state, baseline-export and port-distance by time FE in column (5). Real output of treated firms is 7% higher after 2023 in the saturated specification, significant at the 10 percent level, and operating expenses move by a similar amount but are not distinguishable from zero. Both coefficients halve once industry-by-year effects are included. The export share of sales falls by 1.8 percentage points against a baseline of 11 percent, and the estimate is stable from column (2) onward. Profit before tax over sales declines by about 9 percentage points. The baseline mean of that ratio is inflated by firms with very small sales, so the magnitude should be interpreted accordingly. The sign and significance are robust across columns (2) to (5).

Table A.9 decomposes operating expenses into materials, energy, wages, training, and outsourced manufacturing. None of the five shares moves. The energy share, which is the margin a carbon border charge would be expected to press on, changes by 0.2 percentage points against a baseline of 2.7 percent, and the materials share by 0.3 points against 57 percent. The wage bill, training and outsourcing shares are flat to within a few tenths of a point. Treated firms therefore navigate the policy period with an unchanged input mix, with adjustment taking place within the energy mix, and not between energy and the other inputs.

Entry and exit. Table A.10 shows estimates on whether treated firms are more or less likely to remain in the data after 2022. The outcome is an indicator for the firm being present in a given year, defined on the full balanced panel for every firm with a 2022 record. The post-period coefficients measure survival in the panel and the pre-period ones how early the firm entered. With only firm and year effects treated firms appear 1.5 percentage points more likely to be present. Once industry-by-year effects enter the estimate is zero and stays there through the saturated specification.

Compliance costs. Figure 13 shows the corresponding response on the share of auditing and consulting fees as well as Corporate Social Responsibility (CSR) spending in expenses, both rising noticeably after 2022. This suggests that CBAM-exposed firms are building their compliance and de-carbonization capacity, bringing in advisory and audit services. This possibly relates to the transitional-phase reporting obligations that start in October 2023. These require quarterly embedded-emission calculations for which few Indian firms have the in-house expertise, requiring third-party verification of those numbers. On the other hand, an increase in CSR spending shares could also be related to decarbonization efforts.

Figure 13: Effect on compliance costs as a share of operating expenses



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the share of audit and CSR spending in total operating expenditures, and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *ProwessDx* database.

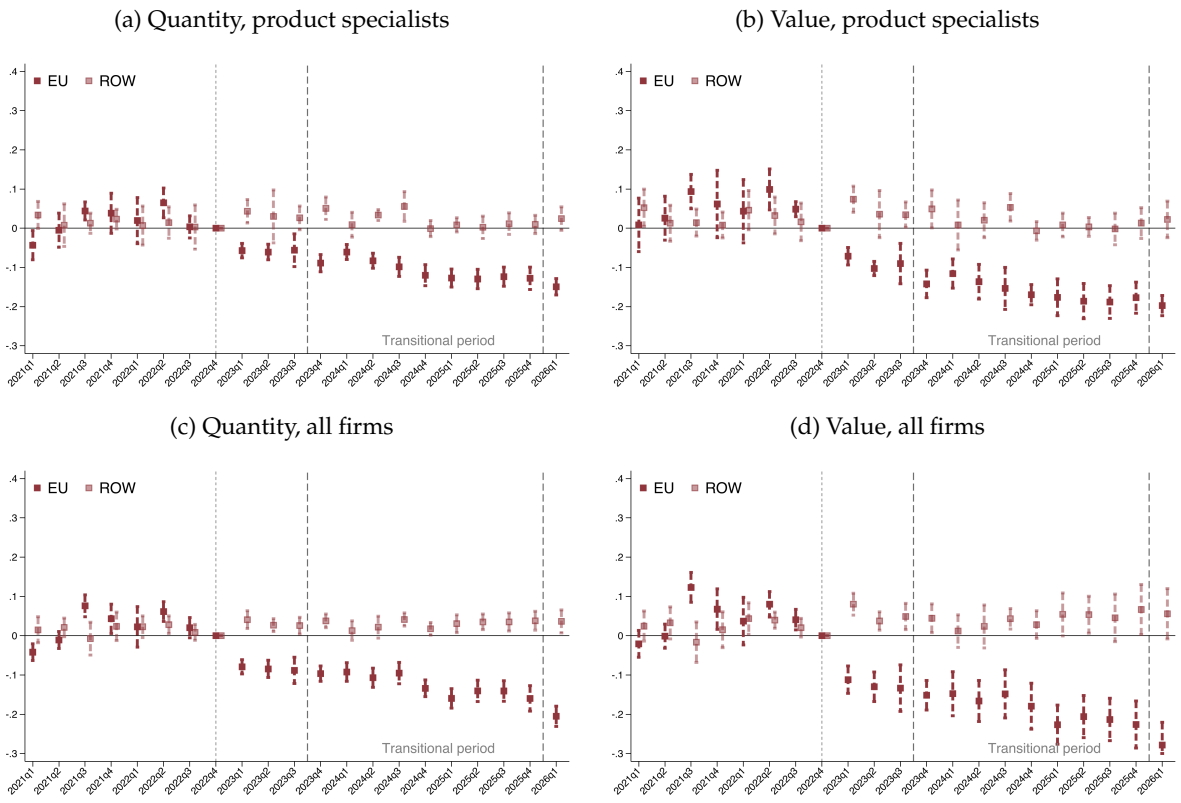
4.D International trade

Sample restrictions. The estimation panel is at the firm × HS6 × quarter level from 2021Q1 to 2026Q1, with 2022Q4 as the reference quarter. I refer to a "line" as a firm-specific product, and each line enters the panel if it shipped, to any destination, in at least one quarter of the 2021Q1-2022Q4 baseline. Once in, it is observed in every quarter of the window, with a zero in quarters without a shipment. In some specifications I impose a further restriction to product specialists, firms for which at least 90 percent of baseline export value, across all destinations, falls within a single product family. A specialist's exposure is not diluted by an unrelated product range, such that a treatment defined at the level of the firm describes the firm's entire business. The restriction is imposed on exposed and comparison firms alike.

Quantity and value exported. Figure 14(a) plots the effect on the quantity a specialist's line ships to the EU and to non-EU destinations. Exposed firms' EU lines fall through the window, reaching about -0.15 per ten percentage points of covered share by 2026Q1 and averaging -0.11 over the post period. The decline begins three quarters before the *transitional phase*, in the quarter after the December 2022 political agreement,

so firms are responding to the announced trajectory of the charge. Shipments by the same firms to other destinations move the other way, flat before the policy and slightly positive from 2023Q1 onward, though the effect on diversion corresponds to only about a fifth of that on EU contraction and is stable across the window.

Figure 14: Effects on exports by destination and type of firm



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 6, where the dependent variable is the inverse hyperbolic sine of the quantity a firm-product line ships to the destination, in the product's own harmonized unit, or of the corresponding value. Treatment is the firm's 2021 share of exports that are CBAM-covered goods to the EU, scaled so that a coefficient is per ten percentage points. The sample is firms whose exported products all belong to one product family in Panels (a) and (b) and all firms in Panels (c) and (d). The regression controls for firm by product, product by quarter, industry by quarter, state by quarter, and baseline exports by quarter. The short dashed line marks the reference quarter, the long dashed lines the start of the transitional phase (2023Q4) and the end of the window. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *Panjiva* database.

Figure 14(b) repeats the exercise with the value of the line's shipments. For specialists the value coefficients track the quantity ones with a somewhat larger magnitude, averaging -0.16 at the EU against -0.11 for quantity, with the non-EU series close to zero. The gap between the two is small and of the same sign at both destinations.

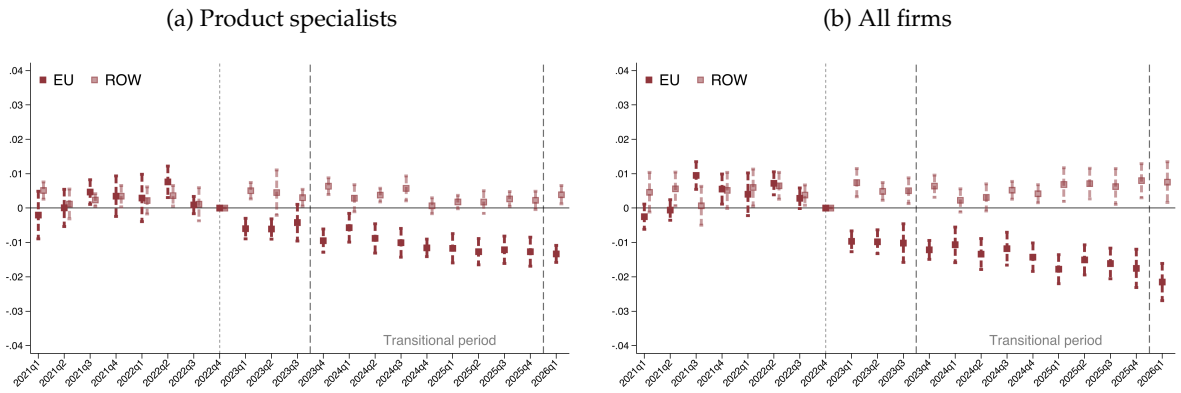
Panels (c) and (d) repeat both outcomes on the full sample of firms. The EU contraction and the diversion are both slightly larger there, and the diversion is more precisely estimated. The one substantive difference is in the pre-period, where on the full sample the coefficients through 2021 and 2022 are slightly above the reference quarter.

Figure A.9 in the appendix restricts the full panel further to those with positive EU exports at baseline, the firms for which the EU outcome is not mechanically zero before the policy. The pattern remains unchanged and the magnitudes are slightly smaller, -0.09 in quantity and -0.13 in value at the EU against 0.02 elsewhere,

so conditioning on prior EU presence does not alter the picture.

Extensive margin adjustment. A firm facing a charge on one destination need not adjust the size of every shipment it makes, it can simply stop exporting to that market. Figure 15 asks how much of the export response takes that form, replacing the quantity of a firm-product line with an indicator for whether the line ships at all in the quarter, estimated as a linear probability model on the same panel and with the same controls. Among product specialists, Panel (a), the probability that an exposed firm's line reaches the EU falls by about half a percentage point per ten percentage points of covered share through 2023, and by 1.0 to 1.3 points from 2024 onward, against a baseline of 11 percent. The same firms' lines to other destinations move the other way, rising by roughly half a point. In the full sample in Panel (b), the pattern is the same and somewhat larger on both sides. The EU indicator falls by about 1 point in 2023 and by 2.2 in 2026Q1, while the non-EU indicator increases by 0.2 to 0.8 points throughout the post period.

Figure 15: Probability of exporting by destination and type of firm



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 6, where the dependent variable is an indicator equal to one if the firm-product line ships a positive quantity to the destination in the quarter. Treatment is the firm's 2021 share of exports that are CBAM-covered goods to the EU, scaled so that a coefficient is per ten percentage points. The sample is firms whose exported products all belong to one product family in Panel (a) and all firms in Panel (b). The regression controls for firm by product, product by quarter, industry by quarter, state by quarter, and baseline exports by quarter. The short dashed line marks the reference quarter, the long dashed lines the start of the transitional phase (2023Q4) and the end of the window. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *Panjiva* database.

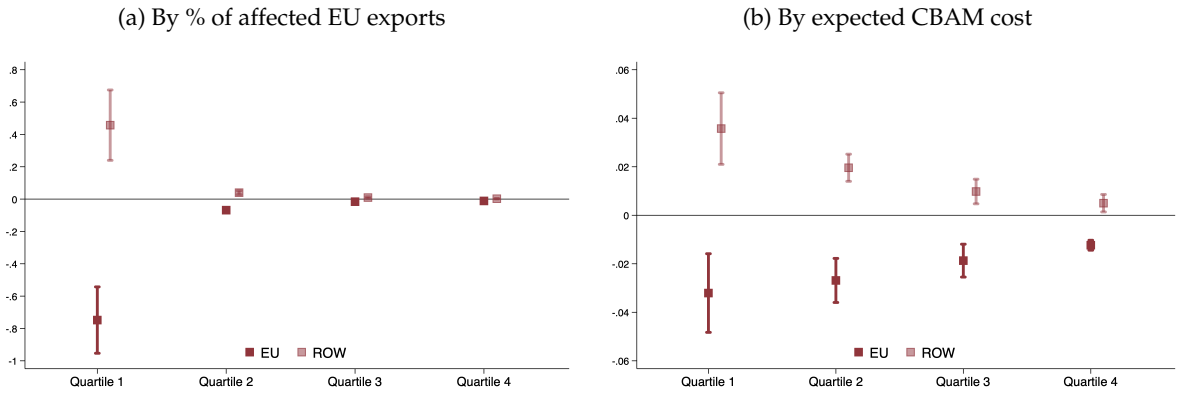
These are changes in how often a line is active, not in how much it carries when active, and the two together describe the same adjustment. Serving a destination has a fixed component, an importer relationship, a customs and compliance routine, or a shipment schedule. When a charge makes that destination less profitable on the margin, the cheapest response for a small line is not to renegotiate its size but to stop sending it and to use the capacity elsewhere. Hence, exposed firms drop EU lines at roughly a tenth of the rate at which they were active, and open or reactivate lines in other markets at about half that rate.

Table A.11 reports the static counterpart on the full panel, the coefficient on treatment interacted with the post-2023Q4 indicator, for a line shipping anywhere in the top panel and to the EU in the bottom panel, progressively adding controls. The first column compares a line only with other lines in the same quarter, the second compares it with other exporters of the same HS6 product in the same quarter, while the last three add industry, state and firm-size trends. Ten percentage points of covered share lower the probability that a line ships to the EU by 1.9 percentage points against a baseline of 9.0 percent, so a fifth of the rate at which those lines were active before the policy. The estimate is 2.1 points when only time effects are held fixed and 1.9 points in every column that compares within product, and it does not move as the trends are

added. The effect on shipping anywhere is far smaller, 0.4 points on a baseline of 40.3 percent, about one percent of the rate.

Heterogeneity. Figure 16 sorts exposed firms into quartiles, by the share of their EU sales that the regulation covers in Panel (a) and by their expected CBAM liability in Panel (b), and re-estimates the participation response within each quartile, keeping every comparison firm. Panel (a) shows the response collapsing as coverage rises. Among firms with only a small share of their EU sales covered, the EU participation effect is very large and non-EU entry rises almost as much. By the second quartile both have shrunk by an order of magnitude. Panel (b) presents a similar gradient along the size of the expected liability. Shipments to the EU fall in every quartile, but less so as the liability rises, while entry into non-EU markets runs the other way, largest where the liability is smallest and close to nothing at the top. In both orderings the least exposed firms show the largest movement in and out of destinations, and the most exposed show the least.

Figure 16: Effects on exports by destination and baseline characteristics, single unit-family firms



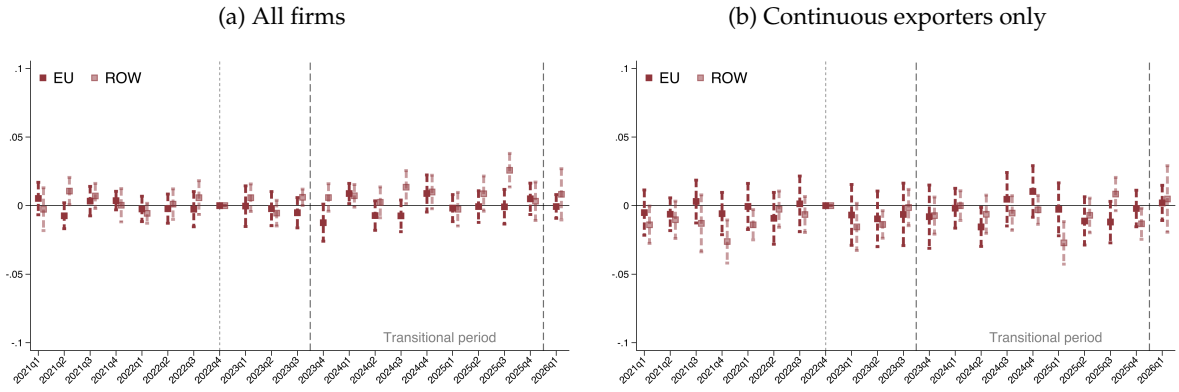
Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 6, where the dependent variable is the inverse hyperbolic sine of the quantity a firm-product line ships to the destination, in the product's own harmonized unit, or of the corresponding value. Treatment is the firm's 2021 share of exports that are CBAM-covered goods to the EU, scaled so that a coefficient is per ten percentage points. The sample is firms whose exported products all belong to one product family: The regression controls for firm by product, product by quarter, industry by quarter, state by quarter, and baseline exports by quarter. The short dashed line marks the reference quarter, the long dashed lines the start of the transitional phase (2023Q4) and the end of the window. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *Panjiva* database.

The firms redirecting are the least exposed ones. Where the EU is a small part of a firm's portfolio, an EU line is close to substitutable with a line somewhere else. The charge makes one destination marginally worse, the firm lets that relationship go and finds an alternative destination. The heavily exposed firms do the opposite, and Section 4.B provides evidence as to why that is the case. Those are the same firms that responded to the policy by investing in *green* upgrading, and a firm that has cut the emission intensity of what it sells manages to also reduce the expected charge itself. Having paid to keep the destination viable, it has every reason to keep serving it.

Effects on prices and pass-through. A large trade literature studies the incidence of tariffs, looking at prices. In the tariff wars of 2018-2019, import prices at the US border moved close to one-for-one with the tariff while foreign export prices barely moved, which was read as complete pass-through to domestic buyers and no incidence on foreign exporters (Amiti et al., 2019; Fajgelbaum et al., 2020). A carbon border adjustment is a different instrument, but the same question applies. Given that the charge is levied on embedded emissions, an exporter can in principle respond on three margins, by cutting the price it receives,

by shipping less, or by making the good cleaner. The price response can be informative of the nature of the response. Figure 17 plots the response of the log unit price of a firm-product line to the EU and to the rest of the world. The unit prices here are free-on-board (FOB) prices at the Indian border, taken from customs export declarations, so they measure what the exporter receives and exclude freight, insurance and any charge levied on entry into the EU.

Figure 17: Effects on prices



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 6, where the dependent variable is the log of unit prices of a firm-product line to a destination. Treatment is the firm's 2021 share of exports that are CBAM-covered goods to the EU, scaled so that a coefficient is per ten percentage points. The sample is all firms in Panel (a) and continuous exporters in Panel (b). The regression controls for firm by product, product by quarter, industry by quarter, state by quarter, and baseline exports by quarter. The short dashed line marks the reference quarter, the long dashed lines the start of the transitional phase (2023Q4) and the end of the window. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *Panjiva* database.

Panel (a) uses every line with an observed price, while Panel (b) only shows the estimate for continuous exporters, lines that report a price in at least sixteen of the twenty-one quarters, so that the estimate is not contaminated by lines entering and leaving the sample. Prices to the EU are flat throughout, with no break at either the beginning of the transitional or the *definitive phase* of CBAM. Restricting to continuous exporters, where composition is held fixed within the line, shows a similar pattern. Prices to the rest of the world drift up very slightly in the later quarters of the window in Panel (a), by under one percent, and that drift disappears among continuous exporters, therefore could potentially reflect compositional changes.

Legally, the CBAM certificate is surrendered by the EU importer, not by the exporter. The only way an Indian firm can bear part of that cost is by accepting a lower price for the goods it sends, and a flat FOB price is evidence that none of the charge is being passed back up the chain, at least up to the first quarter of 2026. However, for most of the sample the charge is a reporting obligation, with certificates due only from 2026. Hence, the price test rules out pass-through of the *anticipated* liability. Whether exporters begin to share the cost once certificates are actually surrendered, and the factor rises from 2.5 percent toward full phase-in, is a question the present window cannot answer.

Placebo exercises. Table A.12 reports four placebo exercises for the EU export quantity result, each on the five-column specification of the main tables. The first two replace the treatment with an exposure that CBAM does not price, estimated among firms with no covered EU exports. Firms whose EU sales at baseline consisted of downstream steel and aluminum-using products, which the regulation leaves outside its scope, show no change in EU shipments after 2023Q4. Firms that exported CBAM products only to non-EU destinations, the same goods without the charge, show no statistically significant effect. The third

row keeps the true treatment and moves the event to 2018 on a window ending in 2021, before the regulation was adopted. The estimate remains insignificant in the preferred specification. The fourth row keeps the true treatment and true timing but takes as outcome the exposed firms' own non-CBAM products to the EU, which the charge does not affect the coefficient is once again insignificant, so the decline is confined to the covered goods. None of the four placebos reproduces the main effect, suggesting that the pattern documented above is consistent with a response to the border charge itself, products-specific shocks, or a trend common among the exposed firms.

5 Theory

The reduced-form estimates compare exposed to unexposed Indian firms, identifying relative responses to CBAM. Global emissions depend on how India's competitors respond, how production shifts across markets, and whether cleaner production extends to output sold outside the EU. Evaluating alternative policies also requires outcomes that have not yet been observed. I therefore build a model of trade and technology adoption in the spirit of Melitz (2003) and Bustos (2011), where heterogeneous suppliers choose whether to serve the EU and whether to adopt a cleaner technology, and, following Almunia et al. (2021), face rising marginal costs that link their sales across markets.

The world consists of four regions, indexed by $j \in \mathcal{M} = \{EU, S, R, TH\}$, namely the EU, India ($S$), a composite of India's rival exporters (R), and third markets (TH), comprising all remaining countries. Each region is a market for the covered goods, and $\mathcal{M}' = \{S, R, TH\}$ denotes the non-EU markets. India and its rivals host heterogeneous suppliers, indexed by origin $o \in \{S, R\}$, which produce differentiated intermediates under monopolistic competition and sell both at home and abroad. Suppliers differ in productivity and in the cost of adopting a cleaner energy recipe, and face fixed costs of entering the EU market and switching recipes. Each supplier operates a plant of fixed capacity, therefore its marginal cost rises with its total output. The two origins share the same structure but differ in their parameters. In each market, they compete with a composite of EU and third-country producers. Abatement takes the form of switching recipes, each defined by an energy-augmenting productivity and an emissions factor.

Preferences and environment. Each region j has a representative household with utility:

$$U_j = B_j \cdot \Lambda(\Xi), \qquad B_j = Y_j^{\gamma_j} O_j^{1-\gamma_j}, \qquad \Lambda' < 0 \tag{7}$$

where B_j is a Cobb-Douglas consumption bundle and Λ captures damages from global emissions Ξ, common to all regions. The bundle consists of a freely traded outside good O_j and a composite of covered intermediates Y_j. Households take global emissions as given, such that Λ does not enter their first-order conditions, and damages affect only welfare. Spending on covered goods is $I_j = \gamma_j I_j^{tot}$, where I_j^{tot} is regional income, and trade in the outside good balances each region's accounts.

The outside good is the numéraire and is produced one-for-one from labor in every region. The covered sectors are small relative to each economy, so every region produces some of the outside good, which pins wages at $w_j = 1$ and makes this sector the residual employer. Labor released or absorbed by the covered sectors therefore moves to or from the outside good at the same wage, and fixed costs paid in labor are costs in units of the numéraire. Each Southern origin hosts a mass N_o of suppliers whose productivity follows a truncated Pareto distribution with shape κ on $[z_{\min}, z_{\max,o}]$. Energy is supplied at fixed prices, with dirty fuel at $p^E = 1$ and clean energy at p_G. Energy payments, including carbon charges levied on energy, accrue

to the region's households.[8]

Carbon prices. Each origin o faces a domestic carbon price p_C^o on the realized emissions of all its output, regardless of destination, with revenues rebated within the origin. India has no explicit carbon price in the covered sectors, so I use an estimated shadow price p_C^S to capture the implicit cost of carbon through fuel taxes and regulation. For other producing countries, I use the effective explicit carbon price where one exists and a shadow price otherwise (Appendix B.1). EU producers face an *EU ETS* price $t_{ETS} = \varsigma\tau$ on output sold in any market, net of their remaining free allocation. Imports into the EU face a CBAM charge $\tau \geq 0$ per unit of embedded emissions, with a deduction for the explicit carbon price c_o already paid at origin. During the phase-in, a further deduction for free allowances leaves each recipe subject to a share ϖ_T of the full charge (Appendix B.8). CBAM covers only direct emissions for iron, steel and aluminium, and both direct and indirect emissions for cement and fertilisers, while domestic carbon prices cover all emissions. In the counterfactual simulations, a share λ of CBAM revenue is rebated to EU households and the remaining $1 - \lambda$ to India.

Demand. In each market m, final producers assemble Y_m using a common three-tier CES system, with elasticities $\sigma > \eta \geq \xi > 1$. The upper tier divides spending between the non-Southern good D_m, at price p_m^D, and the Southern composite M_m, at price index P_m^M:

$$P_m = \left[(p_m^D)^{1-\xi} + (P_m^M)^{1-\xi}\right]^{\frac{1}{1-\xi}}, \qquad s_m^M = \left(\frac{P_m^M}{P_m}\right)^{1-\xi} \tag{8}$$

The middle tier aggregates Indian and rival bundles with elasticity η, giving origin o a share $s_{o,m} = (P_m^o / P_m^M)^{1-\eta} s_m^M$ of total spending in market m. The lower tier aggregates varieties within each origin with elasticity σ. Buyers in market m place a taste weight $d_{o,m}$ on every variety from origin o, such that a variety sold at delivered price $\tilde{p}$ faces demand:

$$x_{o,m} = d_{o,m}\, \tilde{p}^{\,-\sigma} (P_m^o)^{\sigma-1} s_{o,m} I_m, \qquad (P_m^o)^{1-\sigma} = d_{o,m} \int \tilde{p}(i)^{\,1-\sigma} di \tag{9}$$

where the integral is over the origin's active varieties in market m. India's taste weights are normalized to one in every market, and the rivals' weight is normalized to one in their own market. The rivals' weights in the other three markets are calibrated (Appendix B.2).

The non-Southern good combines varieties from EU and third-country producers through a CES aggregator with elasticity η. Both groups produce under monopolistic competition with free entry, so each group's price index falls as its sales increase. They use energy and face their respective domestic carbon prices. EU producers also pay the *EU ETS* price regardless of destination, while third-country producers face CBAM when selling to the EU. Neither group can switch recipes, so their only margin of adjustment is energy use (Appendix B.4).

Technology and recipes. A supplier of productivity z from origin o combines raw energy e and labor n into bundles according to:

$$v = (A_T e)^{\phi_o}\, n^{1-\phi_o} \tag{10}$$

where A_T converts raw energy into useful energy. A recipe is a pair $T = (A_T, \varepsilon_T)$, consisting of an energy-augmenting productivity and an emissions factor per unit of raw energy. Both are normalized to one for

[8] With supply infinitely elastic, a fall in fossil demand never lowers the fuel price. Therefore a channel through which the policy cuts demand, world prices fall, and unpriced users elsewhere burn more, is absent by construction.

the dirty recipe, $D = (1, 1)$, while the clean recipe is $G_o = (A^o_G, \varepsilon^o_G)$, with $\varepsilon^o_G < 1$.[9] Switching recipes costs $F_i = Ff_i$ units of labor per period, paid once per firm regardless of how many markets it serves. The adoption-cost shifter f_i is lognormally distributed with mean one and dispersion s_F, independently of productivity.

The supplier minimizes the cost of energy and labor, including domestic carbon payments on its emissions. Since emissions are proportional to raw energy use, the carbon price enters the effective price of energy. The cost of a bundle is therefore:

$$\bar{C}_{o,T} \propto \varrho_T^{\phi_o} \, w_o^{1-\phi_o}, \qquad \varrho_D = 1 + p^o_C, \qquad \varrho_G = \frac{p^o_G + p^o_C \varepsilon^o_G}{A^o_G} \tag{11}$$

The clean recipe has a lower cost than the dirty one if and only if $A^o_G(1 + p^o_C) > p^o_G + p^o_C \varepsilon^o_G$. Emissions per unit of variable cost, $\mathcal{E}^o_T = \varepsilon_T \phi_o / (\varrho_T A_T)$, depend on the recipe but not on firm productivity:

$$\mathcal{E}^o_D = \frac{\phi_o}{1 + p^o_C}, \qquad \mathcal{E}^o_G = \frac{\varepsilon^o_G \, \phi_o}{p^o_G + p^o_C \varepsilon^o_G}, \qquad \delta_o = \underbrace{\varepsilon^o_G}_{\text{Fuel}} \cdot \underbrace{(A^o_G)^{-1}}_{\text{Efficiency}} \cdot \underbrace{\left(\frac{\varrho_G}{\varrho_D}\right)^{\phi_o - 1}}_{\text{Rebound}} \tag{12}$$

where δ_o is the clean-to-dirty ratio of emissions per unit of output. The fuel factor measures the reduction in emissions per unit of raw energy, while the efficiency factor captures the reduction in raw energy needed to produce a useful unit. The rebound arises because cheaper useful energy induces the firm to use more of it relative to labor, partly offsetting the emissions savings. CBAM applies only to the share $k^o_T(r)$ of emissions covered by the regulation, giving chargeable emissions per unit of variable cost $\mathcal{E}^{o,\text{chg}}_T = k^o_T(r)\mathcal{E}^o_T$ (Appendix B.1).[10]

Capacity. Following Almunia et al. (2021), each plant has a fixed capacity, such that producing more output requires bundles at an increasing rate. A supplier that sells q_m units in each market m has variable cost:

$$\mathcal{C}(Q) = \frac{\bar{C}_{o,T}}{z} \frac{\bar{Q}}{1 + \nu} \left(\frac{Q}{\bar{Q}}\right)^{1+\nu}, \qquad Q = \sum_m q_m, \qquad \nu \geq 0 \tag{13}$$

where Q is total physical output and $\bar{Q}$ is a normalization. Marginal cost $\mathcal{C}'(Q) = (\bar{C}_{o,T}/z)(Q/\bar{Q})^\nu$ falls with productivity and rises with everything the firm sells, in any market. Since $\mathcal{C}$ is homogeneous of degree $1 + \nu$, variable cost is the fraction $1/(1 + \nu)$ of output valued at marginal cost. The energy bill is the share ϕ_o of variable cost, such that each unit of output embeds emissions $\mathcal{E}^o_T \mathcal{C}'(Q)/(1 + \nu)$, proportional to average cost. At $\nu = 0$ marginal cost is constant, $\mathcal{C}'(Q) = \bar{C}_{o,T}/z$.

Pricing and the border wedge. CBAM imposes a charge per unit of output, $t = (\varpi_T \tau - c_o)^+ \mathcal{E}^{o,\text{chg}}_T \mathcal{C}'(Q)/(1 + \nu)$, which depends on the supplier's emissions. The supplier posts a price p, while the buyer pays $\tilde{p} = p + t$. Profit maximization under the demand in (9) then gives:

$$\tilde{p}(z) = \frac{\sigma}{\sigma - 1} \mathcal{C}'(Q) \, \mathcal{T}^o_{T,m}, \qquad \mathcal{T}^o_{T,EU} = 1 + (\varpi_T \tau - c_o)^+ \frac{\mathcal{E}^{o,\text{chg}}_T}{1 + \nu}, \qquad \mathcal{T}^o_{T,m} = 1, \; m \in \mathcal{M}' \tag{14}$$

Setting $\varpi_T = 1$ recovers the full charge. The domestic carbon price is already included in the cost of a bundle, which applies to sales in every destination, and is not added separately to the border charge. Since

[9] Only the ratio p_G / A_G, the price of a useful unit of clean energy relative to dirty, enters any equilibrium object, and it is what plant energy bills measure.

[10] $\mathcal{E}^o_T$ is derived from cost minimization at the effective price ϱ_T, which includes the domestic carbon price but not τ. Abatement against the policy therefore takes the form of switching recipes, not continuous re-optimization in response to the border charge.

marginal cost depends on total output, a firm's markets are linked. Solving for output gives sales in market m, for a firm on recipe T serving the set of markets $\mathcal{S}$:

$$r_m(z) = \sigma\, \mathcal{B}^o_m\, (\mathcal{T}^o_{T,m})^{1-\sigma}\, \bar{C}^{-\tilde{a}}_{o,T} \Big(\frac{\mathcal{Q}^q_{\mathcal{S},T}}{\bar{Q}} \Big)^{\tilde{b}-1} z^{\tilde{a}}, \tag{15}$$

$$\mathcal{Q}^q_{\mathcal{S},T} \equiv \sum_{m' \in \mathcal{S}} \mathcal{B}^o_{m'} (\mathcal{T}^o_{T,m'})^{-\sigma}, \qquad \tilde{a} \equiv \tfrac{\sigma-1}{1+\nu\sigma},\ \tilde{b} \equiv \tfrac{1+\nu}{1+\nu\sigma} \tag{16}$$

where $\mathcal{B}^o_m \propto d_{o,m} (P^o_m)^{\sigma-1} s_{o,m} I_m$ collects the demand terms taken as given by the supplier, and the quantity reach $\mathcal{Q}^q_{\mathcal{S},T}$ weights the markets the firm serves by the units each absorbs (Appendix B.3). When EU sales contract, total output and marginal cost fall, allowing the firm to expand sales elsewhere. The cross-market response has elasticity $-(\sigma-1)\nu/(1+\nu)$ with respect to total firm sales. Pass-through of changes in the cost of a bundle, whether from a different recipe or the domestic carbon price, is $1/(1+\nu\sigma)$, while the border wedge still changes the relative price of EU sales one for one. Without a border charge, operating profit is the share $(1+\nu\sigma)/[\sigma(1+\nu)]$ of sales, including the rent on fixed capacity.

Selection. Every supplier sells in all three non-EU markets, where no border charge applies and the delivered price of a variety is the same across destinations. The supplier chooses whether to export to the EU ($e \in \{0,1\}$), at a fixed cost f_{EU}, and whether to adopt the clean recipe ($g \in \{0,1\}$), at a fixed cost F_i. Operating profit in each configuration is proportional to $z^{\tilde{a}}$. Writing $x \equiv z^{\tilde{a}}$ and suppressing the origin index o, total profit is:

$$\pi(e,g) = R_g x + e\big[K_g x - f_{EU}\big] - g F_i, \qquad R_g \equiv \Pi_{0,g}, \qquad K_g \equiv \Pi_{1,g} - \Pi_{0,g} \tag{17}$$

where $\Pi_{e,g}$ is operating profit per unit of x in configuration (e,g) (Appendix B.3). With rising marginal cost, K_g is the value of selling in the EU net of the sales that EU entry crowds out in the other markets. Let $a \equiv R_G - R_D$ denote the gain from adoption in non-EU markets and $b \equiv K_G - K_D$ the gain in the EU. The cross-difference of (17) is bx, such that exporting to the EU and adopting are complements whenever the clean recipe is cheaper on the EU leg, inclusive of the border charge. A dirty firm enters the EU when $K_D x \geq f_{EU}$, while an EU exporter adopts when the gains across all markets cover its switching cost F_i. When firms enter the EU before adopting, these decisions give rise to two productivity thresholds:

$$z^* = \Big[\frac{f_{EU}}{K_D}\Big]^{\frac{1}{\tilde{a}}} \;<\; z^{**}(f) = \Big[\frac{Ff}{a+b}\Big]^{\frac{1}{\tilde{a}}} \tag{18}$$

This ordering holds when:

$$\underbrace{\frac{Ff}{f_{EU}}}_{\substack{\text{cost of adopting,}\\ \text{relative to exporting}}} \;>\; \underbrace{\frac{a+b}{K_D}}_{\substack{\text{value of adopting,}\\ \text{relative to exporting}}} \tag{19}$$

When the cost of adopting relative to exporting exceeds its relative benefit, firms enter the EU on the dirty recipe and adopt only at higher productivity, leaving an interval of dirty EU exporters between the two thresholds. Otherwise, firms may adopt before entering the EU, based on the gains in non-EU markets alone, or undertake both decisions together. The configuration that takes effect depends on the firm's adoption cost (Appendix B.7).

Aggregation and emissions. A firm is characterized by its productivity and adoption cost, (z_i, f_i), and aggregates integrate the decisions above over both. The price indices in (9) and the green share $\mathrm{g}_{o,m}$ of origin

o's sales in market m follow from the Pareto distribution, with expressions given in Appendix B.5. Since sales scale with $z^{\tilde{a}}$, the observed sales tail identifies $\kappa = \text{tail} \times \tilde{a}$. Emissions per unit of delivered expenditure are $\frac{\sigma-1}{\sigma(1+\nu)}\mathcal{E}_T^o/\mathcal{T}_{T,m}^o$, as marginal cost cancels by (14). The emissions embodied in each trade flow are therefore:

$$\Xi_{o,m} = \frac{\sigma-1}{\sigma(1+\nu)}\, s_{o,m} I_m \Big[\frac{1-\mathrm{g}_{o,m}}{\mathcal{T}_{D,m}^o}\mathcal{E}_D^o + \frac{\mathrm{g}_{o,m}}{\mathcal{T}_{G,m}^o}\mathcal{E}_G^o\Big] \tag{20}$$

Global emissions Ξ also include emissions from EU and third-country producers in every market. The border charge affects emissions through three margins. First, Southern suppliers lose sales in the EU, shifting production toward other suppliers. Second, the border wedge raises delivered prices, reducing the output purchased per unit of expenditure. Third, suppliers adopt cleaner recipes, reducing emissions per unit of output. At the same time, suppliers whose EU sales contract move down their marginal cost curves and expand their sales in other markets, so that some exports are diverted away from the EU. Since adoption applies to the entire plant, suppliers that switch recipes to serve the EU also reduce emissions from goods sold in other markets.

General equilibrium. In the EU and third markets, household income consists of labor income at the pinned wage and energy revenues, including carbon payments, with EU households also receiving their share of CBAM revenue. In the South, labor is employed in variable production, the fixed costs of exporting and adopting, and the outside good. Household income consists of labor income, energy rents, domestic carbon receipts, profits net of fixed costs, including the rent on fixed capacity, and any rebate received:

$$I_o^{tot} = \bar{L}_o + \frac{\phi_o \mathcal{V}_o}{1+\nu} + \Big[R_o - \frac{\mathcal{V}_o}{1+\nu} - \big(f_{EU} N_o^{EU} + F\tilde{N}_o^G\big)\Big] + \mathbb{1}\{o=S\}\,(1-\lambda) R_{\text{CBAM}} \tag{21}$$

where $\mathcal{V}_o$ is the origin's output valued at marginal cost, R_o its total free-on-board revenue across all markets, including its own, and N_o^{EU} and $\tilde{N}_o^G$ the masses of exporters and adopters (Appendix B.6). Since wages are pinned, the border charge reaches firms that never served the EU market only through the markets they share with exporters. Exporters whose EU sales fall expand in other markets, and adopters become cheaper everywhere, which tightens competition for non-exporters in the non-EU markets. CBAM therefore increases exporters' non-EU sales through the fall in their marginal costs, as well as through the adoption gain $a > 0$ for firms induced to switch recipes.

Welfare. Since the damage factor is common and multiplicative, the first-order change in world welfare separates into changes in market welfare and climate damages:

$$\Delta W = \sum_j EV_j + \text{SCC} \times (-\Delta\Xi), \qquad \text{SCC}^* = \frac{\sum_j EV_j}{\Delta\Xi} \tag{22}$$

Here, EV_j is the money-metric equivalent variation for region j, determined by its income and the price index of covered goods. The break-even social cost of carbon SCC^* is the value at which avoided climate damages exactly offset the market welfare cost of the policy.

Carbon leakage. I measure leakage as the change in emissions outside the EU per tonne of emissions reduced inside it. *Southern leakage* compares the change in India's and the rivals' emissions on non-EU sales with the reduction in their emissions on EU sales. I decompose it into trade diversion, where output displaced from the EU is sold in other markets, and the technique spillover, where firms that adopt cleaner recipes to serve the EU also reduce emissions on their non-EU sales. *Production leakage* instead measures the change in emissions of all producers outside the EU relative to the reduction in emissions of EU producers.

Extensions. Two assumptions in the model are consequential, namely the fact that adoption is plant-wide

and that marginal cost rises with total output. To relax those assumptions, I develop two extensions to the model above. The first extension allows a firm to convert only the line that serves the EU, at a fraction of the cost of converting the whole plant, so that an adopter's non-EU sales can stay dirty. Since the two lines are separable only when marginal cost is constant, I develop this extension at $\nu = 0$. The second sets $\nu = 0$ on its own, so that marginal cost is constant and a firm's markets are linked only through prices (Appendix B.9).

6 Quantitative analysis

6.A Identification and estimation

I calibrate the model using parameters taken directly from the data and sixteen moments that identify the remaining parameters. I then examine the model's ability to reproduce outcomes not targeted in the estimation. The parameter set is:

$$\begin{aligned}\Theta = \underbrace{\{\sigma, \eta, \xi, \nu\}}_{\text{External calibration}} \cup \underbrace{\{\kappa, \phi_S, \phi_R, \phi_{EU}, \chi_G, \chi_{G,R}, \delta_R, p_G, A_G, N_S, p_{C,R}, c_R, I_m\}}_{\text{Direct match to data}} \\ \cup \underbrace{\{p_E, z_{\min}\}}_{\text{Normalized}} \cup \underbrace{\{f_{EU}, F, f_{R,EU}, F_R, N_R, d_{R,EU}, d_{R,IN}, d_{R,TH}, p^D_{EU}, p^D_{IN}, p^D_{RV}, p^D_{TH}, \varepsilon_G, \tau, p_C, s_F\}}_{\text{Internal calibration}}\end{aligned} \tag{23}$$

The three elasticities and the curvature of marginal cost are externally calibrated, while the normalizations set the dirty energy price and the productivity floor to one. Every wage is pinned at one by the outside good, so that fixed costs are expressed in units of labor. Table 3 reports each parameter and its source.

Identification. I recover the sixteen internally calibrated parameters from sixteen moments in four steps. The first twelve moments are observed in 2022, before CBAM's transitional phase began. They include the share of Indian plants exporting to the EU, the clean share among those exporters, the rivals' EU participation rate and clean share of EU sales, and India's and the rivals' shares of spending in each of the four markets. These moments identify four fixed costs, four outside prices, the rivals' mass, and their three market shifters:

$$\left\{m_{EU},\, m_G,\, m_{R,EU},\, m_{G,R},\, \{s_{S,m}, s_{R,m}\}\right\} \to \left\{f_{EU}, F, f_{R,EU}, F_R, N_R,\, d_{R,EU}, d_{R,IN}, d_{R,TH},\, \{p^D_m\}\right\} \tag{24}$$

Each participation or adoption moment identifies the corresponding fixed cost through the cutoff it implies. In each market, the combined import share identifies the price of the outside good, p^D_m, while the split of imports between India and its rivals identifies the rivals' shifter, $d_{R,m}$. In the rivals' home market, where the shifter is normalized to one, this split instead identifies the mass of rival suppliers, N_R.

The carbon intensity ratio δ, measuring adopters' emissions per unit of output relative to non-adopters, identifies the clean recipe's emission factor ε_G through:

$$\delta = \frac{\varepsilon_G}{A_G}\left[\frac{p_G}{A_G}\,\frac{p_E + p_C\,\varepsilon_G/p_G}{p_E + p_C}\right]^{\phi_S - 1} \tag{25}$$

Given A_G, p_G, ϕ_S, and the shadow price p_C, this expression has only one unknown, ε_G. The border charge τ is levied per unit of embedded carbon, which the data do not measure in the required units. Instead,

I use the charge as a share of the pre-charge import price, θ, calculated from India's shipments, to recover:

$$\tau = \frac{\theta\,\sigma\,(1+\nu)\,(p_E + p_C)}{(\sigma-1)\,k_D\,\phi_S} \tag{26}$$

where k_D is the chargeable share of the dirty recipe's carbon. The factor $1+\nu$ arises because emissions scale with average cost, while the wedge is measured against marginal cost. Both expressions depend on the domestic shadow price p_C, so I solve for ε_G and τ jointly with p_C.

Indian firms already face a shadow price on carbon through levies on coal and fuel that pass into energy prices, but its level is not directly observed. I recover this price using the adoption response to CBAM's announcement. The reduced-form estimates show that EU-exposed firms increased their probability of adopting a clean recipe relative to unexposed firms following the announcement, before any charge was paid. Let $g_T(\tau; p_C)$ and $g_C(\tau; p_C)$ denote the shares adopting the clean recipe among baseline EU exporters and other firms, respectively. I choose the shadow price $\hat{p}_C$ to match the difference-in-differences estimate:

$$\left[g_T(\tau;\hat{p}_C) - g_T(0;\hat{p}_C)\right] - \left[g_C(\tau;\hat{p}_C) - g_C(0;\hat{p}_C)\right] = \hat{\beta}_{adopt} \tag{27}$$

A higher domestic shadow price raises energy costs for both recipes, but more so for the dirty one. It therefore induces adoption even without CBAM, leaving fewer firms whose adoption can be induced by the border charge.

The remaining parameter is the dispersion in switching costs. Each firm draws a cost $F_i = F f_i$, where $\ln f_i \sim N(0, s_F^2)$. This dispersion determines how closely adoption follows firm size. When $s_F = 0$, all firms face the same switching cost, such that adopters are the largest firms and account for the highest possible share of sales. As s_F increases, some smaller firms with lower switching costs adopt, while some larger firms with higher costs remain on the dirty recipe. The adopters' share of sales therefore falls toward their share of firms. I identify s_F by matching the adopters' share of total sales among EU exporters, v_G.

Estimation. I collect the sixteen internally calibrated parameters in $\vartheta = \{\vartheta_1, \vartheta_0, p_C, s_F\}$, where ϑ_1 contains the twelve parameters in (24) and $\vartheta_0 = \{\varepsilon_G, \tau\}$ contains the two parameters recovered conditional on p_C. All parameters in the first three groups of (23) are fixed before estimation. I recover the remaining sixteen through four nested steps, each requiring the previous ones to be solved. The procedure is as follows:

1. *The clean recipe and border charge.* Given a trial p_C, I solve (25) for ε_G and recover τ from (26).

2. *The twelve baseline parameters.* Holding p_C, s_F and ϑ_0 at their trial values, I adjust the twelve parameters according to the differences between their model-implied moments and the data, using the correspondence in (24). The equilibrium is re-solved until all twelve moments match. Since these moments describe the baseline economy, this step is carried out at $\tau = 0$.

3. *The shadow price.* For each trial p_C, I solve the first two steps and compute the adoption response at the anticipated border charge. If the model predicts a larger response than $\hat{\beta}_{adopt}$, I raise p_C; otherwise, I lower it. I repeat until the model reproduces the difference-in-differences estimate in (27).

4. *The dispersion of switching costs.* For each trial s_F, I solve the first three steps and compare the adopters' share of sales with its observed value. I adjust s_F until the two agree.

Since every wage is pinned by the outside good, the counterfactuals require no further step. The estimated switching cost is large relative to the cost of exporting. Therefore converting a plant costs several hundred

times as much per period as serving the EU, consistent with only 16.4% of EU exporters using the clean recipe at baseline. The estimated shadow carbon price is EUR 7.7 per tonne, and the dispersion of switching costs is $s_F = 1.76$.

Table 3: Parameters

Parameter	Interpretation	Source	Target	Value
		Panel A: External calibration		
σ	Substitution across varieties	Lashkaripour and Lugovskyy (2023), CBAM sectors		5.83
η	Substitution across origins	Lashkaripour and Lugovskyy (2023), same weights		4.24
ξ	Substitution, imports vs outside supply	Set equal to η, as in the trade-based CBAM literature		4.24
ν	Curvature of marginal cost	Almunia et al. (2021), elasticity of exports to dom. sales		1.19
		Panel B: Direct match to data		
ϕ_S	India's energy share of cost	ASI, energy bill over cost of production, CBAM industries		0.21
χ_G	Clean carbon released on site	Value-weighted Scope-1 share of clean recipe emissions		0.336
κ	Pareto tail of productivity	Hill index on the top quarter of ASI plant sales		0.609
p_G	Price of clean relative to dirty energy	Grid tariff over captive-coal cost per kWh		1.79
A_G	Clean energy advantage	ASI plant energy bills across production routes		1.97
N_S	Number of Indian plants	ASI registered plants, CBAM industries, FY2022–23		6,287
I_m	Market sizes, EU, IN, RV, TH (USD bn)	Covered-goods spending by market, 2022		583, 272, 2,644, 705
ϕ_R	Rivals' energy share of cost	CBAM default values by route, rival production mix		0.155
$\chi_{G,R}$	Rivals' clean carbon on site	As for India		0.336
δ_R	Rivals' clean-route intensity	India's measured intensity ratio		0.426
$p_{C,R}, c_R$	Rivals' carbon price; creditable part	Explicit carbon prices at origin, effective (EUR/t)		7.5, 2.8
ϕ_{EU}	EU producers' energy share of cost	ETS product benchmarks over production value		0.085
		Panel C: Internal calibration		
f_{EU}	Cost of exporting to the EU	Share of Indian plants exporting to the EU	$m_{EU} = 0.141$	242,560
F	Cost of switching recipe	Share of EU exporters on the clean recipe	$m_G = 0.164$	7.47×10^7
$f_{R,EU}$	Rivals' cost of entering the EU	Rivals' EU participation	$m_{R,EU} = 0.084$	5,806
F_R	Rivals' cost of switching recipe	Clean share of rivals' EU sales	$m_{G,R} = 0.347$	1.32×10^8
N_R	Number of rival firms	India's share of the rivals' markets	$s_{S,RV} = 0.007$	3.25×10^6
p^D_{EU}	EU outside price	India's share of EU spending	$s_{S,EU} = 0.015$	0.0749
$d_{R,EU}$	Rivals' EU shifter	Rivals' share of EU spending	$s_{R,EU} = 0.197$	0.0306
p^D_{IN}	Indian outside price	India's share of its home market	$s_{S,IN} = 0.872$	0.587
$d_{R,IN}$	Rivals' shifter in India	Rivals' share of India's market	$s_{R,IN} = 0.078$	1.88×10^{-5}
p^D_{RV}	Rivals' outside price	Rivals' share of their home markets	$s_{R,RV} = 0.950$	0.140
p^D_{TH}	Third-market outside price	India's share of third markets	$s_{S,TH} = 0.019$	0.0835
$d_{R,TH}$	Rivals' third-market shifter	Rivals' share of third markets	$s_{R,TH} = 0.394$	0.0659
ε_G	Clean-recipe emission factor	Intensity ratio at first adoption	$\delta = 0.426$	0.702
τ	Border charge per unit of carbon	Charge as a share of the import price	$\theta = 0.204$	3.24
p_C	Domestic shadow carbon price	Adoption response to the announced charge	$\hat{\beta}_{adopt} = 0.018$	EUR 7.7/t
s_F	Dispersion of switching costs	Adopters' share of EU exporters' sales	$v_G = 0.582$	1.76

Notes: This table presents the full parameter set of the model, grouped by how each element is determined. Panel A shows elasticities and the curvature of marginal cost set from the literature, Panel B parameters measured directly in the data, and Panel C parameters recovered by matching the model to the targeted moment shown. Fixed costs are in units of labor per period. The rivals' shifter in their own market is one by normalization, as are India's shifters in every market. The shadow price is converted to euros at the allowance price through the model's tonne conversion.

Validation. I assess the model against eight cross-sectional statistics not targeted in estimation, shown in Figure C.1. The model closely reproduces the size distribution of firms. The top 5% account for 67% of sales, against 67% in the data, while EU exporters are 5.6 times as large as the average firm, against 5.9 in the data. The fit is weaker for adoption, which is more strongly concentrated among larger firms in the model. The correlation between adoption and log sales is 0.45, against 0.28 in the data, while the adoption rate among the middle third of firms is 6%, against 16%. Overall, four of the eight statistics fall within the data's tolerance.

The central test of the model is whether it reproduces how exposed firms responded to the charge they anticipated. For each firm, I sum exports over 2022 and over the last four quarters, from 2025Q2 to 2026Q1, and estimate the difference in changes between exposed and unexposed firms, controlling for industry, state and size-decile effects. I then solve the model at zero charge and at the anticipated charge, and compute the same estimands on the simulated firms. Figure C.2 compares the results for export quantities and values, both to the EU and elsewhere.

On EU sales, the model does well. Exposed firms reduce EU quantities relative to unexposed firms by a similar amount in the data and in the model. EU export values fall by less in the data than in the model, although the model prediction falls within the confidence interval. Outside the EU, both the data and the model show a small increase in exposed firms' sales relative to unexposed firms. Both increases are small relative to the contraction in EU sales.

The contribution of CBAM. The EU is introducing two changes at once, namely CBAM and the phase-out of free allowances for its own producers. When taking the model to the data, I compare three worlds. The *baseline* is the base year, before either change. In the *phase-out only* world, EU producers lose their free allocation and pay the full allowance price, but no border charge is levied, $\varpi_T = \varpi_{TH} = 0$. Under *full CBAM*, both changes apply. Writing X^B, X^P, and X^C for any equilibrium outcome in the three worlds, I define CBAM's contribution as:

$$\Delta^C X \equiv X^C - X^P = \left(X^C - X^B\right) - \left(X^P - X^B\right) \tag{28}$$

The comparison isolates what the border charge adds to a phase-out that would take place under the *EU ETS* even without it and the baseline cancels. I use the same comparison in every counterfactual, either after shutting down a margin or changing a parameter, or when replacing the border charge with another instrument or introducing one alongside it (Appendix C.3). The model yields four main findings.

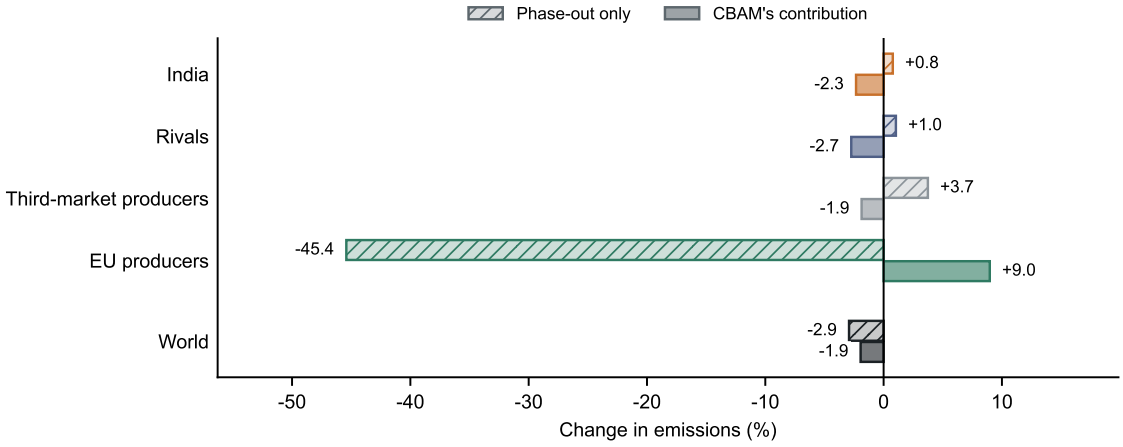
6.B The impact of the border charge on emissions

First, CBAM reduces global emissions through reductions outside the EU, at a low cost per tonne. Figure 18 separates the effect of the full package relative to the 2022 baseline into the phase-out and the border charge. On its own, the phase-out reduces global emissions by 2.9%. EU producers' emissions fall by 45.4%, but foreign emissions rise by 1.5% in total, as foreign suppliers take over part of the EU market and India's EU market share rises by 22%. The border charge reverses this leakage. Relative to the phase-out-only world, CBAM reduces global emissions by a further 1.9%. India's emissions fall by 2.3%, the rivals' by 2.7%, and third-market producers' by 1.9%. EU producers, by contrast, emit 9.0% more than under the phase-out alone, as the border charge helps them retain market share. The global reduction therefore comes from abroad, with the foreign emissions cuts more than offsetting the increase inside the EU. The charge implies a break-even social cost of carbon of USD 11 per tonne. This is well below both the 2021 US interagency estimate of USD 51 (Interagency Working Group on Social Cost of Greenhouse Gases, 2021) and the 2023 EPA central estimate of USD 190 (U.S. Environmental Protection Agency, 2023).

6.C Decomposing the channels

Second, the reduction comes primarily from how foreign suppliers produce, as opposed to how much they sell. Figure 19 decomposes CBAM's contribution to emissions across India and the rivals' sales to the EU and other markets, EU producers' domestic and export sales, and third-market producers. Each change is expressed as a percentage of emissions under the phase-out alone. Within each ledger, I distinguish five channels. *Composition* captures the volume of goods entering or leaving a market at unchanged emissions intensity, while *Market size* captures changes in the size of the destination market. *Scale* captures the effect of the border wedge, which raises the price per tonne and reduces the output purchased per euro of spending, holding the recipe fixed. The remaining two channels concern changes in production. *Recipe switch* measures

Figure 18: The phase-out and CBAM's contribution



Notes: Percentage change in each producer's emissions in the covered sectors. Phase-out only: the end of EU free allocation with no border charge, against the 2022 baseline. CBAM's contribution: full CBAM against the phase-out only, as a percentage of the producer's emissions under the phase-out only. *Source:* model at the estimated parameters of Table 3.

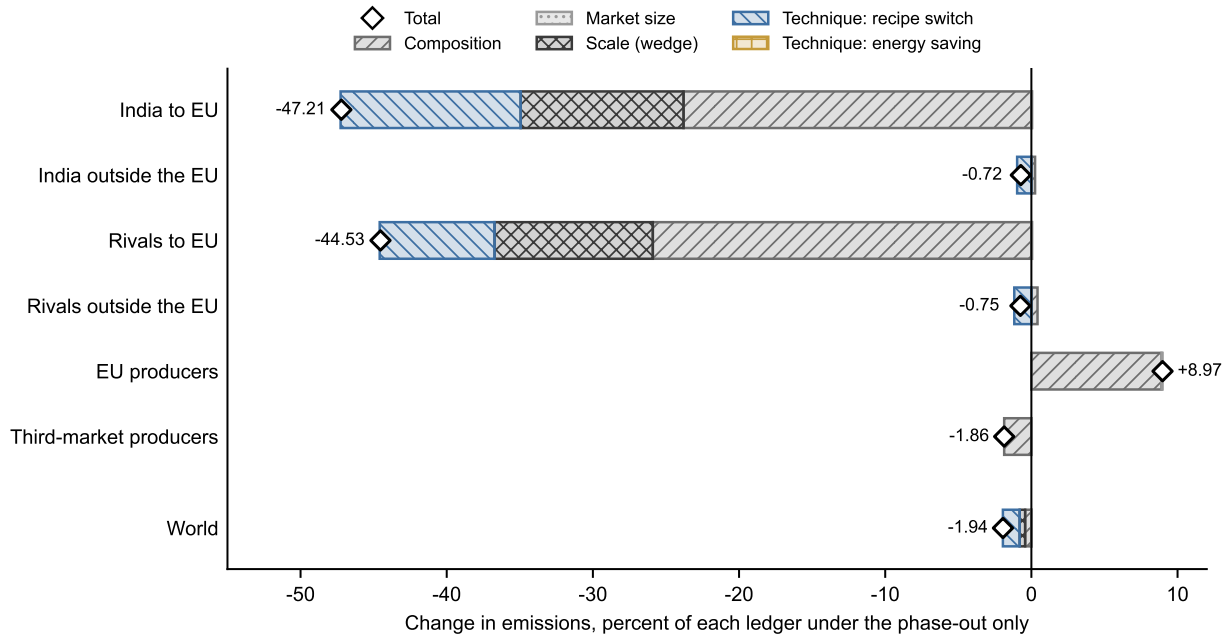
the emissions saved when a supplier moves from the dirty to the clean recipe, while *Energy saving* captures reductions in energy use within a given recipe as energy becomes more expensive. The five channels sum to the exact change in emissions, shown by the diamonds.

The largest proportional reductions occur on sales to the EU. India's EU ledger falls by 47.2% and the rivals' by 44.5%. For the rivals, composition accounts for 25.9 percentage points of the fall, the border wedge for 10.8 and recipe switching for 7.9. Yet India's EU ledger accounts for only 0.3% of global emissions, so even this large reduction lowers global emissions by just 0.13%. The largest contribution comes instead from the rivals' sales to the EU, which reduce global emissions by 1.42%. The rivals' sales outside the EU come next. Emissions on these sales fall by only 0.8%, however given that the market is much larger, this reduces global emissions by 0.50%.

This reduction occurs despite no border charge applying to these sales. Recipe switching lowers the rivals' non-EU emissions by 1.2 percentage points, partly offset by a 0.4-point increase from composition as sales diverted from the EU enter other markets. The reason is that a recipe is a property of the plant, so a supplier that adopts to serve the EU more cleanly also reduces emissions from the output it sells elsewhere. India's non-EU sales show the same pattern on a smaller scale, with recipe switching reducing emissions by 1.0 percentage point and composition adding 0.3 points. Third-market producers' emissions fall by 1.9% as redirected Southern goods displace their output, while EU producers' emissions rise by 9.0% as they regain market share. Globally, recipe switching accounts for 59% of CBAM's emissions reduction, or 1.15 percentage points of the 1.9% fall, compared with 0.43 points from composition and 0.38 from the border wedge.

Figure 20 reports two measures of carbon leakage. The first, Southern leakage, measures the change in emissions from India's and the rivals' non-EU sales per tonne of emissions reduced on their EU sales, both measured as CBAM's contribution. The second, production leakage, measures the change in emissions of all producers outside the EU per tonne of emissions reduced by EU producers. Since the border charge increases EU producers' emissions relative to the phase-out alone, I calculate production leakage for the phase-out and the full package separately, each relative to the 2022 baseline.

Figure 19: Breakdown of emissions, CBAM's contribution



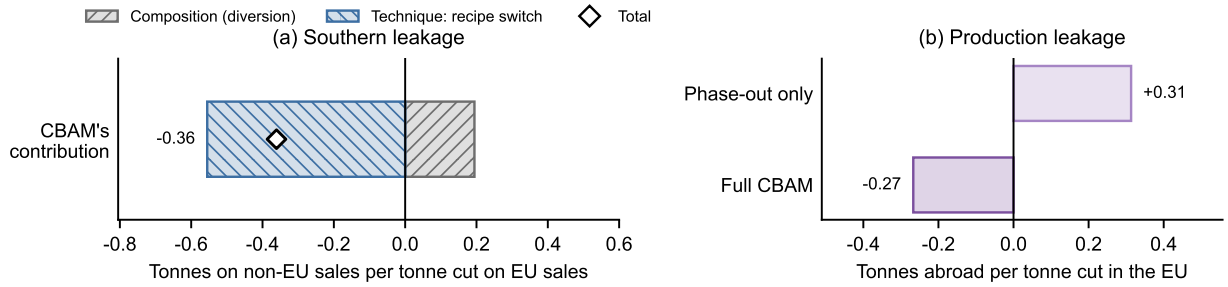
Notes: Each bar is the change in one ledger's emissions, full CBAM against the phase-out only, as a percentage of that ledger's level under the phase-out only. The five channels come from an exact logarithmic-mean decomposition, scaled to the percentage change, and sum to the total, marked by the diamond. Scale is the border wedge and so arises only on EU legs. No producer's carbon price changes between the two worlds, so energy saving is zero. *Source:* model at the estimated parameters of Table 3.

Southern leakage from the border charge is -0.36, meaning that emissions on the South's non-EU sales fall by 0.36 tonnes for every tonne removed from its EU sales. Trade diversion contributes positively to leakage, at 0.19, as emissions displaced from the EU reappear in other markets, where firms whose EU sales contract sell more at a lower marginal cost. However, the technique spillover is -0.56, three times as large and opposite in sign, as firms that adopt cleaner recipes to serve the EU also use them for production sold elsewhere. Relative to global emissions, diversion adds 0.30% outside the EU, while the technique spillover removes 0.86%. Production leakage follows the same pattern, falling from 0.31 under the phase-out alone to -0.27 under the full package. The border charge therefore more than offsets the leakage caused by the phase-out, with plant-wide adoption accounting for the reversal.

To examine how much this result depends on the model's assumptions, I consider two extensions, each re-estimated to match the same moments. The first extension allows firms to convert only the production line serving the EU, at one tenth of the cost of converting the entire plant. Since the two lines are separable only with constant marginal costs, this extension keeps marginal cost constant. The second extension keeps plant-wide adoption but makes marginal cost constant in output. The first requires a higher shadow carbon price to match the observed adoption response, EUR 13.8, and the second a lower one, EUR 3.3, compared with EUR 7.7 in the baseline, while implying switching-cost dispersions of 2.15 and 1.92. The three models perform similarly on moments not targeted in estimation. The constant-cost model predicts a 0.2% increase in exposed firms' non-EU sales, compared with 1.5% in the baseline. Figure 21 compares CBAM's contribution across the three.

Allowing firms to adopt only on their EU production line changes the results substantially. CBAM's contribution falls from 1.9% to 1.3% of global emissions, a 32% smaller reduction, while its break-even carbon

Figure 20: Leakage



Notes: Panel (a): Southern leakage of CBAM's contribution, the change in India's and the rivals' emissions on their non-EU sales per tonne of the fall in their emissions on EU sales, full CBAM against the phase-out only. Diversion is the composition channel of Figure 19 on the Southern non-EU ledgers, and the technique spillover their recipe-switch channel. Panel (b): production leakage, the change in the emissions of India, the rivals and third-market producers per tonne of the fall in EU producers' emissions, each against the 2022 baseline. A negative value means emissions outside the EU fall. *Source:* model at the estimated parameters of Table 3.

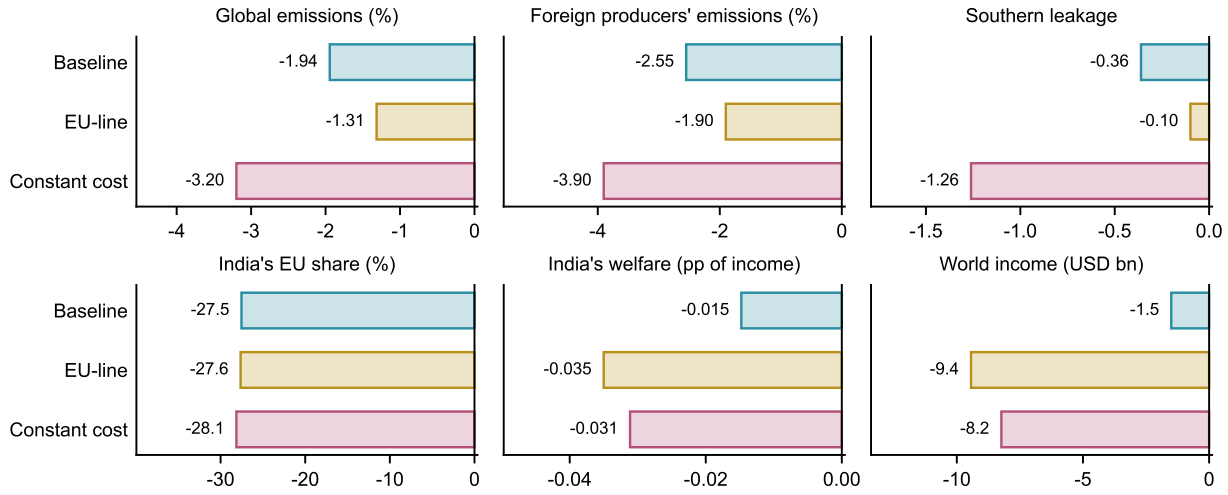
price rises from USD 11 to USD 98 per tonne. Against the constant-cost model, whose cost structure it shares, the reduction is 59% smaller, 1.3% against 3.2%. Southern leakage shrinks from -0.36 to -0.10, so emissions on India's and the rivals' sales outside the EU barely fall. Trade diversion disappears since with constant marginal costs a firm's markets are no longer linked through its cost (Figure C.8). The main difference comes from the technique spillover, which falls from -0.56 to -0.10, as firms that clean their EU production lines continue to produce with the dirty recipe for other markets. As a result, the rivals' non-EU emissions fall by only 0.2%, against 0.8% in the baseline. Figures C.9 and C.10 of the Appendix report the full emissions decompositions for both extensions.

Constant marginal costs raise the gains from CBAM without reversing the results. Global emissions fall by 3.2%, at a break-even price of USD 35 per tonne, while Southern leakage is -1.26. With constant marginal costs, adopting a cheaper recipe leads to a larger expansion in output, raising the return to switching and leading more large firms to adopt. At the same time, diversion vanishes, at 0.01, and the spillover grows to -1.27. The scope of adoption therefore matters more for the emissions results than the cost of expanding production. CBAM's ability to reduce emissions outside the EU rests largely on whether firms adopt cleaner technologies for the entire plant or only for production destined for the EU.

6.D CBAM compared to a conventional tariff

The incentive to adopt cleaner technologies distinguishes CBAM from a conventional tariff. I replace the border charge with a tariff on Southern goods that raises the same revenue, holding the phase-out in place. The tariff reduces India's EU market share by 19%, compared with 28% under CBAM, and cuts global emissions by only 0.5%, against 1.9% under CBAM. It raises world income by USD 0.2 billion, against a loss of USD 1.5 billion under CBAM. Unlike CBAM, a conventional tariff raises the cost of exporting regardless of the supplier's recipe, without rewarding cleaner production. The clean-recipe share among India's EU exporters is therefore only 17%, against 35% under CBAM, while Southern leakage is positive at 0.25. Figure C.6 compares CBAM with the remaining policy alternatives.

Figure 21: CBAM's contribution in the three models



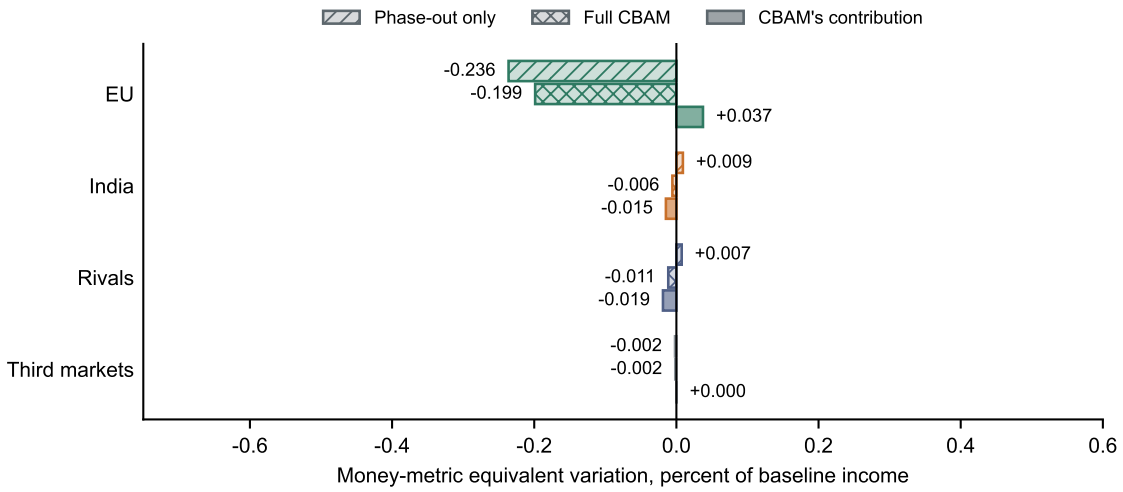
Notes: Each model is re-estimated on the same targets, and CBAM's contribution is full CBAM against the phase-out only in that model. EU-line: firms may convert only the line serving the EU, at a tenth of the plant-wide cost, with constant marginal cost. Constant cost: marginal cost does not rise with output. Outcomes as in Figure C.4. *Source:* model at the estimated parameters of each version.

6.E Cost and responses for India

India bears a cost from CBAM through the loss of EU market share, which cleaner technology adoption helps mitigate. Figure 22 reports each region's money-metric equivalent variation as a percentage of baseline income, for the phase-out alone, for full CBAM, and for CBAM's contribution, the difference between the two. The phase-out alone benefits foreign suppliers. As EU production becomes costlier and loses market share to imports, India gains 0.009% of its baseline income and the rivals 0.007%, while the EU loses 0.24%. The border charge reverses these gains. Relative to the phase-out alone, CBAM costs India 0.015 percentage points of income and the rivals 0.019, while India's EU market share falls by 28%. The EU instead gains 0.037 points through border revenue and the protection of its producers. Relative to the 2022 baseline, the full package leaves India almost unaffected, as the gain from the phase-out and the loss from the border charge nearly cancel.

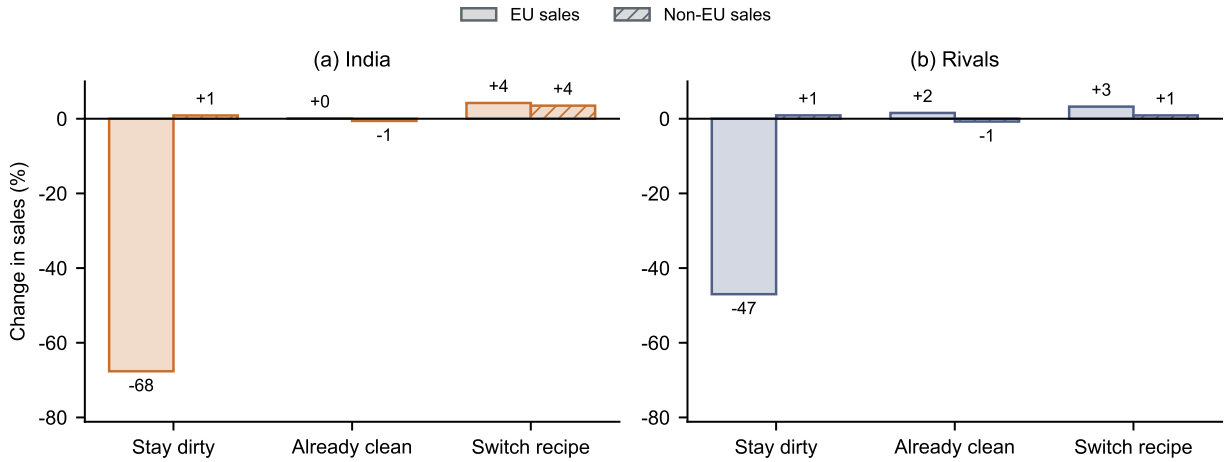
These costs are not borne equally across Indian firms. Figure 23 separates those that remain on the dirty recipe, those already using the clean one, and those that switch in response to the border charge. In India, the firms that stay dirty are 96.3 percent of firms but 41 percent of EU sales. Their EU sales fall 68%, and 64 percent of them stop exporting to the EU. The firms already on the clean recipe hold 57 percent of India's EU sales and barely move, because the charge on a clean plant is small. The 0.27 percent of firms that switch raise their sales by 4% in the EU and 4% outside it. A firm that converts its plant to keep its EU market produces every tonne on the new recipe, including the tonnes it ships to other markets, and the clean recipe is cheaper per useful unit of energy before any charge is levied. The rivals' response is carried by a handful of very large plants: 0.01 percent of rival firms are clean or become clean, and they hold 37 percent of rival EU sales, while the rivals' dirty exporters' EU sales fall 47%. Among India's EU exporters, adoption rises from 15 percent under the phase-out alone to 35 percent, and the clean share of the rivals' EU sales from 34 to 53 percent. Adoption is what limits India's loss. If Indian firms could not adopt, India's EU share would fall 51%, and its loss would double, from 0.015 to 0.030 percentage points of income, while the global reduction would barely change.

Figure 22: Welfare



Notes: Money-metric equivalent variation as a percentage of each region's baseline income. Every denominator is whole-economy income. CBAM's contribution is full CBAM minus the phase-out only. Border revenue is rebated to EU households and is inside the EU figure. *Source:* model at the estimated parameters of Table 3.

Figure 23: Responses of firms by technology decision, CBAM's contribution



Notes: All bars are percentage changes, full CBAM against the phase-out only. Firms are grouped by what they do: stay dirty if they remain on the dirty recipe, already clean if they had adopted under the phase-out alone, and switch recipe if the border charge is what makes them adopt. Each bar is the change in the group's total sales to the EU (solid) and outside it (hatched), including firms that leave the EU. *Source:* model at the estimated parameters of Table 3.

The alternatives open to India have similar implications. Pricing carbon at home at EUR 25 instead of the border charge costs India 0.80 percentage points of income, against 0.015 with the border charge, as a domestic price falls on all of India's output while the charge falls only on what it ships to the EU. This holds at every price between EUR 10 and EUR 85 (Figure C.7). In contrast, a program that raises the efficiency of India's clean recipe by 27 percent, alongside the border charge, raises India's welfare by 0.12 percentage points, lifts adoption among its EU exporters to 50 percent and raises the reduction to 2.4% of global emissions.

7 Concluding remarks

This paper asks whether conditioning access to a major market on the carbon content of production can affect how suppliers abroad produce. I study the EU's CBAM in the context of Indian exporters of covered goods, combining firm-to-firm customs records with administrative and capital-investment data, and classifying 60,000 investment projects into *green*, *transitional* and *vintage* technologies using a Large Language Model. Exposed suppliers respond on several margins. They expand their stock of *green* capital, mostly by upgrading existing production processes instead of installing renewable or carbon-capture capacity, with the response concentrated among firms starting from a dirtier asset base. They substitute purchased grid electricity for their own fossil-based generation, while total energy spending remains unchanged. They also divert covered exports away from the EU, but diversion recovers only about a fifth of the lost EU sales. These responses vary with exposure. Firms with the most at stake in the EU invest to preserve market access, while those with less at stake sell elsewhere. Prices at the Indian border remain unchanged during the *transitional phase*, suggesting no adjustment in export prices in anticipation of the charge.

To move from these responses to emissions and welfare, I build and estimate a four-market model of trade and technology adoption in the spirit of Melitz (2003) and Bustos (2011). Heterogeneous suppliers in India and its competitor countries choose whether to serve the EU and whether to adopt a cleaner technology, with adoption affecting production throughout the plant. Following Almunia et al. (2021), marginal costs rise with output, linking each supplier's sales across markets. Estimated on pre-policy market shares, export participation and the adoption response to the announcement, the model reproduces the trade responses it was not asked to match. Measured against the phase-out of free allowances alone, CBAM reduces global emissions in the covered industries by 1.9%, at an implied cost of USD 11 per tonne, with reductions abroad more than offsetting an increase inside the EU. The reduction comes from how foreign suppliers produce. A supplier that upgrades to keep its EU buyers also cleans the output it sells in markets where carbon is not priced. This spillover outweighs the diversion of dirty output, making leakage negative. A conventional tariff raising the same revenue achieves only a quarter of the emissions reduction, as it penalizes exporting without rewarding cleaner production. India bears the cost mainly through lost EU market share, which adoption helps mitigate. A domestic carbon price would cost India more, while making clean technology more efficient would both reduce emissions further and raise India's income.

The main takeaway relates to the design choices that render cross-border regulation effective. The environmental value of a border charge depends on whether the upgrading it induces extends beyond the regulated destination. When adoption is confined to production destined for the EU, the emissions reduction is a third smaller and emissions on foreign suppliers' sales elsewhere barely fall. Whether upgrading is a decision about the plant or about the production line is therefore central to evaluating CBAM. The evidence here shows that investment in core production processes is consistent with plant-wide upgrading. The same

question extends to due diligence and deforestation regulations that condition market access on how goods are produced. The reduced-form estimates cover the *transitional phase*, when firms reported emissions but paid nothing, responding instead to a charge they anticipated. Whether exporters begin to bear part of the cost once certificates are surrendered, and whether adoption keeps pace as free allowances are withdrawn, remain questions for the *definitive phase*.

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A Appendix

A.1 The CBAM Cost Formula

CBAM prices the emissions embedded in imports of covered goods. Consider a firm i located in the EU that imports products $k \in \mathcal{K}$ from supplier j in country c at time t. The firm's total CBAM liability is

$$\text{Cost}_{i,t} = \sum_{j} \sum_{k \in \mathcal{K}} \underbrace{Q_{kijc,t}}_{\substack{\text{Quantity} \\ \text{imported}}} \max\Big\{ \underbrace{e^{\text{emb}}_{kjc,t}}_{\substack{\text{Embedded} \\ \text{emissions}}} - \underbrace{B_k}_{\substack{\text{ETS product} \\ \text{benchmark}}} \big(1 - \underbrace{\lambda_t}_{\substack{\text{Phase-in} \\ \text{factor}}}\big) - \underbrace{e^{\text{priced}}_{kc,t}}_{\substack{\text{Emissions} \\ \text{priced abroad}}}, 0 \Big\} \underbrace{P^{\text{ETS}}_t}_{\substack{\text{EU ETS} \\ \text{price}}} \tag{29}$$

Deductions. Importers surrender certificates only for emissions in excess of the EU-efficient product benchmark B_k, and receive a further credit $e^{\text{priced}}_{kc,t}$ for emissions already covered by an explicit carbon price in the country of origin. A supplier whose emission intensity is at or below the benchmark net of foreign carbon pricing therefore faces no border charge at all, which is the role of the $\max\{\cdot, 0\}$ operator.

Phase-in factor. The benchmark deduction is scaled by $(1 - \lambda_t)$ and shrinks over time in step with the phase-out of free allocation to EU producers under the *ETS*. The phase-in factor rises from $\lambda_t = 2.5\%$ in 2026 to $\lambda_t = 100\%$ in 2034, at which point the benchmark deduction vanishes and importers pay the full *ETS* price on all embedded emissions not already priced abroad.

Omnibus simplification. Starting in 2025, the scope of the mechanism was narrowed along two dimensions. A *de minimis* threshold exempts importers with covered sales below 50 tonnes per year, and the sale of CBAM certificates was deferred to February 2027. Both provisions delay and attenuate the effective cost in (29) relative to its statutory form, and the threshold in particular removes a large mass of small importers from the regulated population.

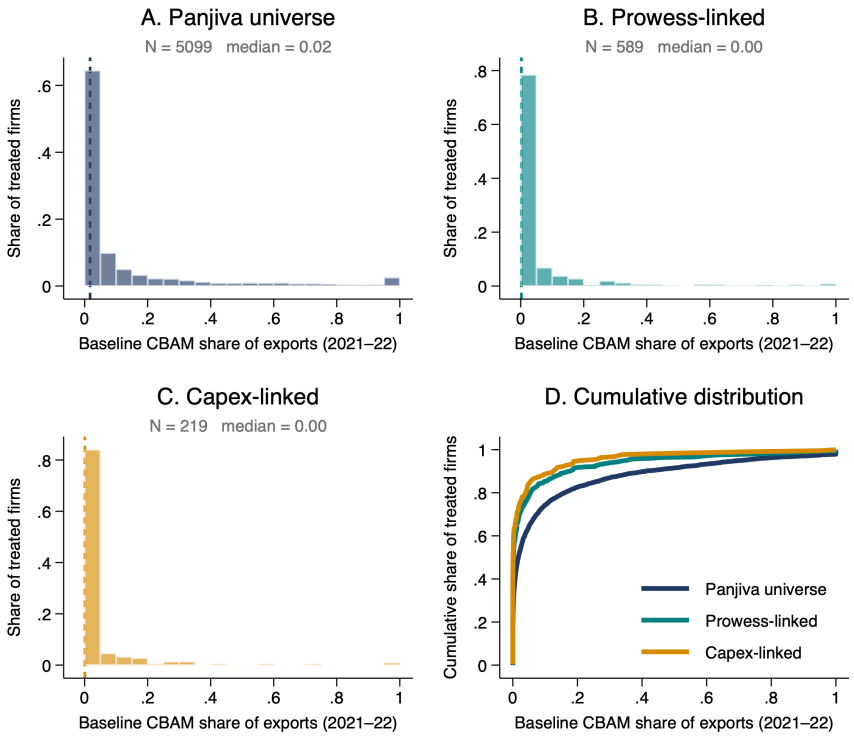
Downstream products. Coverage was initially limited to basic materials and did not extend to goods that embody them further down the value chain (for example, aluminum ingot and aluminum sheet are covered, but an aluminum car door is not). This creates scope for resource shuffling toward downstream stages. In 2025, downstream products were proposed for inclusion starting in 2028.

A.2 Treatment descriptives

This appendix documents the treated population in the three datasets used in the paper. Treatment is fixed throughout, with a firm being treated if its average 2021-22 exports of CBAM-covered goods to the EU are positive, and its exposure being the share of those exports in its total exports over the same window. Layer A is the *Panjiva* universe of 206,251 Indian exporters active in 2021-22, of which 5,099 are treated. Layer B is the 31,910 firms in the *ProwessDx* estimation sample with a FY2022 annual statement, of which 589 are treated. Layer C is the 3,085 Layer B firms that appear in the *CapexDx* investment panel, of which 219 are treated.

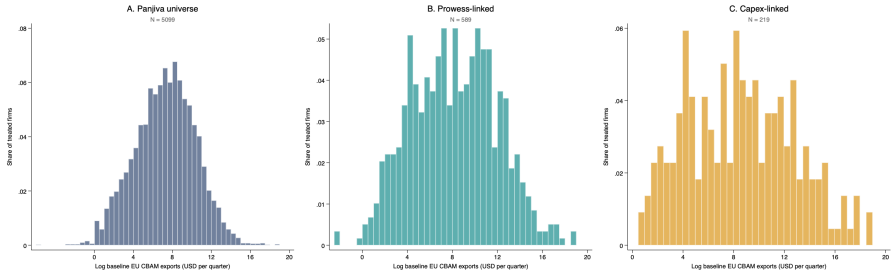
Exposure. Figure A.1(A)-(C) shows the distribution of exposure in each layer and Figure A.1(D) overlays the cumulative distributions. In the universe, 65 percent of treated firms have a share below 5 percent and 3 percent have a share above 0.9. The mass at one is firms that ship nothing but covered goods and only to the EU. Selection into the matched samples removes the upper tail. The share exceeds one half for 8.5 percent of treated exporters, 3.6 percent of *ProwessDx*-linked firms and 1.8 percent of *CapexDx*-linked firms, because large diversified firms are the ones that file statements. Figure A.2 shows that the level of covered EU exports is, by contrast, well spread across all three layers, so the thin shares of matched firms reflect large denominators.

Figure A.1: Distribution of exposure across datasets



Notes: Histograms of the baseline CBAM share among treated firms in bins of width 0.05; dashed lines mark medians. Panels A–C show *Panjiva*, *Prowess*, and *Capex* datasets. Panel D overlays the three cumulative distributions. *Source*: Statistics based on data from *Panjiva*, *CapexDx*, and *ProwessDx* databases.

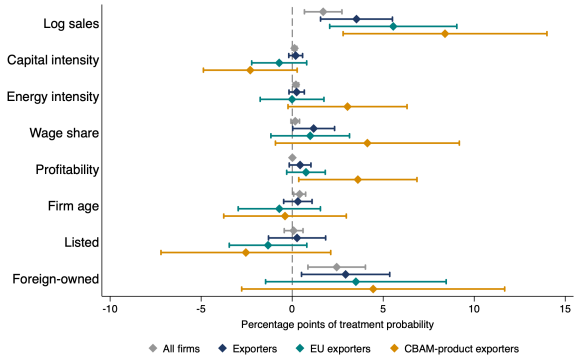
Figure A.2: Distribution of baseline EU exports of covered goods



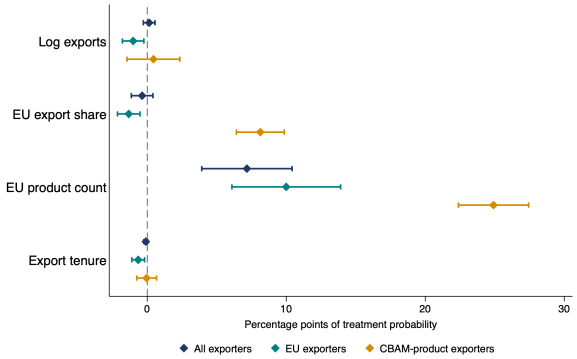
Notes: Log of average quarterly EU exports of CBAM-covered goods over 2021-22, in USD, among treated firms. *Source*: Estimates based on data from *CapexDx* and *ProwessDx* databases.

Figure A.3: Predictors of treatment

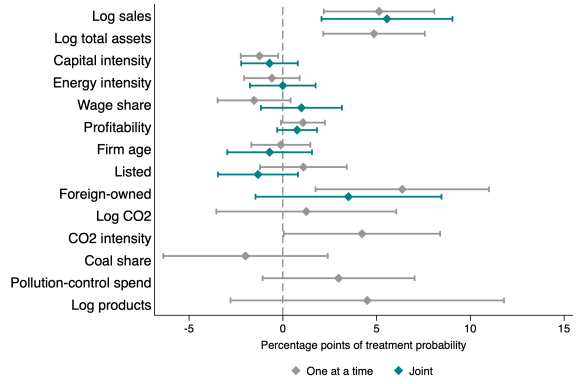
(a) Predictors of treatment within groups, *ProwessDx*



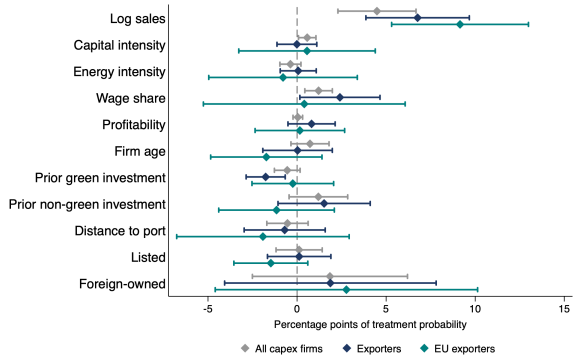
(b) Predictors of treatment in the exporter universe



(c) Univariate and joint predictors among EU exporters



(d) Predictors of treatment in the investment panel



Notes: Each panel presents linear probability models of treatment, in percentage points, on pre-period firm characteristics, with industry and state fixed effects and standard errors clustered by industry. Continuous characteristics are standardized within each sample. Panels (a), (c) and (d) use *ProwessDx* firms, panel (b) the *Panjiva* universe. Series within a panel correspond to progressively tighter comparison groups, from all firms to exporters of CBAM-covered goods. Bars are 95 percent confidence intervals.

Predictors of treatment. Given that treatment is defined by shipping covered goods to the EU, the informative question is which EU exporters, or which exporters of covered goods, are treated. Figure A.3(a) regresses

treatment on FY2022 characteristics within progressively tighter comparison groups in the *ProwessDx* sample. Within EU exporters, a one standard deviation increase in log sales raises the probability of treatment by 5.5 percentage points. Energy intensity, capital intensity, profitability, age, listing status and ownership do not predict it. Figure A.3(b) repeats the exercise in the exporter universe with the trade-side covariates available for every firm. Within EU exporters, the number of HS6 products shipped to the EU raises treatment probability by 10 percentage points per standard deviation, while export value, the EU share of exports and export tenure are flat or slightly negative. Figure A.3(c) adds the sparse *ProwessDx* covariates, estimated one at a time on their own sample. Emissions, emission intensity, coal share, pollution-control spending and product count are all indistinguishable from zero. Figure A.3(d) adds the stock of green and non-green investment announced to end-2021 and distance to the nearest port. Prior green investment does not predict treatment within EU exporters.

Balance. Tables A.1 and A.2 compare treated and untreated firms within the EU-exporter group. The normalized difference exceeds 0.25 only for size (0.43 on log sales), foreign ownership (0.34) and the number of products shipped to Europe (0.67). On capital intensity, energy intensity, wage share, profitability, age and listing it is below 0.13. The joint tests reject, driven by size, which is why the estimation absorbs baseline size interacted with year.

Table A.1: Balance within EU exporters in *ProwessDx* FY2022

	Treated	Untreated	Diff.	Norm. diff.	p	N
Log sales	4.368	3.560	0.808	0.43	0.000	2447
Log total assets	4.280	3.512	0.768	0.40	0.000	2467
Capital intensity	0.282	0.532	-0.250	-0.08	0.042	2436
Energy intensity	0.037	0.042	-0.005	-0.08	0.499	2327
Wage share	0.111	0.137	-0.026	-0.07	0.198	2440
Profitability	0.139	0.183	-0.045	-0.03	0.334	2447
Firm age	29.825	30.293	-0.468	-0.03	0.672	2469
Listed	0.215	0.232	-0.017	-0.04	0.507	2469
Foreign-owned	0.225	0.103	0.123	0.34	0.024	2469
Government-owned	0.009	0.009	-0.000	-0.00	0.938	2469
Pollution-control spend	0.040	0.069	-0.029	-0.13	0.045	2464
Joint F (all covariates, industry FE)			15.40		0.000	2315

Notes: Means by treatment status. Difference is the raw difference, while Normalized difference is the difference divided by the pooled standard deviation. p is from a regression of the covariate on treatment with standard errors clustered by industry. The joint F tests all standardized covariates in a regression of treatment with industry fixed effects.

Table A.2: Balance within EU exporters in *Panjiva*

	Treated	Untreated	Diff.	Norm. diff.	p	N
Log exports	12.206	11.517	0.689	0.28	0.002	35638
EU export share	0.288	0.270	0.018	0.06	0.384	35638
EU product count	1.914	1.247	0.667	0.67	0.000	35638
Export tenure	3.082	2.752	0.330	0.16	0.000	35638
Joint F (all covariates, industry FE)			12.79		0.000	35636

Notes: Means by treatment status. Difference is the raw difference, while Normalized difference is the difference divided by the pooled standard deviation. p is from a regression of the covariate on treatment with standard errors clustered by industry. The joint F tests all standardized covariates in a regression of treatment with industry fixed effects.

A.3 *Green* project classification

Table A.3: Classified *green* investment projects

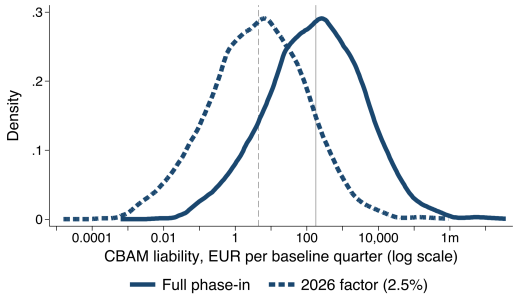
	Projects	Projects per firm-year				Investment per firm-year (USD m)			
		Mean	SD	Min	Max	Mean	SD	Min	Max
Panel A: Projects by type of technology									
Total	68,107	1.2	1.2	1.0	94.8	55.5	357.1	0.0	17,266.0
Green	12,865	1.2	0.9	1.0	19.3	123.7	455.7	0.1	12,631.6
Transitional	671	1.1	0.3	1.0	4.0	92.5	271.9	0.2	2,700.0
Vintage	55,822	1.2	1.1	1.0	86.5	43.8	348.0	0.0	17,266.0
Panel B: Green and transitional projects by industry									
Industries potentially affected by CBAM									
Renewable electricity	4,764	1.3	0.9	1.0	15.0	80.5	145.6	0.1	1,535.6
Organic chemicals	696	1.0	0.2	1.0	2.0	26.4	50.8	0.1	741.5
Steel	404	1.0	0.2	1.0	3.0	83.6	304.6	0.2	2,700.0
Electricity transmission	324	1.1	0.6	1.0	7.3	297.3	401.7	0.3	2,911.8
Cement	309	1.2	0.6	1.0	3.8	94.1	90.2	0.2	360.0
Conventional electricity	265	1.4	0.9	1.0	7.0	452.0	596.5	2.7	2,106.1
Electricity distribution	154	2.5	2.2	1.0	8.3	43.6	28.4	15.9	72.7
Sponge iron	153	1.0	0.1	1.0	2.0	58.5	67.4	3.0	397.2
Minerals	42	1.1	0.4	1.0	3.0	40.9	47.2	1.1	93.1
Fertilisers	24	1.4	0.9	1.0	3.3	375.9	694.7	18.1	1,418.0
Aluminium & aluminium products	22	1.2	0.4	1.0	2.0	22.5	18.2	1.5	48.8
Other ferrous metal products	13	1.0	0.0	1.0	1.0	22.1	16.3	0.5	39.9
Boilers & turbines	11	1.1	0.3	1.0	2.0	67.6	51.3	9.3	106.2
Other	12	1.1	0.3	1.0	2.0	166.5	182.1	5.4	364.1
CBAM-affected (subtotal)	7,193	1.2	0.8	1.0	15.0	90.7	192.9	0.1	2,911.8
Other industries									
Railway transport infrastructure services	1,672	2.2	2.6	1.0	18.1	832.0	1,096.9	7.9	5,343.7
Housing construction	628	1.2	1.1	1.0	17.8	111.7	1,155.3	0.2	15,152.0
Transport logistics services	536	1.6	2.9	1.0	27.8	332.0	1,561.9	1.0	9,415.8
Drugs & pharmaceuticals	446	1.0	0.2	1.0	3.5	55.9	369.7	0.1	4,050.0
Inorganic chemicals	267	1.1	0.3	1.0	3.0	669.6	1,515.1	0.5	7,918.7
Other electronics	253	1.2	0.4	1.0	4.0	367.5	922.1	0.4	5,110.1
Shipping transport infrastructure services	193	1.8	3.3	1.0	21.2	70.8	133.4	2.3	649.1
Sugar	187	1.0	0.2	1.0	3.0	29.1	21.7	1.7	99.3
Road transport infrastructure services	121	1.3	1.5	1.0	10.0	241.9	251.7	2.0	1,283.8
Alcoholic beverages	110	1.0	0.1	1.0	2.0	19.9	21.2	1.9	101.7
Other	1,259	1.1	0.4	1.0	5.0	207.0	800.6	0.2	10,853.8
All green and transitional	12,865	1.2	0.9	1.0	19.3	123.7	455.7	0.1	12,631.6

Notes: The table presents descriptive statistics on classified *CapexDx* projects announced between 2013 and 2025 and classified against the taxonomy. Panel A splits projects by the technologies they are mapped to: *green* projects are those classified as *green* in the main analysis, transitional projects match at least one transition-tier technology, and vintage projects match a conventional technology or none at all. Categories overlap because a project may match technologies of several tiers simultaneously, so rows need not sum to the total. The per-firm-year statistics divide each firm's projects by the number of years the firm is active, and report the mean, standard deviation, minimum and maximum across firms. Investment is the project cost deflated to 2020 USD, counted only for projects under implementation or completed (not those just announced). Panel B reports all *green* and transitional projects of Panel A by the firm's industry (projects in both categories counted once). Industries potentially affected by CBAM are listed individually with a subtotal. Those with fewer than ten projects in the panel are pooled. Remaining industries show the ten largest by project count, with the rest collapsed into "Other". *Source: CapexDx* database and own classification.

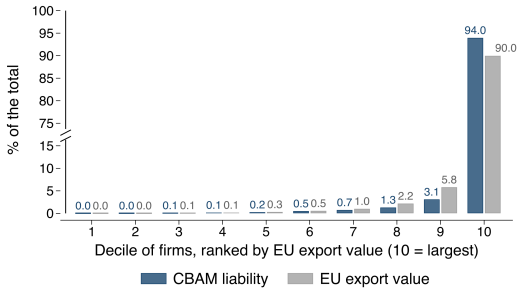
A.4 Liability and trade descriptives

Figure A.4: The ex-ante CBAM liability of exposed firms

(a) Distribution of the liability



(b) Aggregate liability by exporter size



Notes: Panel (a) presents kernel densities of the liability in euros per quarter on a log scale, at full phase-in (solid) and at the 2026 factor of 2.5 percent (dashed). Thin grey lines mark the medians. Panel (b) ranks firms by average quarterly EU exports and divides them into deciles. Bars give each decile's share of the aggregate full phase-in liability and of the group's EU export value, labeled with their values. The vertical axis is cut between 15 and 75 percent. *Source: Panjiva* shipment records and the European Commission's *Default Values for the Transitional Period of the CBAM*.

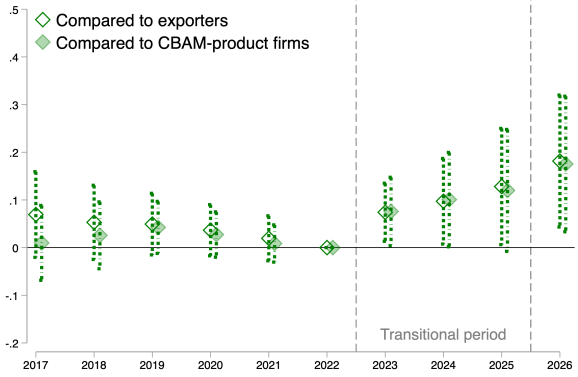
Table A.4: Length of trade relationships

Exporter-buyer pairs observed in	Share of pairs (%)	Share of value (%)
One year only	72.9	22.7
Two years	16.4	21.8
Three or more years	10.7	55.6
of which five or more	2.5	28.9
Years observed, median / p90	1.0 / 3.0	
Pairs	4,968,002	

Notes: Exporter-buyer pairs in the *Panjiva* exporter-consignee-HS6 panel, 2016-2022, classified by the number of distinct years in which the pair is observed trading. Share of value is the share of total export value over the window carried by the pairs in each class. *Source: Panjiva* database.

A.5 *Green* upgrading

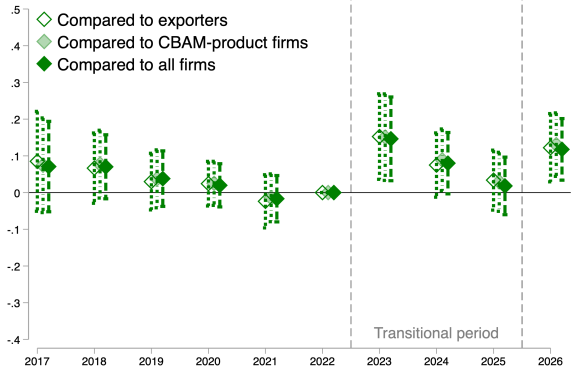
Figure A.5: Effects on cumulative *green* investment - alternative control groups



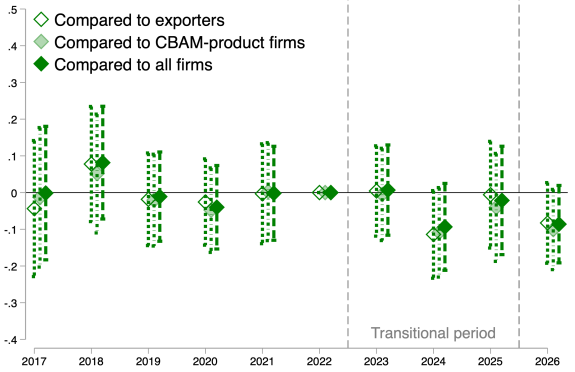
Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the log of cumulative *green* investment and the control groups are non-CBAM affected exporting firms and non-CBAM affected, CBAM-covered product manufacturing firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *CapexDx* database.

Figure A.6: Effects on investment flow

(a) *Green* investment



(b) Non-*green* investment



Notes: These figures report coefficients of dynamic difference-in-differences regressions based on Equation 5, where the dependent variable is the log of investment flow and the control groups are all firms in the database, non-CBAM affected exporting firms and non-CBAM affected, CBAM-covered product manufacturing firms in the database. Panel (a) presents the results for *green* investment, while Panel (b) reports the results for non-*green* investment. The regressions control for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *CapexDx* database.

Table A.5: Intensive margin upgrading

	(1)	(2)	(3)	(4)	(5)
Green investment (stock)	0.301**	0.251**	0.253**	0.181*	0.181*
	(0.128)	(0.108)	(0.108)	(0.102)	(0.102)
Baseline Mean	9.96	9.96	9.96	9.96	9.96
Green investment (flow)	0.063	0.056	0.056	0.070*	0.070*
	(0.039)	(0.037)	(0.037)	(0.036)	(0.036)
Baseline Mean	1.86	1.86	1.86	1.86	1.86
Non-green investment (flow)	-0.048	-0.109**	-0.108**	-0.064	-0.063
	(0.055)	(0.053)	(0.052)	(0.047)	(0.047)
Baseline Mean	2.66	2.66	2.66	2.66	2.66
Share of green investment (flow)	0.019*	0.019**	0.018**	0.019**	0.019**
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Baseline Mean	0.02	0.02	0.02	0.02	0.02
Share of green projects (#, flow)	0.015*	0.017**	0.016**	0.015**	0.015*
	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)
Baseline Mean	0.02	0.02	0.02	0.02	0.02
Observations	234,207	234,207	234,207	234,207	234,207
Firm FE	x	x	x	x	x
Year FE	x				
Industry x Year FE		x	x	x	x
State x Year FE			x	x	x
BL Exports x Year FE				x	x
Distance to Port x Year FE					x

Notes: This table reports coefficients of static difference-in-differences regressions based on Equation 5, where the control group is all firms in the database. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source:* Estimates based on data from the *CapexDx* database.

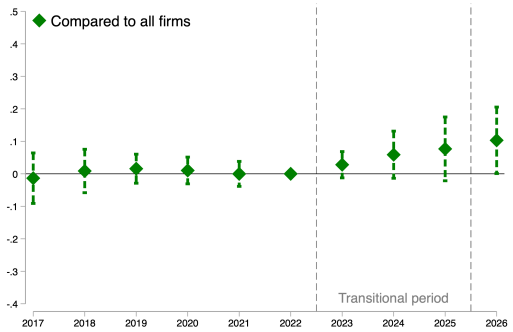
Table A.6: Extensive margin upgrading

	(1)	(2)	(3)	(4)	(5)
Any green investment	0.017*	0.018**	0.017**	0.018**	0.018**
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Baseline Mean	0.02	0.02	0.02	0.02	0.02
First green investment	0.009	0.013**	0.012**	0.014**	0.013**
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)
Baseline Mean	0.02	0.02	0.02	0.02	0.02
Observations	234,207	234,207	234,207	234,207	234,207
Firm FE	x	x	x	x	x
Year FE	x				
Industry x Year FE		x	x	x	x
State x Year FE			x	x	x
BL Exports x Year FE				x	x
Distance to Port x Year FE					x

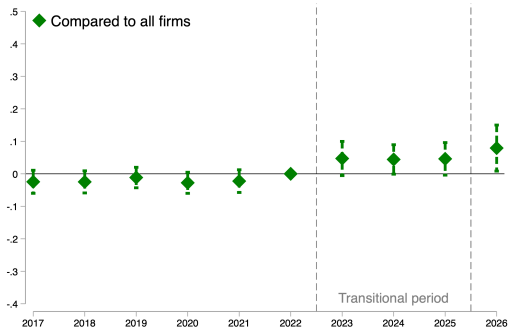
Notes: This table reports coefficients of static difference-in-differences regressions based on Equation 5, where the dependent variable is binary and the control group is all firms in the database. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source:* Estimates based on data from the *CapexDx* database.

Figure A.7: Effects on investment by type

(a) *Green* technologies



(b) Transitional technologies



Notes: These figures report coefficients of dynamic difference-in-differences regressions based on Equation 5, where the dependent variable is the log of cumulative investment and the control group is all firms in the database. Panel (a) presents the results for *green* investment, while Panel (b) reports the results for transitional investment. The regressions control for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *CapexDx* database.

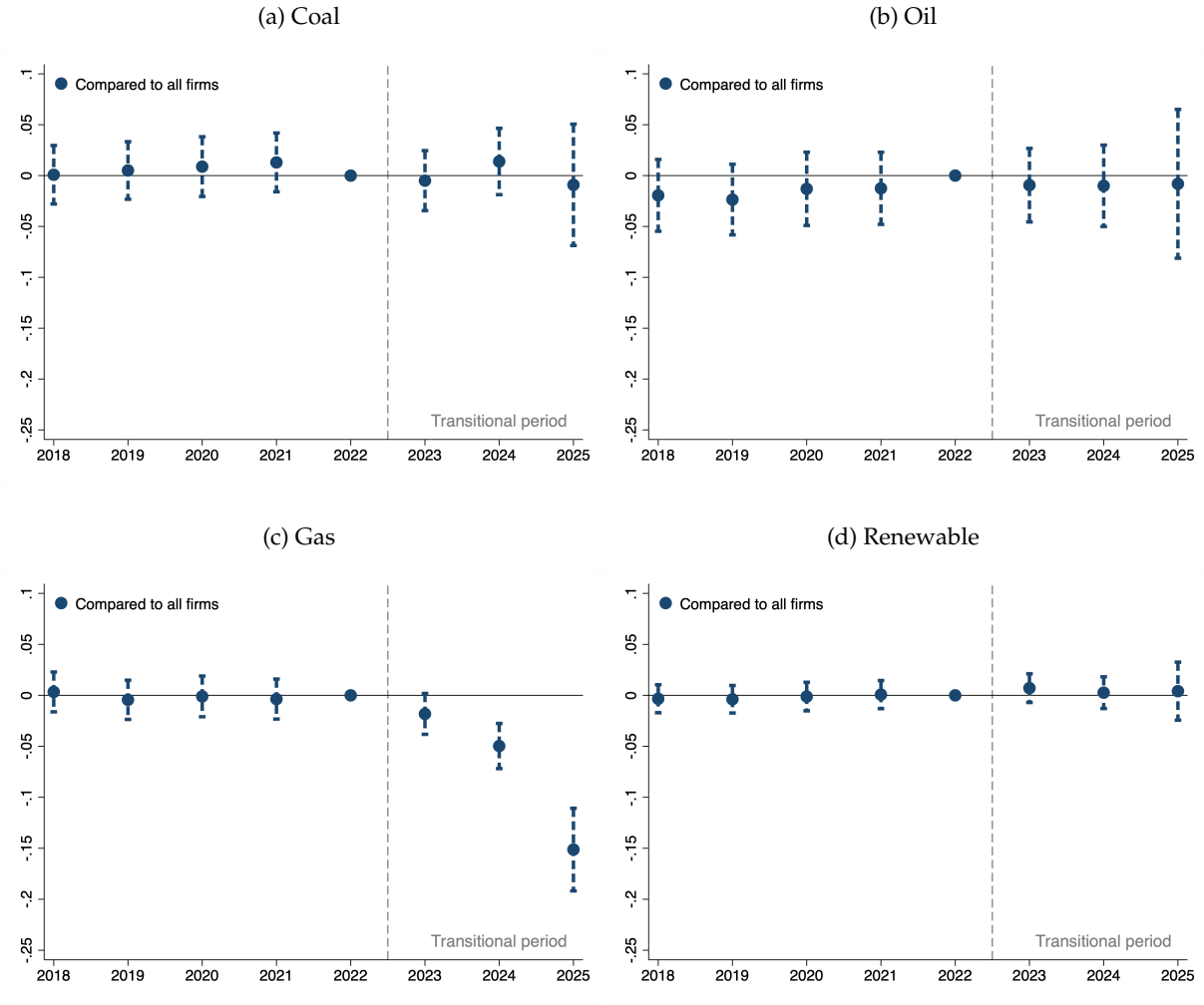
Table A.7: Cumulative green investment - placebo exercises

	(1)	(2)	(3)	(4)	(5)
Carbon-intensive uncovered EU exporters	-0.082**	-0.013	-0.015	-0.021	-0.021
	(0.039)	(0.013)	(0.016)	(0.015)	(0.015)
Baseline Mean	9.34	9.34	9.34	9.34	9.34
CBAM-product exporters, non-EU destinations	0.008	-0.011	-0.012	-0.014	-0.014
	(0.055)	(0.045)	(0.044)	(0.045)	(0.045)
Baseline Mean	9.34	9.34	9.34	9.34	9.34
Placebo timing (post = 2019)	0.066	0.024	0.024	0.001	0.001
	(0.059)	(0.039)	(0.039)	(0.039)	(0.039)
Baseline Mean	10.88	10.88	10.88	10.88	10.88
Domestic-facing green investment	0.028	0.032	0.033	0.031	0.031
	(0.023)	(0.022)	(0.022)	(0.021)	(0.021)
Baseline Mean	1.04	1.04	1.04	1.04	1.04
Observations	234,207	234,207	234,207	234,207	234,207
Firm FE	x	x	x	x	x
Year FE	x				
Industry x Year FE		x	x	x	x
State x Year FE			x	x	x
BL Exports x Year FE				x	x
Distance to Port x Year FE					x

Notes: This table reports coefficients of static difference-in-differences regressions based on Equation 5, where the dependent variable is the log of cumulative investment and the control group is all firms in the database. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source:* Estimates based on data from the *CapexDx* database.

A.6 Production process and firm performance

Figure A.8: Effect on fuel use as a share of power and fuel expenditure, by fuel



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the share of fuel to the total power and fuel expenditure winsorised at the 1st and 99th percentiles and the control group is all non-CBAM affected firms in the database. The regression controls for firm FE, industry by year FE, state by year FE, as well as baseline export size by year FE. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *ProwessDx* database.

Table A.8: Firm sales, profits, and expenses

	(1)	(2)	(3)	(4)	(5)
Log real output	0.151**	0.070*	0.070*	0.070*	0.070*
	(0.064)	(0.039)	(0.041)	(0.042)	(0.042)
Baseline Mean	1.35	1.35	1.35	1.35	1.35
Observations	165,603	165,603	165,603	165,603	165,603
Export share of sales	-0.0080	-0.015***	-0.017***	-0.018***	-0.018***
	(0.0079)	(0.005)	(0.006)	(0.005)	(0.005)
Baseline Mean	0.112	0.112	0.112	0.112	0.112
Observations	52,822	52,822	52,822	52,822	52,822
Profit margin	-0.288	-0.085***	-0.087***	-0.088***	-0.088***
	(0.178)	(0.024)	(0.028)	(0.029)	(0.029)
Baseline Mean	0.370	0.370	0.370	0.370	0.370
Observations	165,603	165,603	165,603	165,603	165,603
Log operating expenses	0.195**	0.053	0.056	0.056	0.056
	(0.081)	(0.046)	(0.047)	(0.048)	(0.048)
Baseline Mean	0.325	0.325	0.325	0.325	0.325
Observations	208,676	208,676	208,676	208,676	208,676
Firm FE	x	x	x	x	x
Year FE	x				
Industry x Year FE		x	x	x	x
State x Year FE			x	x	x
BL Exports x Year FE				x	x
Distance to Port x Year FE					x

Notes: This table reports coefficients of a static difference-in-differences regressions based on Equation 5. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source: ProwessDx* database.

Table A.9: Firm costs as a share of expenses

	(1)	(2)	(3)	(4)	(5)
Materials / operating expenses	0.018***	0.0038	0.0028	0.0030	0.0030
	(0.005)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Baseline Mean	0.569	0.569	0.569	0.569	0.569
Observations	70,448	70,448	70,448	70,448	70,448
Power and fuel / operating expenses	0.0005	0.0019	0.0018	0.0018	0.0018
	(0.0012)	(0.0015)	(0.0016)	(0.0016)	(0.0016)
Baseline Mean	0.027	0.027	0.027	0.027	0.027
Observations	208,676	208,676	208,676	208,676	208,676
Wage bill / operating expenses	-0.0051**	-0.0025	-0.0030	-0.0030	-0.0030
	(0.0023)	(0.0033)	(0.0031)	(0.0031)	(0.0031)
Baseline Mean	0.240	0.240	0.240	0.240	0.240
Observations	208,676	208,676	208,676	208,676	208,676
Training and welfare / operating expenses	-0.0003**	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Baseline Mean	0.0051	0.0051	0.0051	0.0051	0.0051
Observations	208,676	208,676	208,676	208,676	208,676
Outsourced mfg / operating expenses	0.0010	-0.0004	-0.0004	-0.0005	-0.0005
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Baseline Mean	0.0067	0.0067	0.0067	0.0067	0.0067
Observations	208,676	208,676	208,676	208,676	208,676
Firm FE	x	x	x	x	x
Year FE	x				
Industry x Year FE		x	x	x	x
State x Year FE			x	x	x
BL Exports x Year FE				x	x
Distance to Port x Year FE					x

Notes: This table reports coefficients of a static difference-in-differences regressions based on Equation 5. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source: ProwessDx* database.

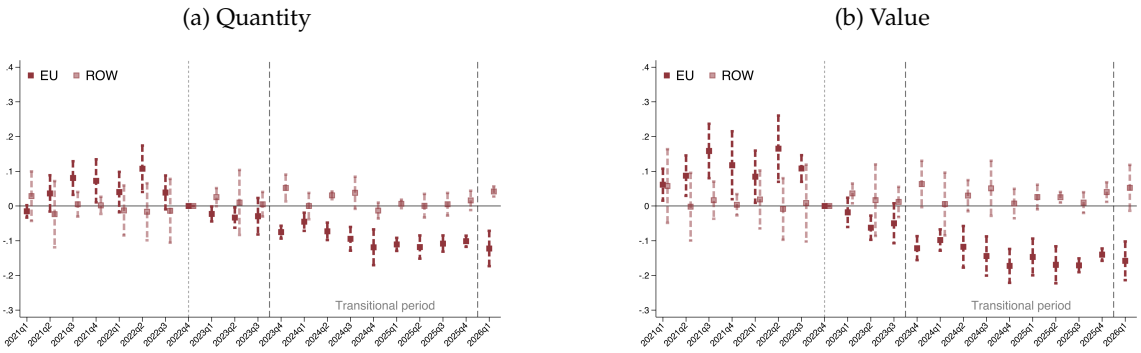
Table A.10: Probability of appearing in the panel

	(1)	(2)	(3)	(4)	(5)
Presence in the panel	0.015	-0.0033	-0.0019	-0.0004	-0.0001
	(0.013)	(0.0113)	(0.0127)	(0.0125)	(0.0127)
Baseline Mean	1.00	1.00	1.00	1.00	1.00
Observations	1,860,112	1,860,112	1,860,112	1,860,112	1,860,112
Firm FE	x	x	x	x	x
Year FE	x				
Industry x Year FE		x	x	x	x
State x Year FE			x	x	x
BL Exports x Year FE				x	x
Distance to Port x Year FE					x

Notes: This table reports coefficients of a static difference-in-differences regressions based on Equation 5. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source: ProwessDx* database.

A.7 International trade

Figure A.9: Effects on exports, EU exporters at baseline



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 6, where the dependent variable is the inverse hyperbolic sine of the quantity a firm-product line ships to the destination, in the product's own harmonized unit, or of the corresponding value. Treatment is the firm's 2021 share of exports that are CBAM-covered goods to the EU, scaled so that a coefficient is per ten percentage points. The sample is firms with positive EU exports at baseline. The regression controls for firm by product, product by quarter, industry by quarter, state by quarter, and baseline exports by quarter. The short dashed line marks the reference quarter, the long dashed lines the start of the transitional phase (2023Q4) and the end of the window. Standard errors are clustered by industry. The 90% confidence intervals are shown. *Source:* Estimates based on data from the *Panjiva* database.

Table A.11: Effects on the extensive margin

	(1)	(2)	(3)	(4)	(5)
$\mathbb{P}$**(line ships, any destination)**	-0.0049**	-0.0049***	-0.0035	-0.0043**	-0.0043**
	(0.0020)	(0.0019)	(0.0024)	(0.0021)	(0.0021)
Baseline Mean	0.403	0.403	0.403	0.403	0.403
Observations	3,997,959	3,997,959	3,997,959	3,997,959	3,997,959
$\mathbb{P}$**(line ships to the EU)**	-0.0207***	-0.0186***	-0.0191***	-0.0191***	-0.0191***
	(0.0023)	(0.0019)	(0.0020)	(0.0021)	(0.0021)
Baseline Mean	0.090	0.090	0.090	0.090	0.090
Observations	3,997,959	3,997,959	3,997,959	3,997,959	3,997,959
Firm x Product FE	x	x	x	x	x
Quarter FE	x				
HS6 x Quarter FE		x	x	x	x
Industry x Quarter FE			x	x	x
State x Quarter FE				x	x
BL Exports x Quarter FE					x

Notes: This table reports coefficients of a static difference-in-differences regressions based on Equation 6, where the outcome is binary. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source: Panjiva* database.

Table A.12: Trade placebo exercises

	(1)	(2)	(3)	(4)	(5)
Downstream-product EU exporters	-0.0003	-0.0013	-0.0011	-0.0001	-0.0001
	(0.0025)	(0.0021)	(0.0022)	(0.0022)	(0.0022)
Baseline Mean	0.061	0.061	0.061	0.061	0.061
Observations	294,252	294,252	294,252	294,252	294,252
CBAM-product exporters, non-EU destinations	0.0019***	0.0013	0.0012	0.0016	0.0016
	(0.0006)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Baseline Mean	0.061	0.061	0.061	0.061	0.061
Observations	294,252	294,252	294,252	294,252	294,252
Placebo timing (post = 2018)	0.0134*	0.0085	0.0085	0.0090	0.0090
	(0.0069)	(0.0054)	(0.0055)	(0.0056)	(0.0057)
Baseline Mean	0.081	0.081	0.081	0.081	0.081
Observations	362,040	362,040	362,040	362,040	362,040
Non-CBAM products of exposed firms	0.0017**	-0.0001	-0.0004	-0.0007	-0.0007
	(0.0008)	(0.0016)	(0.0015)	(0.0014)	(0.0014)
Baseline Mean	0.075	0.075	0.075	0.075	0.075
Observations	380,142	380,142	380,142	380,142	380,142
Firm FE	x	x	x	x	x
Quarter FE	x				
Industry x Quarter FE		x	x	x	x
State x Quarter FE			x	x	x
BL Exports x Quarter FE				x	x
Distance to Port x Quarter FE					x

Notes: This table reports coefficients of a static difference-in-differences regressions based on Equation 6. The regression controls are shown. Standard errors are clustered by industry in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *Source: Panjiva* database.

B Theory Appendix

B.1 Carbon prices and policy reach

For every producing country other than India, I use its effective explicit carbon price where one exists, and the shadow price p_C otherwise. The explicit price $\bar{p}_c$ is net of free allowances and exemptions, and replaces the shadow price.[11] For the rival composite, the carbon price is the production-weighted average, $p_C^R = \bar{p}_C^R + \omega_R p_C$, where $\bar{p}_C^R$ is the weighted explicit component and ω_R is the share of production in countries without an explicit price. Third-country producers follow the same rule, $q_m^{\mathrm{TH}} = \bar{p}_m^{\mathrm{TH}} + \omega_m^{\mathrm{TH}} p_C$, with weights based on the producers supplying market m. Only the explicit component is credited against the border charge. Thus, $c_S = 0$, c_R is the rivals' explicit price weighted by their EU exports, and c_{TH} is the corresponding price for third-country producers. No other market imposes a border charge.

The instruments also differ in which emissions they cover. Let $\chi_{T,s}^o$ denote the share of emissions from recipe T in sector s that arise directly from production (Scope 1), with the remainder arising from electricity generation. An instrument with reach r_s covers a fraction r_s of these indirect emissions, in addition to direct emissions. Weighting by emissions $e_{T,s}^o$ across the origin's EU-bound basket, the fraction covered is:

$$k_T^o(r) \equiv \frac{\sum_s e_{T,s}^o \left[\chi_{T,s}^o + (1 - \chi_{T,s}^o)\, r_s\right]}{\sum_s e_{T,s}^o}, \qquad k_T^o(r^{\mathrm{dom}}) = 1 \tag{B.30}$$

This gives the fraction of recipe T's emissions covered by the instrument. At the border, $r_s = 0$ for iron, steel and aluminium and $r_s = 1$ for cement and fertilisers, while the domestic carbon price covers all emissions. For the dirty recipe, incomplete coverage matters only for aluminium, where much of the carbon is emitted at the power stations supplying smelters. It matters more for the clean recipe, which relies largely on electrification and shifts emissions from the plant to the power station, although some remain on site. Where only direct emissions are covered, $k_G^o(0)$ gives the share of the clean recipe's emissions subject to the charge. An adopter therefore pays only on a fraction of an emissions intensity that switching has already reduced, even though it still emits the full $\mathcal{E}_G^o$. I calculate emissions using the actual intensities $\mathcal{E}_T^o$, while prices and selection depend on the covered intensities $k_T^o(r)\mathcal{E}_T^o$.

The supplier's cost-minimization problem for a bundle is:

$$\min_{e,n} \;\; p_T e + w_o n + p_C^o\, k_T^o(r^{\mathrm{dom}})\, \varepsilon_T\, e \qquad \text{s.t.} \qquad (A_T e)^{\phi_o} n^{1-\phi_o} = 1 \tag{B.31}$$

with $p_D = 1$ and $w_o = 1$. The energy bill and the carbon bill are linear in the same variable and collect into one coefficient on e. Dividing by the A_T useful units each raw unit delivers gives the price of effective energy $\varrho_T = (p_T + k_T^o(r^{\mathrm{dom}}) p_C^o \varepsilon_T)/A_T$, and:

$$\bar{C}_{o,T} = \frac{\varrho_T^{\phi_o}\, w_o^{1-\phi_o}}{\phi_o^{\phi_o}(1-\phi_o)^{1-\phi_o}}, \qquad \frac{\bar{C}_{o,G}}{\bar{C}_{o,D}} = \left(\frac{p_G^o + p_C^o \varepsilon_G^o}{A_G^o(1 + p_C^o)}\right)^{\phi_o} \tag{B.32}$$

Since the bundle has constant returns, a plant producing Q units uses $v(Q) = \frac{1}{z}\frac{\bar{Q}}{1+\nu}(Q/\bar{Q})^{1+\nu}$ bundles, and its energy bill, inclusive of the domestic carbon payment, is $\phi_o \mathcal{C}(Q)$, the measured share of variable cost at every level of output.

Adoption reduces unit costs when $(A_G^o - \varepsilon_G^o)p_C^o > p_G^o - A_G^o$. If $A_G^o > \varepsilon_G^o$, it is cost-reducing at any

[11] The explicit price is taken to include whatever implicit pricing the country also applies. A country with a low effective explicit price therefore faces a lower carbon cost than India's shadow price.

nonnegative carbon price when $A^o_G > p^o_G$, and only above $p^o_C = (p^o_G - A^o_G)/(A^o_G - \varepsilon^o_G)$ when $\varepsilon^o_G < A^o_G < p^o_G$. If $A^o_G \le \varepsilon^o_G$ and $p^o_G \ge A^o_G$, adoption never reduces costs.

B.2 Demand

The lower tier is $X^o_m = [\int d^{1/\sigma}_{o,m} x^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}$. Only relative weights are identified, since multiplying all Southern weights in a market by the same factor can be offset by an adjustment in the non-Southern price p^D_m. I therefore normalize India's weights to one in every market, $d_{S,m} = 1$, and the rivals' weight to one in their home market, $d_{R,R} = 1$, which pins down N_R. This leaves $d_{R,EU}$, $d_{R,S}$ and $d_{R,TH}$ to be calibrated.

A weight below one has the same effect on demand as an iceberg trade cost $d^{1/(1-\sigma)}_{o,m}$ applied to the origin's home cost. The two interpretations differ, however, in how emissions are accounted for. Under a literal iceberg cost, the units lost in transit must still be produced and generate emissions. Moreover, since CBAM is levied per tonne delivered, the charge would account for a smaller share of the delivered cost. The terms that each supplier takes as given are:

$$\mathcal{B}^o_m \equiv \tfrac{1}{\sigma}\big(\tfrac{\sigma}{\sigma-1}\big)^{1-\sigma} d_{o,m}(P^o_m)^{\sigma-1} s_{o,m} I_m \tag{B.33}$$

B.3 Pricing under rising marginal cost

A supplier on recipe T that serves the set of markets $\mathcal{S}$ chooses the price p_m it receives in each market, taking the per-unit charge $t_m = (\mathcal{T}^o_{T,m} - 1)\mathcal{C}'(Q)$ as given, since CBAM is set by the plant's verified emissions per tonne. Writing $\mathcal{D}^o_m \equiv d_{o,m}(P^o_m)^{\sigma-1} s_{o,m} I_m$, the supplier solves:

$$\max_{\{p_m\}_{m\in\mathcal{S}}} \sum_{m\in\mathcal{S}} p_m\, \mathcal{D}^o_m\, (p_m + t_m)^{-\sigma} - \mathcal{C}\Big(\sum_{m\in\mathcal{S}} \mathcal{D}^o_m\, (p_m + t_m)^{-\sigma}\Big) \tag{B.34}$$

The first-order condition is $\sigma(p_m - \mathcal{C}'(Q)) = \tilde{p}_m$, so the delivered price is $\tilde{p}_m = \mu(\mathcal{C}'(Q) + t_m) = \mu\, \mathcal{T}^o_{T,m}\, \mathcal{C}'(Q)$, with $\mu \equiv \sigma/(\sigma-1)$, and the price received is $p_m = [\mu \mathcal{T}^o_{T,m} - (\mathcal{T}^o_{T,m} - 1)]\, \mathcal{C}'(Q)$. At a given marginal cost, the charge raises the delivered price by μt_m. Summing demand over markets gives output $Q = (\sigma-1)\mathcal{Q}^q_{\mathcal{S},T}\, \mathcal{C}'(Q)^{-\sigma}$, where $\mathcal{Q}^q_{\mathcal{S},T}$ is the quantity reach in (16). Substituting marginal cost and solving:

$$\mathcal{C}'(Q) = \Big(\frac{\bar{\mathcal{C}}_{o,T}}{z}\Big)^{\frac{1}{1+\nu\sigma}} \Big(\frac{(\sigma-1)\mathcal{Q}^q_{\mathcal{S},T}}{\bar{Q}}\Big)^{\frac{\nu}{1+\nu\sigma}} \tag{B.35}$$

which gives the sales in (16), with the constant $(\sigma-1)^{\tilde{b}-1}$ absorbed into $\bar{Q}$. Total sales replace $\mathcal{B}^o_m(\mathcal{T}^o_{T,m})^{1-\sigma}$ with the sales reach $\mathcal{Q}^r_{\mathcal{S},T} \equiv \sum_{m\in\mathcal{S}} \mathcal{B}^o_m(\mathcal{T}^o_{T,m})^{1-\sigma}$. Free-on-board revenue net of variable cost is $R/\sigma + \frac{\nu}{1+\nu}\mathcal{C}'(Q)Q$, so operating profit is:

$$\Pi(z) = \Big[\mathcal{Q}^r_{\mathcal{S},T} + \kappa_\nu\, \mathcal{Q}^q_{\mathcal{S},T}\Big]\, \bar{\mathcal{C}}^{-\tilde{a}}_{o,T} \Big(\frac{\mathcal{Q}^q_{\mathcal{S},T}}{\bar{Q}}\Big)^{\tilde{b}-1} z^{\tilde{a}} \equiv \Pi_{e,g}\, x, \qquad \kappa_\nu \equiv \frac{(\sigma-1)\nu}{1+\nu} \tag{B.36}$$

Without a border charge, the two reaches coincide and profit is the share $(1+\nu\sigma)/[\sigma(1+\nu)]$ of sales, which exceeds $1/\sigma$ because it includes the rent on fixed capacity. The charge lowers both reaches, and disproportionately more the quantity reach, since an EU unit is more expensive and its sales drop. Holding demand fixed, sales in market m respond to the quantity reach with elasticity $\tilde{b} - 1 < 0$. When the other markets carry no charge, this gives the cross-market elasticity $(\tilde{b}-1)/\tilde{b} = -(\sigma-1)\nu/(1+\nu)$ with respect to total firm sales. I take ν from this elasticity, estimated by Almunia et al. (2021), setting $-(\sigma-1)\nu/(1+\nu) =$

-2.624, which gives $\nu = 1.19$. I choose $\bar{Q}$ so that each origin's baseline price level matches the constant-cost model, leaving every calibration target unchanged.

Since the charge per unit is proportional to average cost while the wedge is measured against marginal cost, the factor $1/(1+\nu)$ enters $\mathcal{T}^o_{T,EU}$ in (14). The measured charge as a share of the shipment's value pins the wedge irrespective of ν, $\mathcal{T}^o_{D,EU} - 1 = \mu\theta$. Given the measured energy share, rising marginal cost therefore implies $1+\nu$ times as much carbon per unit of energy spending as constant marginal cost.

B.4 Non-Southern producers

The non-Southern good in each market combines an EU bundle and a third-country bundle, with weights a_m and $1-a_m$ and elasticity η. Each bundle consists of symmetric varieties, aggregated with elasticity σ and produced by monopolistically competitive firms. Each firm charges a markup $\mu \equiv \sigma/(\sigma-1)$ over unit cost and enters at a fixed cost f^k_m in units of the outside good, $k \in \{EU, TH\}$. Free entry determines the mass of varieties of each group as $R^k_m/(\sigma f^k_m)$, where $R^{EU}_m = \omega_m R^D_m$ and $R^{TH}_m = (1-\omega_m)R^D_m$ split non-Southern revenue $R^D_m = (1-s^M_m)I_m$. The resulting price indices are:

$$p^k_m = \mu\, c^k_m \Big(\frac{R^k_m}{\sigma f^k_m}\Big)^{\frac{1}{1-\sigma}}, \qquad p^D_m = \Big[a_m (p^{EU}_m)^{1-\eta} + (1-a_m)(p^{TH}_m)^{1-\eta}\Big]^{\frac{1}{1-\eta}}, \qquad \omega_m = a_m \Big(\frac{p^{EU}_m}{p^D_m}\Big)^{1-\eta} \tag{B.37}$$

where $c^{EU}_m = c_{EU}$ and $c^{TH}_m = c_{TH,m}\mathcal{T}^{TH}_m$ are unit costs, inclusive of any border charge. I calibrate to the base-year p^D_m and the observed EU share of non-Southern supply, so that every non-Southern cost is measured relative to the base year. Entry amplifies changes in demand group by group. When CBAM shifts EU spending toward EU producers, more of them enter and their price index falls further, while third-country producers, who pay the charge, lose sales and exit. When Southern goods are diverted into another market, its non-Southern producers lose sales and exit, raising their price index.

EU producers use energy with emission factor ε_{EU}, at ϕ_{EU} per unit of sales. They pay an effective carbon price net of free allowances, $q_{EU} = \max\{\bar{q}_{EU}, \varpi_{EU} t_{ETS}\}$, where $\bar{q}_{EU}$ is the effective price paid in the base year and $\varpi_{EU} = 1 - \text{cf}\,\text{fa}_{EU}$ is the share of emissions not covered by free allowances. Here fa_{EU} is the base-year free allocation, scaled by the phase-in factor cf. The baseline therefore already includes carbon pricing. EU producers pay the effective ETS price, while third-country producers pay q^{TH}_m and, on sales to the EU, the border charge. Neither has a choice of production recipe, but both can reduce energy use in response to higher carbon costs. Their cost indices and emissions intensities are

$$\begin{gathered} W_{EU} = \Big(\frac{p^E + q_{EU}\varepsilon_{EU}}{p^E + \bar{q}_{EU}\varepsilon_{EU}}\Big)^{\mu\phi^c_{EU}}, \qquad \mathcal{E}_{EU} = \frac{\varepsilon_{EU}\phi^c_{EU}}{p^E + q_{EU}\varepsilon_{EU}}, \qquad \phi^c_{EU} = \phi_{EU}\frac{p^E + \bar{q}_{EU}\varepsilon_{EU}}{p^E}, \\ W_m = \Big(\frac{p^E + q^{\text{TH}}_m}{p^E + q^{\text{TH}}_{m,0}}\Big)^{\mu\phi_m}, \qquad \mathcal{E}^{\text{TH}}_m = \frac{\varepsilon_m\phi_m}{p^E + q^{\text{TH}}_m}, \\ \mathcal{T}^{TH}_{EU} = 1 + \big(\varpi_{TH}\tau - c_{TH}\big)^+ k_{TH}(r)\,\mu\,\mathcal{E}^{\text{TH}}_{EU} \end{gathered} \tag{B.38}$$

with $\mathcal{T}^{TH}_m = 1$ for $m \in \mathcal{M}'$, ϕ^c_{EU} the energy cost share inclusive of base-year carbon payments, and $\mathcal{E}$ emissions per unit of sales. Unit costs in (B.37) are $c_{EU} = \bar{c}_{EU} W_{EU}$ and $c_{TH,m} = \bar{c}_{TH,m} W_m$, relative to their base-year levels. The Cobb-Douglas energy share allows emissions intensity to respond to carbon prices even without a change in recipe.[12]

[12] The calibrated level already embeds past adoption, with ϕ_{EU} being below India's ϕ_S, reflecting earlier EU decarbonization.

The EU share ω_m in (B.37) divides non-Southern emissions into those produced in the EU, which do not count as leakage, and those produced in third countries:

$$\Xi_{D,m} = \underbrace{(1-s_m^M) I_m\, \omega_m \mathcal{E}_{EU}}_{\Xi_m^{EU}} + \underbrace{(1-s_m^M) I_m\, (1-\omega_m)\, \frac{\mathcal{E}_m^{\mathrm{TH}}}{\mathcal{T}_m^{TH}}}_{\Xi_m^{TH}}, \qquad \Xi = \sum_{o,m} \Xi_{o,m} + \sum_m \Xi_{D,m} \tag{B.39}$$

EU ETS revenue is $R_{ETS} = t_{ETS} \sum_m \Xi_m^{EU}$. I treat the outside good as carbon-free, such that Ξ measures emissions in the covered sectors.

B.5 Aggregation

Each firm is characterized by productivity z_i and an adoption cost f_i, drawn independently from $G \otimes K$. Productivity follows a truncated Pareto distribution, $\Pr(Z \leq z) = [1-(z_{\min}/z)^\kappa]/[1-(z_{\min}/z_{\max,o})^\kappa]$, with $z_{\max,o} = z_{\min} N_o^{1/\kappa}$, while adoption costs are lognormal, $\ln f \sim N(-\frac{1}{2}s_F^2, s_F^2)$. The costs of a bundle are common to all firms within an origin, as is the export threshold for firms that remain dirty. The adoption threshold $z^{**}(f)$ varies with the adoption cost, as does the export threshold $z^*(f)$ for firms that adopt before exporting. Let $\bar{G}_o$ denote the survival function and $\bar{z}(f) \equiv \max\{z^*(f), z^{**}(f)\}$. The masses of exporters and adopters, together with the adoption-cost-weighted mass of adopters, are:

$$N_o^{EU} = N_o \int \bar{G}_o\big(z^*(f)\big)\mathrm{d}K, \qquad N_o^G = N_o \int \bar{G}_o\big(z^{**}(f)\big)\mathrm{d}K, \qquad \tilde{N}_o^G = N_o \int f\, \bar{G}_o\big(z^{**}(f)\big)\mathrm{d}K \tag{B.40}$$

To aggregate sales across firms, define the competitiveness integral, with $\nu_\kappa \equiv \tilde{a} - \kappa$. Truncation ensures that it is finite:

$$Z_o(\zeta) \equiv N_o \int_\zeta^{z_{\max,o}} z^{\tilde{a}}\, \mathrm{d}G(z) = \frac{N_o\, \kappa z_{\min}^\kappa}{1-(z_{\min}/z_{\max,o})^\kappa}\, \frac{z_{\max,o}^{\nu_\kappa} - \zeta^{\nu_\kappa}}{\nu_\kappa} \tag{B.41}$$

By (16), a firm in configuration (e,g) contributes $\tilde{p}^{1-\sigma} = \mu^{1-\sigma} \psi_{e,g,m}^o z^{\tilde{a}}$ to the price index of market m, with configuration weight:

$$\psi_{e,g,m}^o \equiv (\mathcal{T}_{g,m}^o)^{1-\sigma}\, \bar{C}_{o,g}^{-\tilde{a}} \left(\frac{\mathcal{Q}_{e,g}^q}{\bar{Q}}\right)^{\tilde{b}-1} \tag{B.42}$$

which depends on the set of markets the firm serves. An EU exporter sells less in every other market than a non-exporter of the same productivity. Integrating (9) over the firms active in each market, at the prices in (14), gives the origin-specific price indices:

$$(P_{EU}^o)^{1-\sigma} = d_{o,EU}\mu^{1-\sigma} \int \Big[\psi_{1,D,EU}^o \big\{Z_o(z^*(f)) - Z_o(\bar{z}(f))\big\} + \psi_{1,G,EU}^o\, Z_o(\bar{z}(f))\Big]\mathrm{d}K \tag{B.43}$$

$$\begin{aligned}(P_m^o)^{1-\sigma} = d_{o,m}\mu^{1-\sigma} \int \Big[&\psi_{0,D,m}^o \big\{Z_o(z_{\min}) - Z_o(z^*(f))\big\} \\ &+ \psi_{1,D,m}^o \big\{Z_o(z^*(f)) - Z_o(\bar{z}(f))\big\} + \psi_{1,G,m}^o\, Z_o(\bar{z}(f))\Big]\mathrm{d}K, \quad m \in \mathcal{M}'\end{aligned} \tag{B.44}$$

written for the case in which firms export before adopting, with the other orderings of Appendix B.7 entering the same way. The three non-EU price indices of a given origin therefore differ only through their taste weights. The share of origin-o expenditure on clean-recipe varieties in market m is the clean terms of

(B.43)–(B.44) over the whole:

$$\mathrm{g}_{o,m} = \frac{\int \sum_{e} \psi^{o}_{e,G,m}\{\cdot\}\,\mathrm{d}K}{\int \sum_{e,g} \psi^{o}_{e,g,m}\{\cdot\}\,\mathrm{d}K} \tag{B.45}$$

where $\{\cdot\}$ is the mass of each configuration in the brackets above, and the sums run over the configurations that sell in m. The shares account for the different border wedges faced by dirty and clean varieties. CBAM revenue is calculated on charged (not total) emissions, weighting each recipe's contribution to (20) by its coverage fraction $k^{o}_{T}(r)$:

$$R_{\text{CBAM}} = \frac{\sigma-1}{\sigma(1+\nu)} \sum_{o} s_{o,EU} I_{EU} \left[(\varpi_D \tau - c_o)^{+} \frac{(1-\mathrm{g}_{o,EU}) k^{o}_{D}(r)}{\mathcal{T}^{o}_{D,EU}} \mathcal{E}^{o}_{D} + (\varpi_G \tau - c_o)^{+} \frac{\mathrm{g}_{o,EU} k^{o}_{G}(r)}{\mathcal{T}^{o}_{G,EU}} \mathcal{E}^{o}_{G} \right] + (\varpi_{TH}\tau - c_{TH})^{+} k_{TH}(r)\, \Xi^{TH}_{EU} \tag{B.46}$$

B.6 General equilibrium

Income in the EU and the third markets is given by:

$$I^{tot}_{EU} = \bar{L}_{EU} + \phi_{EU} \sum_{m} \omega_m R^{D}_{m} + \lambda R_{\text{CBAM}}, \qquad I^{tot}_{TH} = \bar{L}_{TH} + \sum_{m} \phi_m \frac{(1-\omega_m) R^{D}_{m}}{\mathcal{T}^{TH}_{m}} \tag{B.47}$$

EU ETS receipts are already included in the carbon component of producers' energy payments, so they are not added separately to income. Non-Southern producers make zero profits under free entry, and their entry costs are paid to labor at the pinned wage.

For Southern producers, the costs of a bundle already include domestic carbon payments. Dividing delivered expenditure by the border wedge removes the border charge, and dividing by the markup μ gives output valued at marginal cost:

$$\mathcal{V}_o = \frac{\sigma-1}{\sigma} \sum_{m} s_{o,m} I_m \left[\frac{1-\mathrm{g}_{o,m}}{\mathcal{T}^{o}_{D,m}} + \frac{\mathrm{g}_{o,m}}{\mathcal{T}^{o}_{G,m}} \right] \tag{B.48}$$

Variable cost is the share $1/(1+\nu)$ of $\mathcal{V}_o$. Of it, the share ϕ_o pays for energy, including domestic carbon payments, and the share $1-\phi_o$ for labor, both of which accrue to households in the origin. Free-on-board revenue is $R_o = \sum_m s_{o,m} I_m - \sum_T (\varpi_T \tau - c_o)^{+} \Xi^{\text{chg},T}_{o,EU}$, and satisfies $\mathcal{V}_o + \frac{1}{\sigma}\sum_m s_{o,m} I_m = R_o$. Thus, the border charge is deducted from the origin's revenue and enters EU receipts, without being counted twice. Operating profit is $R_o - \mathcal{V}_o/(1+\nu)$, the sum over firms of (B.36), which includes the rent on fixed capacity. Labor is employed in variable production, exporting and adoption, and the rest of the endowment $\bar{L}_o$ in the outside good at the pinned wage, which gives household income (21). I set $\bar{L}_o$ so that baseline income equals the origin's GDP. The policy therefore moves Southern income only through energy rents, domestic carbon receipts, profits net of fixed costs and the rebate. The rebate enters India's income because it is a transfer from the EU to India in the counterfactuals.

Definition 1 (General equilibrium)**.** *Given parameters and policy* $(\tau, \{\varpi_T\}, \varpi_{TH}, \varpi_{EU}, \varsigma, \lambda)$*, an equilibrium consists of export and adoption cutoffs* z^{*} *and* $z^{**}(\cdot)$ *for each origin; price indices and shares* $(P^{o}_{m}, P^{M}_{m}, P_m, s_{o,m}, \mathrm{g}_{o,m})$ *in every market; non-Southern prices* p^{D}_{m} *and EU shares* ω_m*; incomes and spending* (I^{tot}_{j}, I_j)*; and revenues* R_{CBAM}

and R_{ETS}. These objects satisfy the following conditions: Each supplier prices according to (14) *and chooses* (e, g) *optimally according to* (17)*. Price indices aggregate these choices as in* (B.43)-(B.44)*, demand satisfies* (8)-(9)*, and non-Southern prices satisfy* (B.37)*. Southern income is given by* (21) *and income in the EU and third markets satisfies* (B.47)*, with every wage pinned down by the outside good. Finally, CBAM revenue from* (B.46) *is divided between the EU and India according to* λ*.*

B.7 Configurations

The four configurations in (17) are lines in $x = z^{\tilde{a}}$, with slopes R_D, $R_D + K_D$, R_G and $R_G + K_G$, and intercepts 0, $-f_{EU}$, $-F_i$ and $-(f_{EU} + F_i)$. The firm's value is their upper envelope, which is convex and piecewise linear in x. Each configuration is chosen over at most one interval, and the chosen configurations appear in increasing order of slope.

Three orderings are possible. When (19) holds, the firm first exports with the dirty recipe and then adopts the clean one, with cutoffs z^* and z^{**}. When adoption is profitable on non-EU sales before EU entry becomes profitable, $F_i/a < f_{EU}/K_G$, the firm first adopts and then exports, with cutoffs $(F_i/a)^{1/\tilde{a}}$ and $(f_{EU}/K_G)^{1/\tilde{a}}$. Otherwise, it adopts and enters the EU simultaneously, at $((f_{EU} + F_i)/(K_D + a + b))^{1/\tilde{a}}$. The two middle configurations exclude each other, because the gains on the two legs, a and b, are nonnegative whenever the clean recipe has the lower cost and the lower wedge.

B.8 The phase-in

During the phase-in, importers deduct the free allocation that an equivalent EU producer would still receive from their chargeable emissions. For each sector and production technique, this deduction is the CBAM factor cf_t times the default benchmark $b_{T,s}$, against charged emissions $e^o_{T,s}$ per tonne. The phase-in reduces the deduction, but not the charge itself. For recipe T of origin o, the fraction of the full charge payable is the average across sectors, weighted by their share of charged emissions:

$$\varpi^o_T(t) = \sum_s \tilde{e}^o_{T,s} \max\Big\{1 - \text{cf}_t \frac{b_{T,s}}{e^o_{T,s}},\ 0\Big\}, \qquad \varpi_{EU}(t) = 1 - \text{cf}_t\, \text{fa}_{EU} \tag{B.49}$$

where $\tilde{e}^o_{T,s}$ is sector s's share of the recipe's charged emissions in the origin's EU exports.

A firm deciding whether to adopt before the charge begins takes into account the legislated phase-in over the life of its plant. I use the discounted average of the annual factors to construct the anticipated charge that identifies the adoption response:

$$\varpi^{PV}_T = \frac{\sum_{t=t_1}^{t_1+L-1} (1+r)^{-(t-t_0)} \varpi_T(t)}{\sum_{t=t_1}^{t_1+L-1} (1+r)^{-(t-t_0)}} \tag{B.50}$$

where t_0 is the decision year, t_1 the first year of operation, L the plant's operating life and $\text{cf}_t = 0$ after the last year of the phase-in schedule.

B.9 Extensions

Constant marginal cost. Setting $\nu = 0$ in (13) makes marginal cost constant in output, $\mathcal{C}'(Q) = \bar{C}_{o,T}/z$, so that $\tilde{a} = \sigma - 1$ and $\tilde{b} = 1$. Sales in market m become $r_m(z) = \sigma \mathcal{B}_m^o \Psi_{T,m}^o z^{\sigma-1}$, with $\Psi_{T,m}^o \equiv (\bar{C}_{o,T} \mathcal{T}_{T,m}^o)^{1-\sigma}$, and no longer depend on the other markets the firm serves. Pass-through is complete, operating profit is $1/\sigma$ of delivered revenue, and there is no capacity rent. In (17), $R_g = \sum_{m \in \mathcal{M}'} \mathcal{B}_m \Psi_{m,g}$ and $K_g = \mathcal{B}_{EU} \Psi_{EU,g}$, so the gain from EU entry is no longer net of any crowding out, and the cutoffs in (18) take the exponent $1/(\sigma - 1)$. Since sales scale with $z^{\sigma-1}$, the observed sales tail identifies $\kappa = \text{tail} \times (\sigma - 1)$. A firm's EU leg then affects its other sales only through its recipe, so diversion requires the price indices of shared markets to move. Variable cost is $\mathcal{V}_o$, and emissions, revenue and welfare follow from the expressions above at $\nu = 0$.

EU-line adoption. A firm serving the EU can operate its EU production line on the clean recipe while keeping the rest of the plant on the dirty one, at a cost λF_i. With constant marginal costs, the two lines are separable, so I develop this extension at $\nu = 0$. The firm therefore chooses among five configurations, the four in (17) and EU-line adoption, with profit $\pi(1, L) = (R_D + K_G)x - f_{EU} - \lambda F_i$. The EU-line configuration is chosen over the productivity range:

$$z \in \left[\left(\frac{\lambda F_i}{b} \right)^{\frac{1}{\sigma-1}}, \left(\frac{(1-\lambda) F_i}{a} \right)^{\frac{1}{\sigma-1}} \right), \qquad \text{non-empty iff} \qquad \lambda < \frac{b}{a+b} \tag{B.51}$$

If conversion costs were proportional to the capacity converted, the appropriate cost share would be the EU share of a dirty exporter's baseline sales:

$$\lambda_o^{\text{prop}} = \left. \frac{K_D}{R_D + K_D} \right|_{\tau=0} \tag{B.52}$$

This is roughly 4% for both origins. Converting a production line is unlikely to be that cheap, since part of the cost of a new furnace or power contract does not vary with the output it serves. I therefore set $\lambda = 0.1$ for both origins.[13]

At $\tau = 0$, $b/(a+b) = \lambda_o^{\text{prop}} < \lambda$, so the EU-line band is empty. The border charge increases the advantage of the clean recipe on EU sales, raising $b/(a+b)$ above λ and opening the band for intermediate-productivity exporters. These firms convert their EU line but remain below the threshold for plant-wide adoption, $z_p^{**}(f) = [(1-\lambda)F_i/a]^{1/(\sigma-1)}$. In the EU price index and green share, the clean term begins at $\bar{z}$ as before, while in the non-EU indices it begins only at z_p^{**}. An EU-line adopter therefore sells clean output to the EU and dirty output elsewhere, allowing resource shuffling within the plant. I re-estimate the model on the same adoption target, counting both EU-line and plant-wide adopters. The constant-cost model is recovered when $\lambda \geq 1$.

[13] At $\lambda = \lambda_o^{\text{prop}}$, the estimated shadow price is implausibly high, at EUR 72 per tonne. At $\lambda = 0.5$, EU-line adoption is never chosen and the model coincides with the constant-cost model.

C Quantitative analysis

C.1 Parameters directly measured in the data

The Pareto tail κ is estimated using a Hill index on the top quarter of plant sales in the Annual Survey of Industries (ASI), pooled across the covered industries. The estimated sales-tail coefficient is 0.999. Since sales scale with $z^{\tilde{a}}$, this implies $\kappa = \text{tail} \times \tilde{a} = 0.609$. I adjust κ whenever σ or ν changes, preserving the measured sales tail in every exercise. I use the population of all producers, since every Indian plant serves the three non-EU markets.

The energy share of cost $\phi_S = 0.21$ is measured as the energy bill divided by the cost of production in the covered ASI industries, weighted by India's production values. Under rising marginal cost, the energy bill is the share ϕ_S of variable cost at every level of output, so its measurement does not depend on ν. The bill includes energy purchased as raw materials, notably coking coal and coke used as reductants and gas used as feedstock, so that it covers the inputs responsible for the direct emissions charged at the border. Since India's shadow carbon price is already reflected in the observed energy bill, the measured share differs from the Cobb-Douglas exponent, which is defined at zero carbon prices. I therefore set the exponent to $\phi_S(p_E + p_C)$, so that the model's dirty emissions intensity matches the measurement and the border charge does not change mechanically with the estimated shadow price. Company accounts from Prowess provide an alternative measure.

The clean recipe. The relative price of clean energy, $p_G = 1.79$, is the grid electricity tariff divided by the cost of captive coal power per kWh. I estimate the clean recipe's energy advantage A_G from the ASI plant-level fuel schedule, regressing the log energy bill per tonne of output on the electricity share of energy, with plant and product-by-year fixed effects. The estimated bill ratio implies $A_G/p_G = 1.10$, giving $A_G = 1.97$. This ratio determines the clean recipe's energy-cost advantage before carbon pricing. The on-site emissions share $\chi_G = 0.336$ is the value-weighted Scope-1 share of total Scope-1 and Scope-2 emissions for clean production routes. Where the border charge covers only direct emissions, an adopter is therefore charged on roughly one-third of its actual emissions. This treatment follows the regulation's coverage rules. The intensity ratio $\delta = 0.426$ comes from an event study of first clean adoption in the Prowess panel, measuring the within-firm change in carbon emissions per rupee of sales. It is a calibration target: given A_G, p_G and ϕ_S, it pins down the clean recipe's emissions factor ε_G.

The charge scale $\theta = 0.204$ measures the announced border charge as a share of the pre-charge import price. I construct it from India's shipment-level exports to the EU, multiplying chargeable embedded emissions per unit by an allowance price of EUR 85 per tonne, dividing by the customs unit value, and aggregating with India's export values as weights. Chargeable emissions include only direct emissions for steel and aluminium, as specified in Annex II of the regulation, but total emissions for cement and fertilisers. For steel, I use the transitional default intensities, which reflect India's blast-furnace production, and for aluminium the direct-emissions defaults of the definitive regulation. Shipments are observed in 2023 and carried back to 2022 using the change in the shipment-level charge between the two years. The resulting share is the target used to identify the charge per unit of carbon τ. With rising marginal cost, emissions per unit of output scale with average cost, the fraction $1/(1+\nu)$ of marginal cost. The measured θ fixes the border wedge whatever ν, and it therefore implies $1+\nu$ times as much carbon per unit of energy spending as at constant marginal cost, which enters the conversion of every carbon price between euros and the model's units.

The number of plants $N_S = 6,287$ is the multiplier-weighted count of registered ASI plants in the covered industries in 2022–23.

The four markets are constructed for 2022 using all covered goods. For the EU, I measure apparent consumption by dividing Comext extra-EU imports in each block of covered six-digit codes by the import penetration of the matching Prodcom product group, excluding exempt EEA suppliers and Switzerland. I construct the three non-EU markets from world production and bilateral trade, measured in tonnes. Each group's home sales equal production less exports to other groups, and each market consists of its buyers' home sales plus imports. I value tonnes at a common sector unit value, so that tonnage shares correspond to value shares. The resulting market sizes I_m are USD 583, 272, 2,644 and 705 billion for the EU, India, the rivals' home markets and third markets, respectively. They also determine the eight Southern market shares targeted in Panel C.

The rival block. Rivals are the 21 origins that together account for 90% of EU imports of covered goods, excluding India, exempt suppliers and the United States. The United States sells almost entirely in its home market and is assigned to the third-market block. The rivals' energy share $\phi_R = 0.155$ is constructed from official CBAM country defaults, which reflect each origin's production routes. I apply these intensities to a common product mix, add the electricity component for metals, and weight origins by production value, since home sales carry the same intensity as exports. The rivals' carbon price combines effective explicit prices where they exist, with China's price set to zero for steel in the base year, and India's shadow price elsewhere. This gives $p_{C,R} = \bar{p}_{C,R} + \omega p_C$, with a production-weighted explicit component of EUR 0.65 and a shadow-price weight $\omega = 0.88$. At the estimated shadow price, the combined price is EUR 7.5 per tonne. Under Article 9, only explicit carbon prices are creditable against CBAM. Weighting these instead by EU export values gives $c_R =$ EUR 2.8, higher than the production-weighted explicit price because origins with explicit carbon pricing account for a disproportionate share of EU exports. I set the rivals' on-site share $\chi_{G,R}$ and intensity ratio δ_R to India's values.

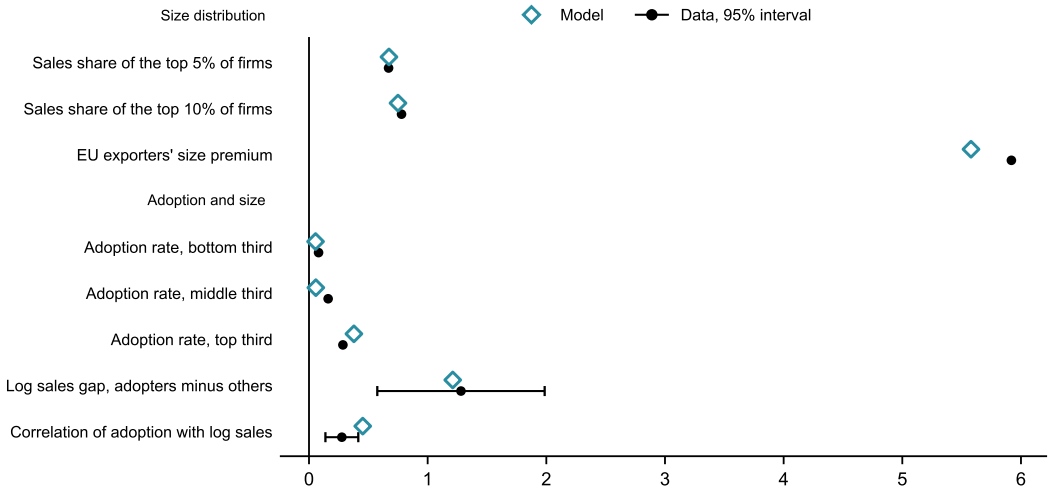
The EU sector's energy share $\phi_{EU} = 0.085$ is constructed on the ETS-benchmark basis, using the product benchmarks for free allocation together with the corresponding electricity component, divided by production value.

The curvature of marginal cost $\nu = 1.19$ is taken from the cross-market elasticity estimated by Almunia et al. (2021), $-(\sigma - 1)\nu/(1 + \nu) = -2.624$, at the calibrated σ. Both origins face the same ν. The capacity normalization $\bar{Q}$ is set so that each origin's baseline price level equals that of the constant-cost model, which leaves every calibration target unchanged.

The legislated inputs are taken from the regulation and enter only the counterfactuals. The route benchmarks $b_D = 1.405$ and $b_G = 0.604$ tonnes per tonne are the ETS product benchmarks for blast-furnace and direct-reduction steel, from Implementing Regulation (EU) 2025/2620. The free-allocation factor cf_y follows the legislated schedule, starting at 0.975 in 2026 and falling to zero in 2034. I set the synchronization of the EU ETS with the border charge to one by assumption.

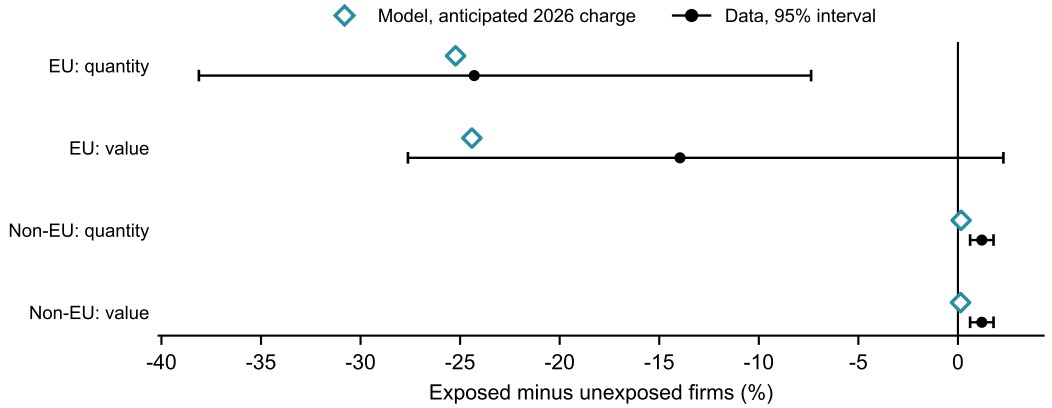
C.2 Validation

Figure C.1: Held-out cross-sectional moments



Notes: This figure compares the model with cross-sectional moments that did not enter the estimation. Filled circles are the data, with 95 percent intervals where a standard error exists, and hollow diamonds the model. Size is total sales. The adoption rows are computed among EU exporters.

Figure C.2: Model-implied vs. empirical responses



Notes: This figure compares model-implied responses with their reduced-form counterparts. Filled circles are the data with 95 percent intervals, hollow diamonds the model. Export rows: OLS of each firm's long difference, last four quarters against 2022, on a dummy for exporting covered goods to the EU in 2021, with industry, state and size-decile effects, standard errors clustered by industry and firm-equal weights. Quantity and value rows are percent changes, $100(e^{\hat{\beta}} - 1)$, with the 95 percent interval transformed the same way. In the model, every firm serves every non-EU market.

C.3 Counterfactuals and measurement

In the phase-out-only world, $\varpi_{EU} = 1$ and $\varpi_T = \varpi_{TH} = 0$; under full CBAM, $\varpi_{EU} = \varpi_T = \varpi_{TH} = 1$. The charge as levied in any given year uses the factors in (B.49). Each modification is applied consistently to the baseline, phase-out-only and full-CBAM worlds. Eliminating adoption by origin o sets $F_o \to \infty$. Each policy alternative is evaluated relative to the phase-out-only world without that policy.

Policy instruments. An ad valorem *tariff* t on EU imports replaces the border charge, multiplying every EU import wedge by $1+t$. Its revenue is $R_{\text{TAR}} = \frac{t}{1+t}[\sum_o s_{o,EU} + (1 - s^M_{EU})(1 - \omega_{EU})]I_{EU}$, which accrues to the EU. I choose t to match CBAM revenue under the full package. Unlike CBAM, the tariff raises the delivered price of both recipes in the same proportion and gives no direct incentive to adopt. *India's own carbon price* $\bar{p}_S$ follows the rule of Appendix B.1, $p^S_C = \max\{\bar{p}_S, p_C\}$, with the explicit component creditable at the border, $c_S = \bar{p}_S$. It is considered both as a replacement for the border charge and as a price credited against it, and it reaches prices by the fraction $1/(1+\nu\sigma)$ of the change in the cost of a bundle. A full *rebate* of CBAM revenue to India sets $\lambda = 0$. The *efficiency programme* raises A^S_G alongside the border charge.

Decomposing emissions. Emissions in each ledger equal spending times the producer's market share times emissions per unit of spending. For a Southern leg, $\Xi_{o,m} = \frac{\sigma-1}{\sigma(1+\nu)} s_{o,m} I_m h(\mathrm{g}_{o,m}, \iota)$, where $h(\mathrm{g}, \iota) \equiv (1-\mathrm{g})\iota_D + \mathrm{g}\iota_G$ and $\iota_T \equiv \mathcal{E}^o_T / \mathcal{T}^o_{T,m}$. For non-Southern producers, $\Xi = s\, I\, \mathcal{E}$, with s the share of EU or third-country producers and $\mathcal{E}$ emissions per unit of spending. Between any two worlds 0 and 1, let $\ell \equiv (\Xi^1 - \Xi^0)/(\ln \Xi^1 - \ln \Xi^0)$ denote the logarithmic mean. The change in emissions is decomposed into five channels:

$$\Delta\Xi = \ell\Big[\underbrace{\ln \tfrac{s^1}{s^0}}_{\text{composition}} + \underbrace{\ln \tfrac{I^1}{I^0}}_{\text{market size}} + \underbrace{\ln \tfrac{h(\mathrm{g}^0,\iota^1)}{h(\mathrm{g}^0,\iota^0)}}_{\text{scale}} + \underbrace{\ln \tfrac{h(\mathrm{g}^1,\iota^1)}{h(\mathrm{g}^0,\iota^1)}}_{\text{recipe switch}} + \underbrace{\ln \tfrac{\mathcal{E}^1}{\mathcal{E}^0}}_{\text{energy saving}}\Big] \tag{B.53}$$

Southern producers have no energy-saving channel, while non-Southern producers have no recipe-switching channel. Summing the ledgers channel by channel gives an exact decomposition of aggregate emissions.

Leakage. Define emissions on Southern sales outside the EU as $\Xi^{\mathcal{M}'}_{\text{South}} \equiv \sum_o \sum_{m \in \mathcal{M}'} \Xi_{o,m}$ and on Southern sales to the EU as $\Xi^{EU}_{\text{South}} \equiv \sum_o \Xi_{o,EU}$. Let Δ^c denote the contribution of channel c in (B.53). Southern and production leakage are

$$L_S = \frac{\Delta\Xi^{\mathcal{M}'}_{\text{South}}}{-\Delta\Xi^{EU}_{\text{South}}} = \underbrace{\frac{\Delta^{\text{comp}}\Xi^{\mathcal{M}'}_{\text{South}}}{-\Delta\Xi^{EU}_{\text{South}}}}_{\text{diversion}} + \underbrace{\frac{\Delta^{\text{recipe}}\Xi^{\mathcal{M}'}_{\text{South}}}{-\Delta\Xi^{EU}_{\text{South}}}}_{\text{technique spillover}} + \frac{\Delta^{\text{size}}\Xi^{\mathcal{M}'}_{\text{South}}}{-\Delta\Xi^{EU}_{\text{South}}}, \tag{B.54}$$

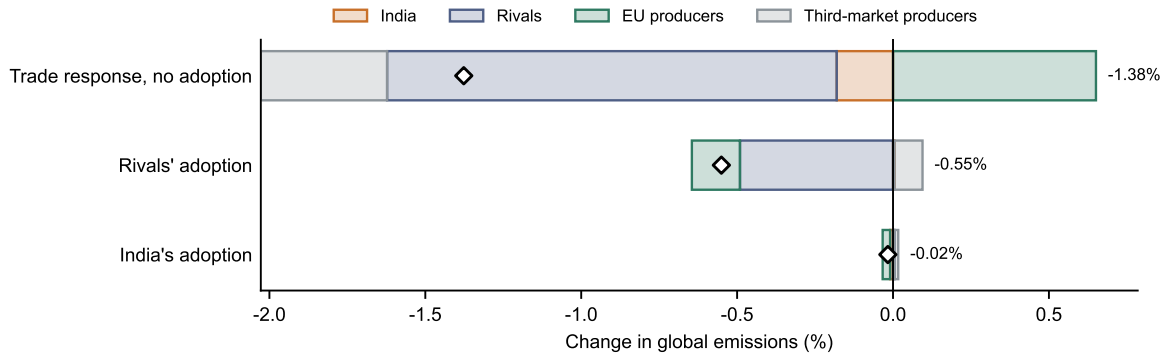
$$L_P = \frac{\Delta\big[\sum_{o,m}\Xi_{o,m} + \sum_m \Xi^{TH}_m\big]}{-\Delta\sum_m \Xi^{EU}_m}$$

The remaining market-size term in L_S is small because spending outside the EU barely changes. I calculate Southern leakage for CBAM's contribution, but production leakage for the phase-out alone and for the full package, both relative to the baseline. CBAM's contribution cannot be used for production leakage because EU producers expand when the border charge is introduced.

C.4 Counterfactual simulations

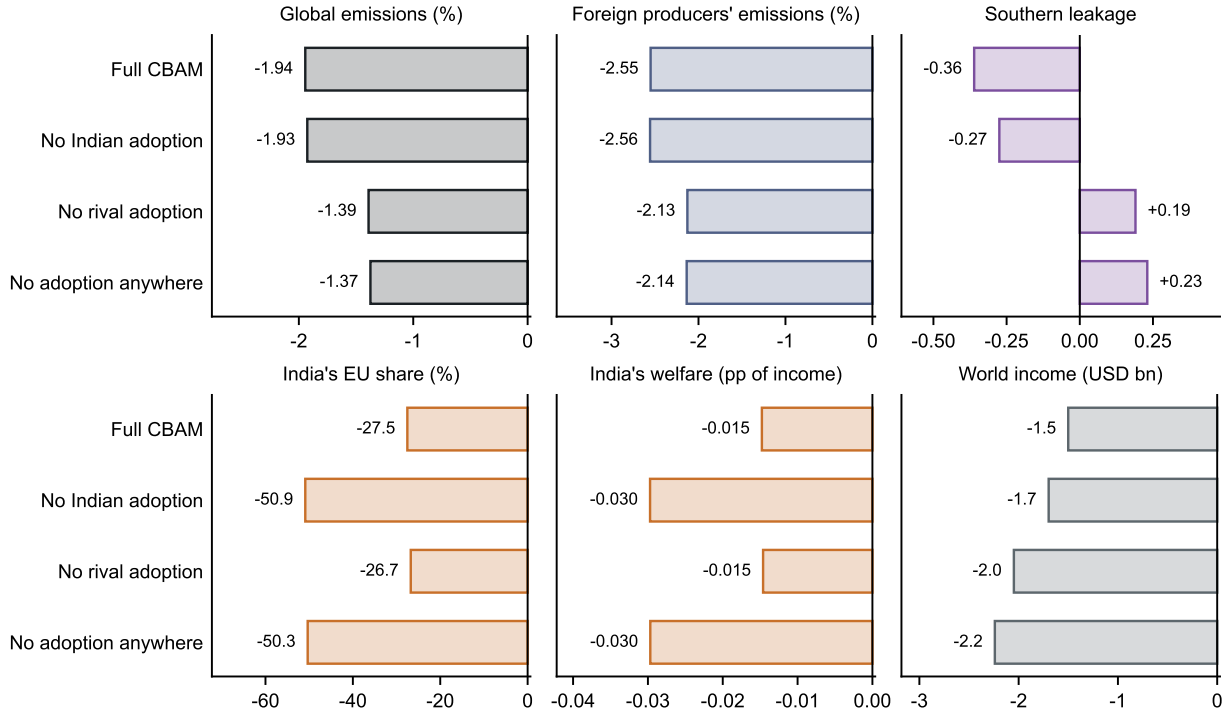
C.4.1 Decomposition and margins of adjustment

Figure C.3: Decomposition of CBAM's contribution



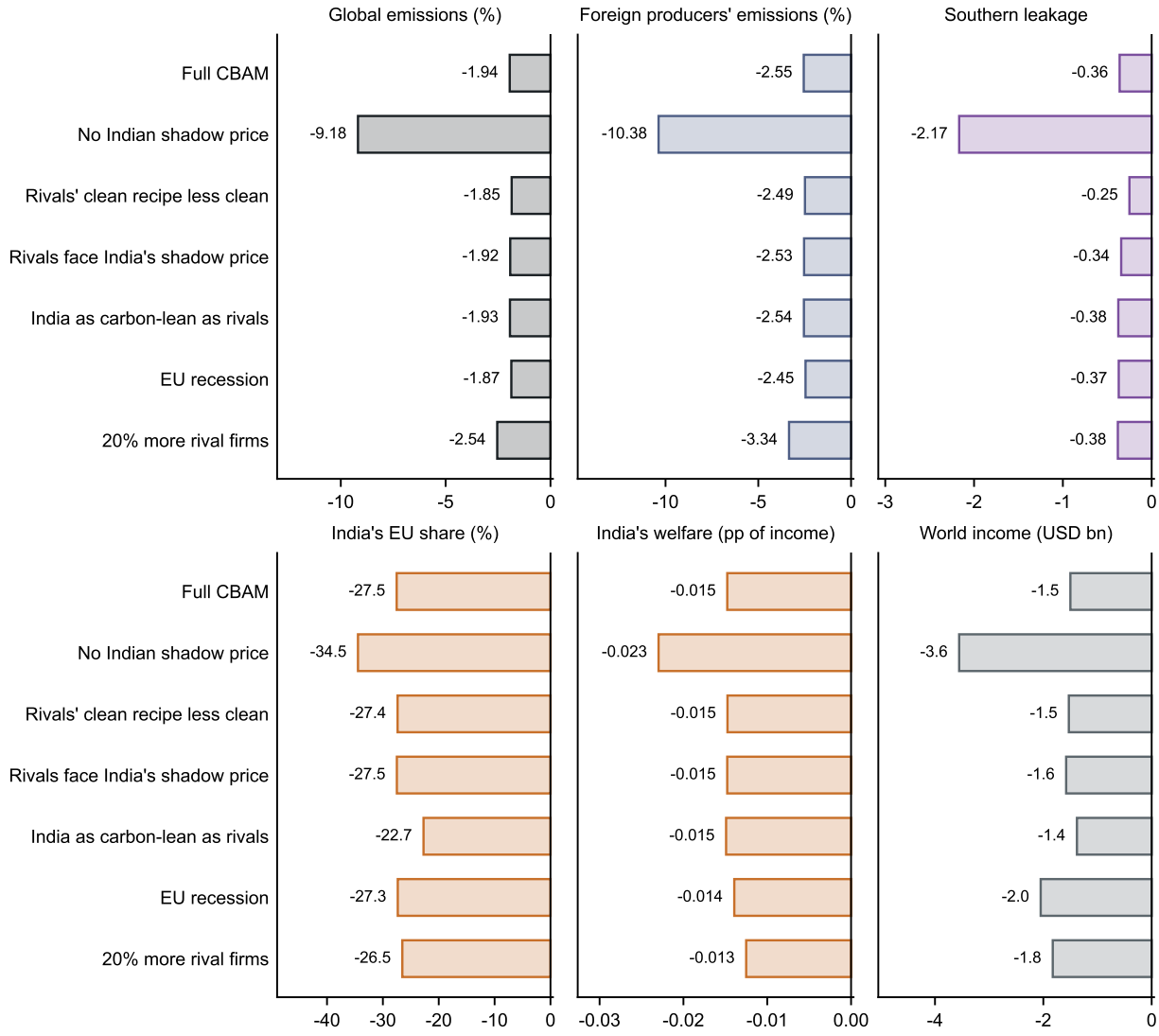
Notes: Shapley decomposition of CBAM's contribution to emissions over India's and the rivals' adoption, as a percentage of global emissions under the phase-out only. Each term is computed as full CBAM against the phase-out only within the same world, and each bar stacks the contribution of each producer. The trade response is the border charge with no adoption anywhere. *Source:* model at the estimated parameters of Table 3.

Figure C.4: Shutting down margins of adjustment



Notes: Each row is CBAM's contribution, full CBAM against the phase-out only, in a world with one mechanism removed. The first row is the unaltered experiment. Global emissions: the change as a percentage of the phase-out-only world's emissions. Foreign producers: India, the rivals and third-market producers. Southern leakage: as in Figure 20(a). India's EU share: percentage change relative to the phase-out only. India's welfare: percentage points of baseline income. World income: the change in world money-metric welfare, in USD billion; positive is a gain. *Source:* model at the estimated parameters of Table 3.

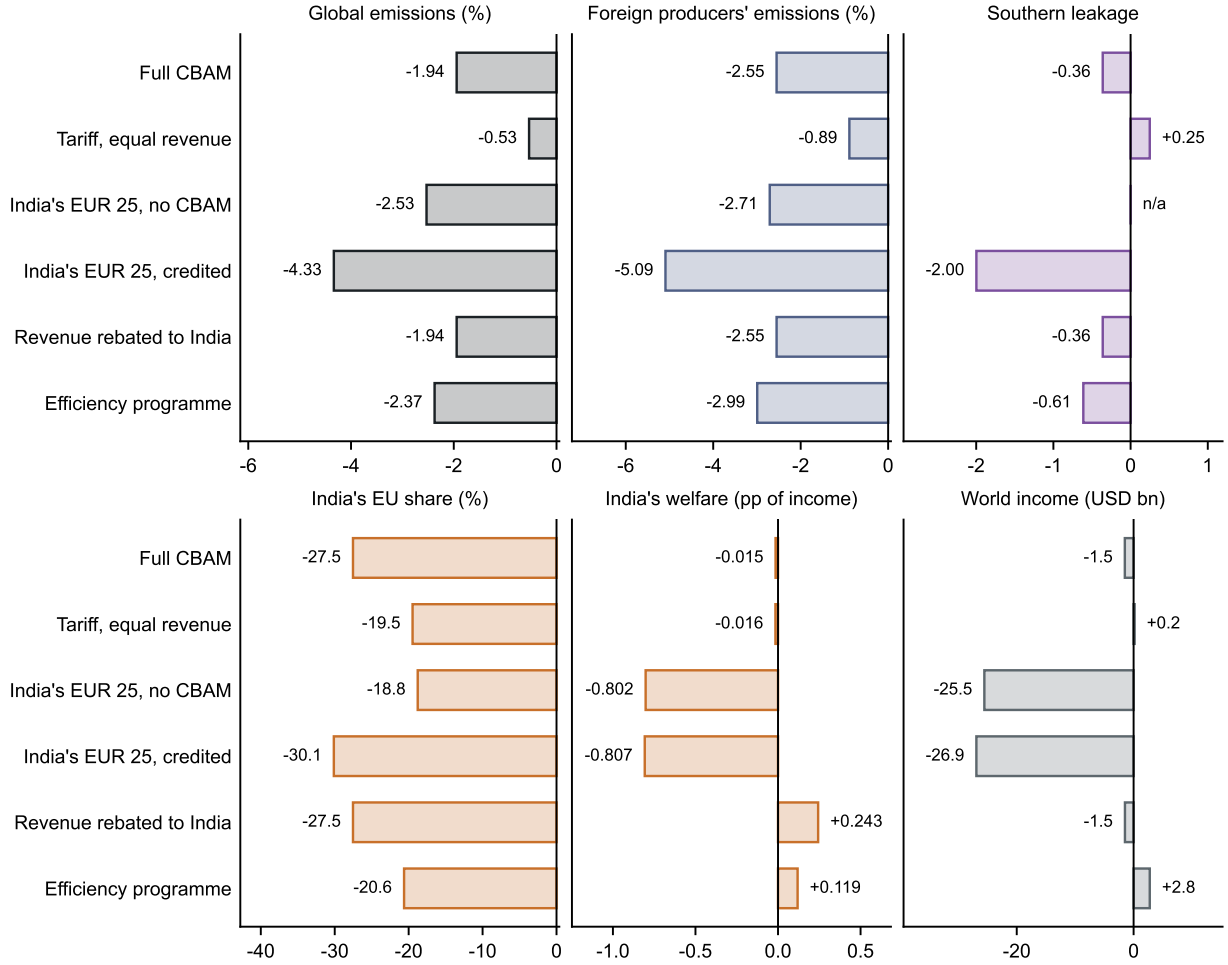
Figure C.5: CBAM's contribution in alternative worlds



Notes: Each row is CBAM's contribution inside an altered world. The worlds are: India's shadow price set to zero; the rivals' clean recipe less clean, an intensity ratio of 0.6 instead of 0.43; the rivals' domestic carbon price set to India's shadow price; India's energy share set to the rivals'; EU spending 10% lower; and 20% more rival firms. Outcomes as in Figure C.4. *Source:* model at the estimated parameters of Table 3.

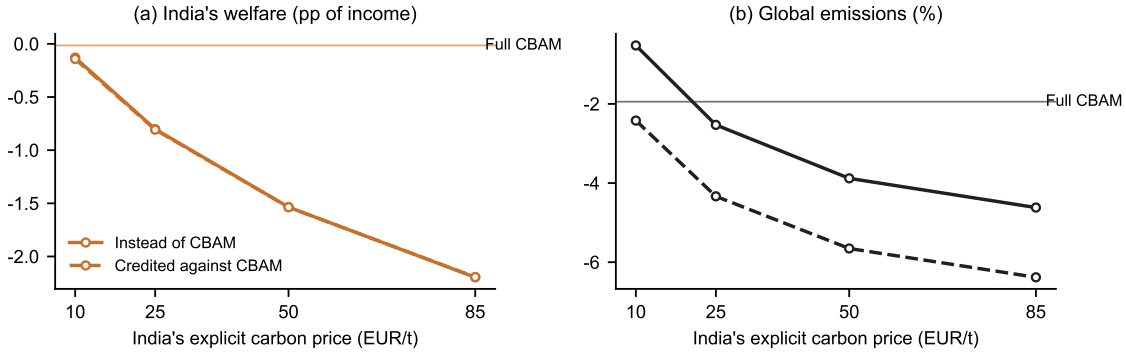
C.4.2 Policy alternatives

Figure C.6: The border charge and its alternatives



Notes: Each row is an instrument added to the phase-out, against the phase-out only. The tariff replaces the border charge at the rate that raises the same revenue. India's price replaces the border charge, or is credited against it. The rebate returns all border revenue to India. The efficiency programme raises India's clean energy advantage A_G by 27 percent alongside the border charge. Southern leakage is not reported where the instrument barely moves the South's EU-bound emissions. Outcomes as in Figure C.4. *Source:* model at the estimated parameters of Table 3.

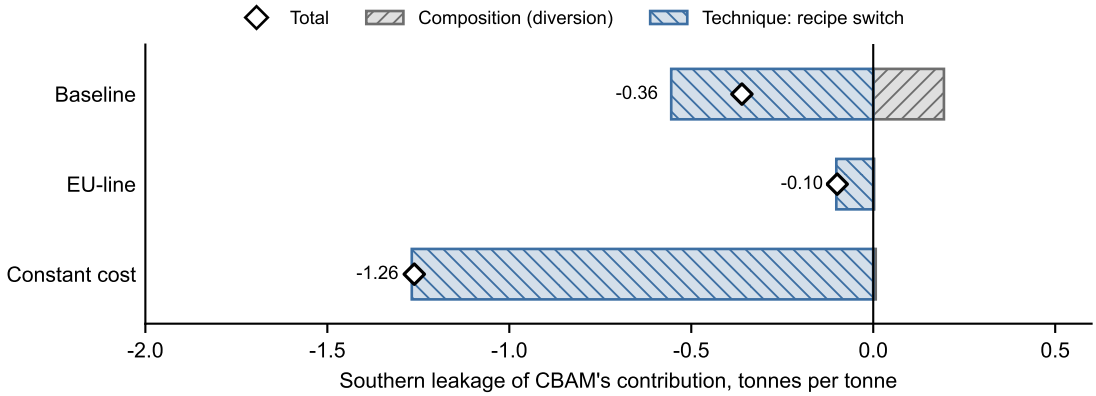
Figure C.7: India's own carbon price



Notes: India's explicit carbon price replaces the border charge (solid) or is credited against it (dashed), at EUR 10, 25, 50 and 85 per tonne, each added to the phase-out and measured against the phase-out only. The horizontal line is the border charge. *Source:* model at the estimated parameters of Table 3.

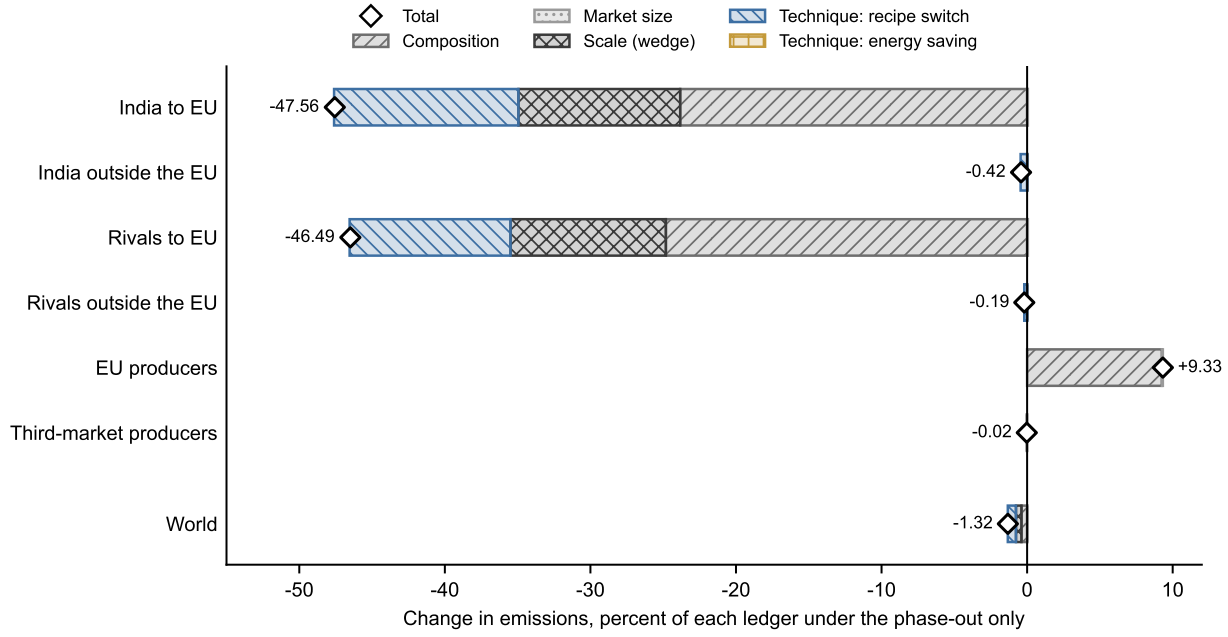
C.4.3 Extensions

Figure C.8: Southern leakage of CBAM's contribution in the three models



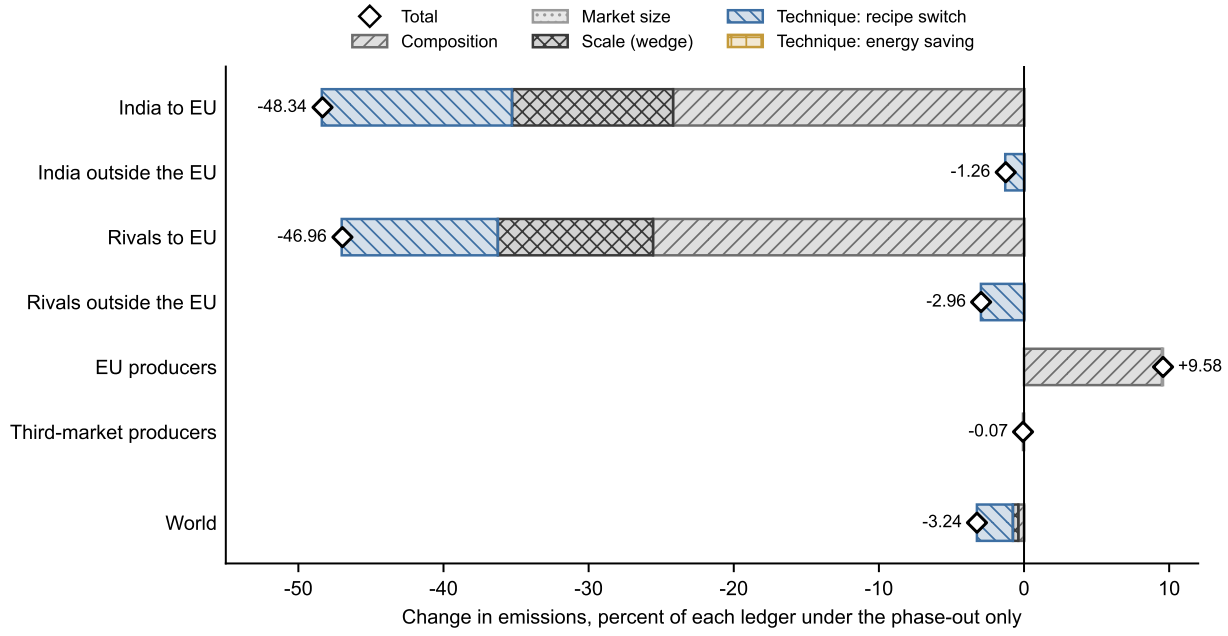
Notes: Southern leakage of CBAM's contribution in each model, split into diversion and technique spillover, which sum to the total marked by the diamond. *Source:* model at the estimated parameters of each version.

Figure C.9: Breakdown of emissions, CBAM's contribution, EU-line model



Notes: As Figure 19, CBAM's contribution in the EU-line model at its own estimates. *Source:* model at the estimated parameters of the EU-line version.

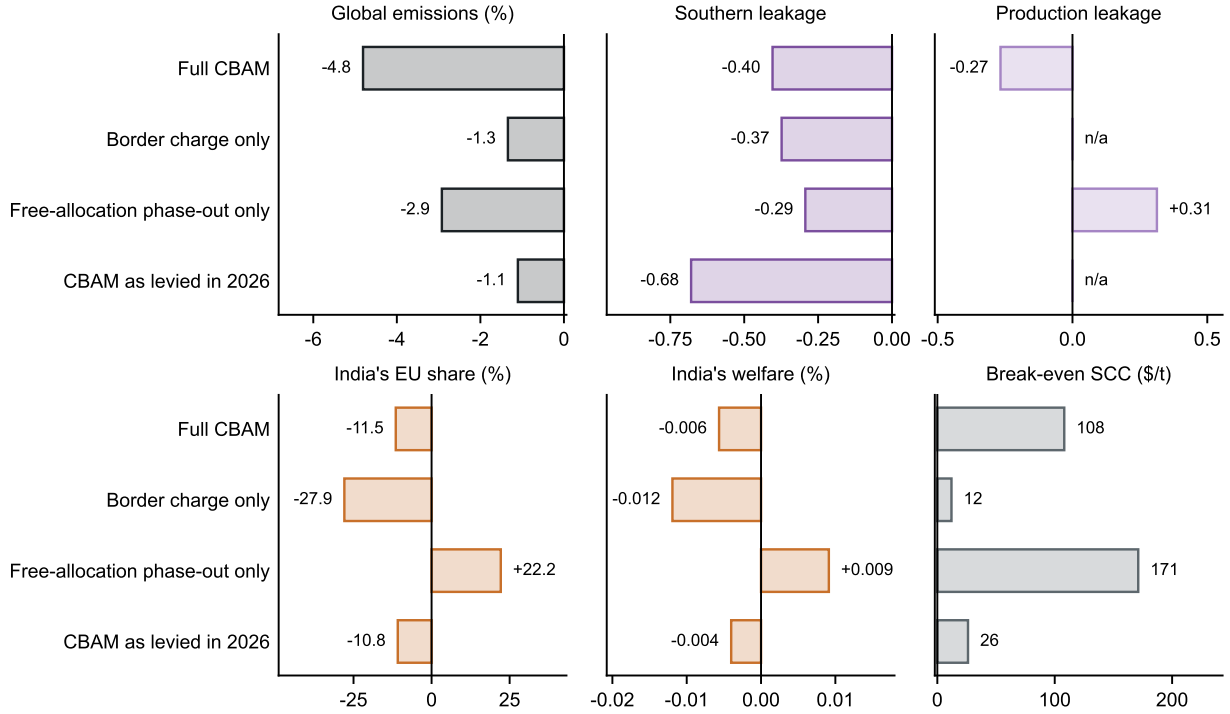
Figure C.10: Breakdown of emissions, CBAM's contribution, constant-cost model



Notes: As Figure 19, CBAM's contribution in the constant-cost model at its own estimates. *Source:* model at the estimated parameters of the constant-cost version.

C.4.4 The two parts of full CBAM, and the 2026 charge

Figure C.11: The two parts of full CBAM and the 2026 charge



Notes: Border charge only: the full charge with EU free allocation at its 2022 level. Phase-out only: the end of free allocation with no border charge. CBAM as levied in 2026: the levied charge with the 2026 free-allocation deduction. Production leakage is not defined where EU producers' emissions rise. Outcomes as in Figure C.4.

D Supplementary appendix

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D.1 *Center for Monitoring the Indian Economy* databases

ProwessDx and *CapexDx* are two related databases provided through the *Center for Monitoring the Indian Economy*. The former tracks company financials, while the latter tracks new capacity expansion projects from announcement to completion. Table D.1 presents summary statistics on the number of unique firms in each database, as well as the overlap between the two.

Table D.1: Firm coverage across CapEx and Prowess

Category	Number of Firms
Total CapEx firms	45,819
Total Prowess firms	56,521
CapEx only	32,481
Prowess only	43,183
CapEx ∩ Prowess	13,338
Unique firms (union)	89,002

D.1.1 *CapexDx* database processing

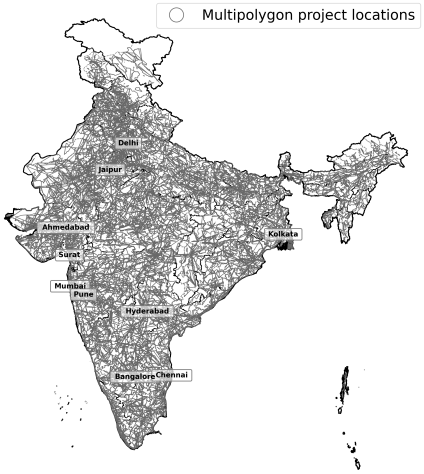
***CapexDx* database description.** The *CapexDx* database contains roughly 146,000 unique projects, along with information on the company code, the address of the company and the address of the project itself, various events relating to the project from announcement to completion, as well as financial information on the investments along with the dates when the investments were made. Lastly, it also includes the titles of the projects.

The datasets are presented in *vintages*, i.e. snapshots of the database at different points in time, specifically in March of each year, between 2014 and 2026 (except 2015). While the latest *vintage* theoretically is cumulative, in practice I observe firms in older vintages not being present in the latest one, therefore before dealing with unique firms, geocoding their addresses, as well as classifying their projects, I append all available *vintages* and work with unique firms across all years.

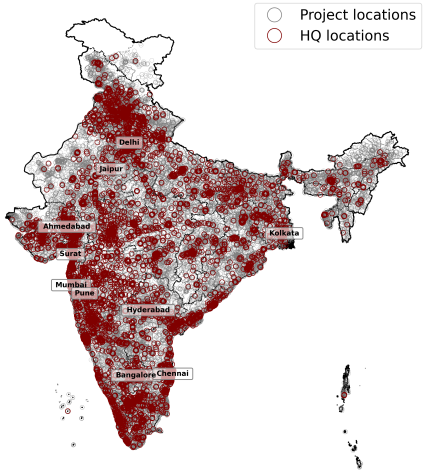
***CapexDx* geolocation.** I follow a multi-step process to geolocate the entries included in the *CapexDx* dataset. The goal of this process is twofold; first, it aims at eventually mapping the coordinates of the various projects onto their corresponding districts through the shapefiles. Second, it aims at enabling the calculation of distances between firms in *CapexDx* and firms in *Panjiva*, as part of the firm-to-firm matching process between the two databases. Due to the latter objective, I proceed to geolocate both addresses of firms (which can be thought of as headquarter locations) and addresses of individual projects corresponding to each firm. The latter will be used to geolocate *CapexDx*, however both sources will be used when mapping to *Panjiva*. This is exactly because it is plausible that either address was used by shippers when exporting.

Figure D.1: Geolocated *CapexDx* projects

(a) Multipolygon locations



(b) Point locations & headquarters



I start with the Company Registered Office Addresses, included in the *Project Detail* files, and utilize *Google Maps* API to geolocate them. Next, I utilize the Project Addresses through the *Project Location* files. For those addresses, some already contain coordinates, while some do not. For those that do not already contain coordinates, I again utilize *Google Maps* API to geolocate them. After merging back with the ones already containing addresses, as well as with the company registered addresses, I split geometries into points (Figure D.1(b)) and polygons (Figure D.1(a)). Polygons come from project-level observations that already have coordinates from *CapexDx* and usually refer to road and railway projects. Point addresses are spatially joined to districts using a simple "within" test, while polygon addresses are intersected with district boundaries and assigned to the district with the largest overlapping area (computed in an equal-area projection). The results are recombined, standardized district identifiers are attached, and any addresses that fail spatial matching are recovered via a fallback string-based method that tokenizes and matches normalized district names against the address text, keeping only unique best matches. Roughly 6% of all projects are polygons.

Table D.2 presents descriptives of the aforementioned process. As can be seen, all addresses were successfully geolocated, while some 8% were not identified to be within India and were subsequently dropped.

Table D.2: *CapexDx* geolocation summary

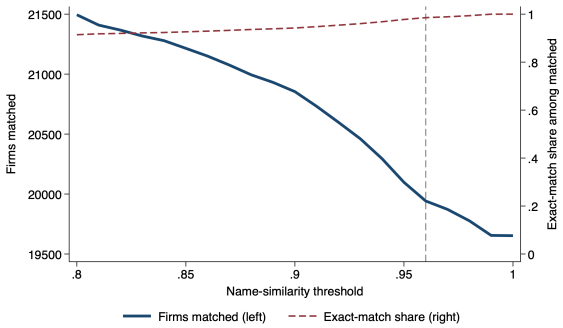
Step	Count
Unique addresses attempted - registered	67,759
Successfully geolocated addresses - registered	67,757
Unique addresses attempted - projects	20,632
Successfully geolocated addresses - projects	20,632
Projects already containing coordinates - projects	43,721
Addresses matched	121,590
Addresses located within India overall	121,411
Geolocation success rate - registered (%)	100.00
Geolocation success rate - projects (%)	100.00
Within India (% of attempted overall)	91.90

D.1.2 Recovery of Corporate Identification Numbers (CINs) for *CapexDx* firms

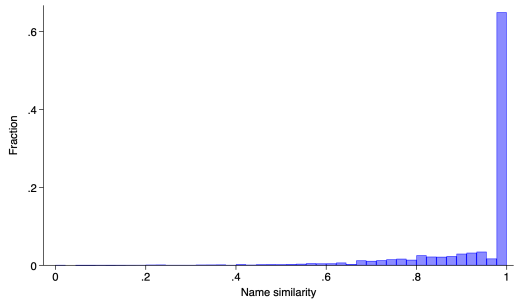
While *ProwessDx* contains CINs for all firms, *CapexDx* does not. I therefore match the 32,481 firms present in *CapexDx* but absent from *ProwessDx* to their CINs using *QuickCompany*, a public registry of Indian firms. I query each firm name and scrape the returned results, obtaining an ordered list of candidates of decreasing relevance for each query. I then compute a fuzzy similarity score between each candidate and the queried name. Results beyond the fifth are rarely relevant, so I retain the first five candidates per query and keep those with a similarity above 0.96; Figure D.2(a) shows how the name-matching procedure responds to the similarity threshold. The solid line (left axis) reports the number of *CapexDx* firms that would be matched to a *QuickCompany* record at each cutoff, while the dashed line (right axis) reports the share of those matches that are exact normalized-name matches (similarity of 1), a proxy for precision. Figure D.2(b) shows that 64.1% of the retained candidates have a similarity of exactly one.

Figure D.2: Descriptive statistics on the matching process with CINs

(a) Matched firms and exact-share vs. threshold



(b) Distribution of match similarity



Panel (a) plots the number of firms matched (left axis) and the share of matches that are exact normalized-name matches (right axis) as a function of the similarity threshold; the vertical line marks the 0.96 cutoff adopted here, illustrating that the recovered set is stable to small changes in the threshold. Panel (b) shows the distribution of similarity scores among these retained candidates. *Source: QuickCompany.in* and *CapexDx*.

I then keep the most similar candidate per firm (the first in case of ties), yielding 19,957 recovered CINs (61.4% of the firms searched), of which 98.5% are exact name matches. Because a high string similarity need not imply the correct firm, I manually verify a random sample of 100 matches and find 96% to be correct (Table D.3), confirming that the procedure recovers genuine identifiers.

Table D.3: Manual validation of recovered CIN matches.

	Checked	Correct
Exact-name matches (similarity $= 1$)	50	96.0%
Near matches ($0.96 \leq$ similarity < 1)	50	96.0%
Population-weighted overall		96.0%

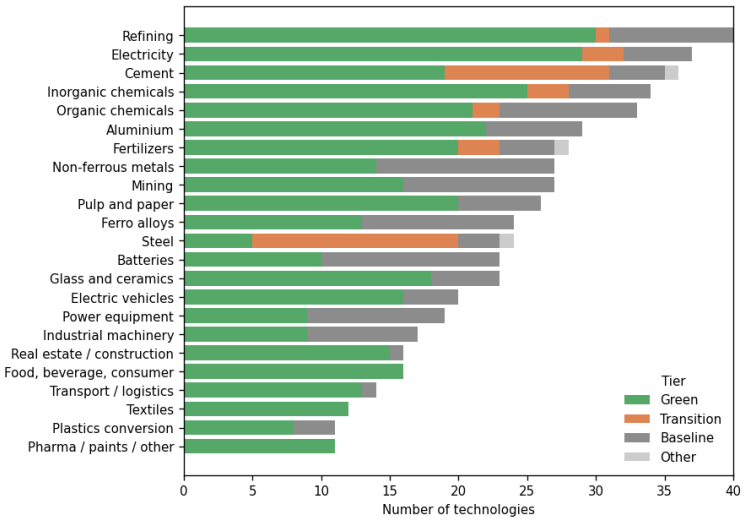
Notes: A random sample of matched firms (stratified into exact and near matches) was manually verified against the Quick-Company record. *Correct* is the share judged to be the same firm. The overall figure reweights the two strata by their shares in the matched set.

D.1.3 *Green* project classification

Given that capital expenditure projects in the *CapexDx* database do not contain identifiers for being *green* or contributing to emissions reductions, I follow a multi-step process to classify and map them to specific de-carbonization technologies. Project records contain only a short title and a set of structured fields (firm industry, product, capacity, location), which are too sparse for keyword-based coding. For example, a title such as "Sponge Iron Plant" is consistent with both a high-emission coal-based technology and a near-zero-emission hydrogen-based one. To deal with this, I construct a pipeline that proceeds in six steps: (A) the construction of a taxonomy, (B) the assignment to broad sectors, (C) the mapping to specific technologies, (D) the retrieval of text from online searches and re-classification based on that text, (E) the aggregation of this information to firm-level indicators, and (F) the manual validation of the labels assigned to projects. The process is described in more detail below.

(A) The taxonomy of technologies. I compile a catalog of 547 sector technologies spanning 23 emissions-intensive sectors. Each of them is obtained through a scientific, sector-specific sources, including International Energy Agency (2020, 2018a, 2021, 2018b, 2023, 2024a,b); Mission Possible Partnership and International Aluminium Institute (2022); European Fuel Manufacturers Association (Concawe) (2019b,a, 2022); Association of European Ferro-Alloy Producers (2019); Brinkmann et al. (2014); International Copper Association (2023); International Council on Mining and Metals (2024); Confederation of European Paper Industries (2013); Cerame-Unie (2021); International Electrotechnical Commission (2024); GEA Group (2024); World Economic Forum (2024); Ascentium (2025); Energy Alternatives India (2023); McKinsey and Company (2024); Actiza Industries (2025); Hossain et al. (2024); Mordor Intelligence (2026). For each technology, I record its sector, sub-sector, position in the production process, and a *tier* that captures its emissions intensity. The assigned tier takes four values, namely *green* (low-carbon technology), *transitional* (emissions-reducing but not zero), *baseline* (conventional, high-emission reference), or *co-benefit*. Figure D.3 summarizes the taxonomy by sector, and Table D.7 lists the top 5 technologies, counted as the number of projects to which they were mapped, for the most relevant industries to CBAM.

Figure D.3: Summary of technologies by sector and tier



The tier distinction allows me to separate genuine *green* investment from both transitional technologies and from conventional capacity expansions. Of the 547 levers, 371 are classified as green, 39 as transitional, and 134 baseline, with the remainder co-benefit or shared across sectors.

(B) Sector assignment Before any project is classified, I assign it to a small set of candidate sectors, which narrows down the set of technologies that the model considers further in the pipeline. Assignment uses two signals: (i) The firm's industry pins down a primary sector: I map each of the 134 industry codes in *CapexDx* to an emissions-intensive sector (e.g. *Renewable electricity* maps onto Electricity), assigning service industries with small to no de-carbonization margin, such as education, retail, software, hospitality, to an out-of-scope category. Second, given that some *green* technologies are deployed across industries irrespective of a firm's core business, the project's product mix triggers a set of *cross-cutting* sectors. These are Electricity, Power equipment, Industrial machinery, Electric vehicles, and Batteries. This second channel is what allows the procedure to recognize, for instance, a captive solar plant or a battery-storage installation announced by a cement or steel producer, which the firm's industry alone would miss.

A project is in scope if it is assigned to at least one candidate sector, and out of scope otherwise. Out of scope projects are coded non-green by construction. Of the 90,167 announced projects in the entire period, 72,668 are in scope and 17,499 end up being out of scope. Table D.4 reports the assignment categories and the number of projects activating each cross-cutting trigger.

Table D.4: Project assignment

	Projects	**Share**
Panel A. Assignment categories		
Project universe (announced 2010Q1 - 2026Q1)	90,167	100.0%
in scope ($\geq$1 candidate sector)	72,668	80.6%
out of scope (no sector, no trigger)	17,499	19.4%
Panel B. Cross-cutting sector triggers		
Electricity	10,144	11.3%
Power equipment	1,538	1.7%
Industrial machinery	690	0.8%
Electric vehicles	553	0.6%
Batteries	405	0.4%

Notes: A project is in scope if its firm's industry assigns it to a carbon intensive sector, or its products trigger a cross-cutting sector. Panel B counts projects activating each cross-cutting trigger. A project may activate more than one, so the entries need not sum to the in-scope total. Shares are with respect to the project universe.

(C) Mapping to technologies Within each project's candidate sectors, I map specific technologies to the project, through the use of a Large Language Model (LLM), *Claude Opus* 4.7. For every project, the model receives the structured record (title, products, capacities, firm industry, and location) together with the list of candidate technologies, presented as the union of the technologies in its assigned sectors and including the *baseline* (conventional) entries as explicit anchors. *Claude Opus* is used with constrained, i.e. structured, outputs, so that the model can only return technology identifiers that exist in the provided list and the response is guaranteed to be machine-readable. A project may map to several technologies. For example, an integrated cement plant that announces a clinker line and a waste-heat recovery boiler matches a baseline and a transition technology simultaneously. For each matched technology, the model returns its tier, a confidence score in $[0, 1]$, a short evidence string, and a "needs text" flag. The flag indicates that the *green* versus conventional determination cannot be made from the structured fields alone (the sponge-iron ambiguity discussed above is one such example). In that sense, including the baseline anchors is important as it lets the model code conventional capacity expansion as baseline, and the output limitation keeps fabricated technologies negligible (12 of roughly 75,000 matched rows reference an out-of-catalog identifier, which I drop).

The choice of which LLM to use is consequential and I validate it directly. On a random sample of projects, a smaller model (*Claude Haiku* 4.5) systematically over-predicts green. Specifically, it codes 64% of projects as green, at a median confidence of only 0.45, and raises the "needs text" flag on 53% of cases, against 22% for *Claude Opus* 4.7 on the same projects, as shown in Table D.5.

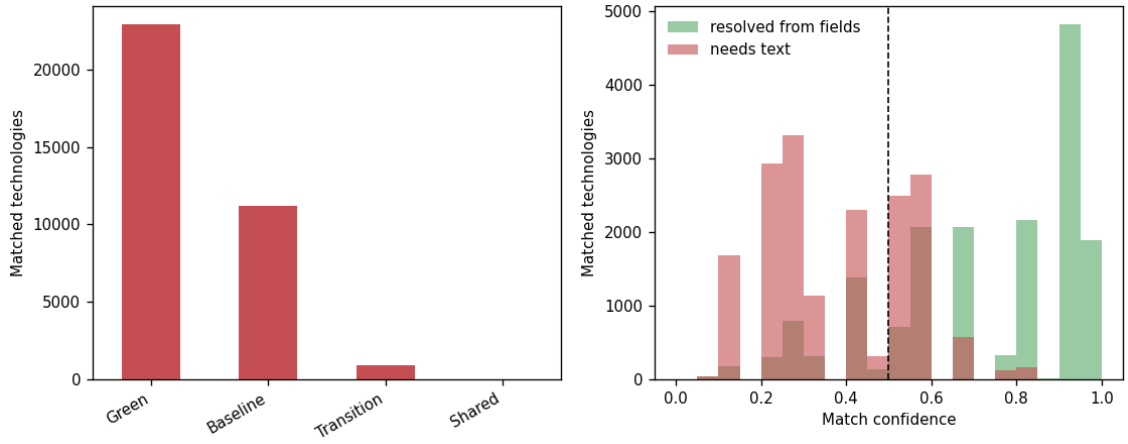
Table D.5: Classifier calibration on a random sample of projects

	Claude Haiku 4.5	**Claude Opus 4.7**
Match rate	68%	46%
Green/transition rate	61%	36%
Median confidence	0.45	0.50
Needs-text rate	50%	22%

Notes: Metrics computed on a fixed random sample of 200 in-scope projects scored by each model. 'Green/transition rate' is the share of projects coded green or transition; 'needs-text' the share flagged as unresolvable from structured data alone; 'median confidence' the median across projects of the maximum match confidence.

Therefore, I use *Claude Opus* 4.7 throughout. Figure D.4 reports the resulting distribution of matched technology tiers and confidence scores. This first pass leaves a sizeable share of projects flagged as needing text to be classified. These are projects whose *green* status genuinely hinges on information absent from the records, motivating the retrieval step described below. Panel D.4(a) shows matched technologies by tier. Most assignments are *green*, but a considerable number are baseline (conventional) and transitional ones are rare. Panel D.4(b) decomposes match confidence by whether a match was flagged as needing text. Matches the model resolves directly from the structured fields concentrate at high confidence, mostly above the 50%, whereas matches needing text cluster at low confidence. The uncertain ones are, therefore, the ones escalated to web retrieval, while the labels accepted from structured data alone are mostly high-confidence.

Figure D.4: Summary of mapping projects to technologies



(D) Targeted retrieval and re-classification The first pass at classifying projects based on fields flagged a substantial set of projects as needing more information. I resolve these by retrieving project-specific web text and re-classifying it. The retrieval set is the union of the projects flagged as needing text and the projects assigned a green or transition lever at low confidence (below 0.5), totaling 19,565 projects. The latter are the cases where additional evidence could either confirm or overturn a classification as *green*. I initiate a web search for each of those projects, comprising of the firm name and the project's fields, I retrieve the top results, and retain their text snippets. This recovers usable text for 98.7% of the set. The remainder have no web footprint and retain the label assigned to them in step (C). Table D.6 summarizes coverage.

Table D.6: Text retrieval and reclassification

Panel A: Coverage	
Projects escalated to retrieval	19,565
Text retrieved	19,308 (98.7%)
snippets	19,304
snippets & page	4
empty	253
error	4
Panel B: Reclassification effect	
Green to non-green (downgrades)	8,734
Non-green to green (upgrades)	477
Population green, before retrieval	30.8%
Population green, after retrieval	19.4%

I then re-run each of these projects through the same *Claude Opus* 4.7 classifier, now appending the retrieved snippets to the prompt and instructing the model to use them to settle the *green*-versus-conventional question, re-flagging those that need text, only if the text still does not resolve it. Of the re-classified projects, 8,734 are downgraded from *green* to non-*green* and only 477 are upgraded, so the share of classified projects coded green falls from 31% to 19%. In other words, the structured-data pass systematically *over*-coded *green* when returning low confidence scores, most often by reading sector or product cues as evidence of a *green* technology that the project text does not in fact support, while the retrieval step removed these false positives. I treat the post-retrieval labels as final wherever text is available.

Table D.7: Green and transitional technology taxonomy (top 5 for relevant sectors)

Type	Process stage	Technology description	Tier	Projects
Steel				
Secondary steelmaking (induction)	Steelmaking	Induction furnace for steelmaking	Transition	396
Sinter plant auxiliary	Raw material preparation	Sinter plant waste heat recovery	Transition	162
Iron ore preparation	Raw material preparation	Iron ore pellet plant (high-quality pellets for DRI or BF)	Transition	109
Secondary steelmaking	Steelmaking	Scrap-based electric arc furnace	Green	33
Byproduct utilisation	Granulation	Granulated blast furnace slag plant (for cement clinker substitution)	Green	7
Cement				
Clinker substitution	Cement blending	Fly ash from coal-fired power plants used as a supplementary cementitious material	Green	190
Clinker production auxiliary	Excess heat recovery for electricity generation	Excess heat recovery system for on-site electricity generation	Transition	125
Clinker substitution	Cement blending	Ground granulated blast furnace slag	Green	104
Grinding	Grinding and milling	Vertical roller mill (raw meal and cement grinding)	Transition	19
Renewable power for cement	Electricity supply	Renewable-based captive power generation at cement plant (solar, wind, small hydro)	Green	13
Aluminium				
Secondary aluminium production	Scrap melting and casting	Secondary aluminium production via scrap remelt and casting	Green	19
Smelter power supply decarbonisation	Electricity supply to smelter	Grid connection with low-carbon renewable power purchase agreements	Green	4
Demand-side material efficiency	Product design	Lightweighting and ease-of-repair design in aluminium-using products	Green	2
Scrap sorting and purification	Pre-melt scrap processing	Alloy separation, sorting, and purification technology for aluminium scrap	Green	0
Smelter power supply	Electricity generation for smelter	Captive hydropower supplying aluminium smelter	Green	0
Fertilizers				
Enhanced-efficiency fertilizers	Fertilizer product formulation	Enhanced-efficiency fertilizers with slow-release coatings and nitrification inhibitors	Green	10
Energy efficiency	Ammonia plant retrofit or new-build	Adoption of catalysts, large centrifugal compressors, process integration	Transition	9
Nutrient use efficiency	Fertilizer application practice (downstream)	Four-R stewardship with precision agriculture	Green	5
Ammonia production	Electrolytic hydrogen with renewables	Electrolyser supplied by renewable energy with hydrogen buffer storage	Green	1
Fertilizer product substitution	Fertilizer formulation downstream of ammonia	Substitution from urea to ammonium nitrate and calcium ammonium nitrate	Green	1
Electricity				
Solar power (variable renewable energy)	Generation	Utility-scale solar photovoltaic power plant (ground-mounted, crystalline silicon modules)	Green	3,322
Wind power (variable renewable energy)	Generation	Onshore wind turbine power plant	Green	1,441
Bioenergy power (dispatchable renewable)	Generation	Bioenergy power plant (solid biomass combustion, biomethane combined-cycle, or biogas)	Green	722
Solar power (distributed)	Generation (behind-the-meter)	Distributed and rooftop solar photovoltaic installation (residential and commercial)	Green	452
Hydropower (dispatchable renewable)	Generation and storage	Large hydropower (reservoir and run-of-river)	Green	434
Organic chemicals				
Bioethylene	Primary chemical production	Bioethanol dehydration to bioethylene	Green	670
Plastic mechanical recycling	Material efficiency (post-consumer plastic)	Mechanical (back-to-polymer) plastic recycling	Green	19
Electrolytic methanol	Primary chemical production	Electrolytic hydrogen plus carbon dioxide to methanol synthesis	Green	7
Bioplastics	Primary chemical production (renewable)	Bioplastics (polyethylene, polyethylene terephthalate, polylactic acid)	Green	6
Biomass-to-methanol	Primary chemical production	Biomass gasification to methanol	Green	5
Refining				
Synthetic hydrocarbons from green hydrogen	Refinery transformation	Synthetic kerosene, diesel, methanol from green hydrogen and carbon capture	Green	5
Hydrotreated vegetable oil co-processing	Refinery transformation (renewable feedstock)	Hydrotreated vegetable oil co-processing in existing hydrotreaters	Green	3
Indian policy enabler	Policy framework	Indian National Green Hydrogen Mission and refinery green hydrogen integration	Green	2
Lignocellulosic biomass co-feeding	Refinery transformation	Lignocellulosic biomass pyrolysis-oil co-processing in fluid catalytic cracker	Green	2
Alkaline electrolysis	Hydrogen production	Alkaline water electrolysis with continuous low-carbon grid electricity	Green	1
Ferro alloys				
Waste heat recovery to electricity	Energy efficiency	Waste heat recovery for electricity via Organic Rankine Cycle (ORC)	Green	5
Renewable Power Purchase Agreements	Energy supply	Renewable Power Purchase Agreements for ferro alloy submerged-arc furnaces	Green	3
Submerged arc furnace	Carbothermic smelting	Closed (hermetic) submerged-arc furnace for ferro-chrome, silicon, ferro-silicon	Green	1
Ferro alloy scrap recycling	Recycling	Ferro alloy recycling within steel and aluminium recycling streams	Green	1
Ferro alloy slag valorisation	By-product valorisation	Ferro alloy slag valorisation for road construction, concrete aggregate, cement additive	Green	1
Batteries				
Indian policy enabler	Policy framework	Production Linked Incentive (PLI) Advanced Chemistry Cell battery storage scheme	Green	54
Hydrometallurgical battery recycling	End-of-life recycling	Hydrometallurgical battery recycling	Green	9
Pyrometallurgical battery recycling	End-of-life recycling	Pyrometallurgical battery recycling	Green	4
Sodium-ion batteries	Cell chemistry	Sodium-ion batteries	Green	3
Solid-state batteries	Cell chemistry	Solid-state lithium batteries (sulphide, oxide, polymer electrolyte)	Green	2
Power equipment				
Direct-drive magnetgenerator wind turbine	Wind turbine manufacturing	Direct-drive permanent magnet synchronous generator wind turbine	Green	12
High-voltage direct current (HVDC) converter	Transmission equipment	High-voltage direct current voltage-source converter for long-distance transmission	Green	6
Indian policy enabler	Policy framework	Indian PLI National Programme on High-Efficiency Solar PV Modules	Green	3
Fixed-bottom offshore wind turbine foundations	Offshore wind installation	Fixed-bottom offshore wind foundations	Green	1
Floating offshore wind platforms	Offshore wind installation (emerging)	Floating offshore wind platforms	Green	0

(E) Final indicators I then collapse the technology level labels to a project level *green* indicator. Subsequently, I aggregate to the firm level to create the final dataset. A project is coded *green* if any of the technologies it is mapped to is of *green* or transition tier, and non-*green* otherwise. Projects that were already out of scope are by construction coded as non-*green*, based on the assumption that they did not have much room to lower emissions in the first place. My baseline *green* indicator applies a confidence floor, that is it equals one only when the project has a green or transition lever assigned at a confidence of at least 0.5, which discards the residual marginal cases, while retaining the well-evidenced ones. Across the full universe of 90,167 projects, 15.6% are *green* and 13.9% *green*-confirmed. Restricting to the 72,662 in-scope, i.e. classifiable, projects, the corresponding shares are 19% and 17%.

Alongside the binary indicator, I retain each project's tier (*green* versus transition) and the sector of its primary lever, which support the heterogeneity analysis. Table D.8 lists, for each sector, the median confirmed-*green* project as an illustration of what the classification captures.

Table D.8: Example green capacity-expansion projects (median per sector)

Project	Year	Tier	Lever sector	Technology	Label Source	M USD 2020
Dwarka Biofuel Complex Project (Sustainable Aviation Fuel or Hydrotreated Vegetable Oil)	2025	Green	Refining	REFINING-HVO-COPROCESS	v2-retrieval	519
Rola (Valsad) Lithium-ion Advanced Chemistry Storage Cell Manufacturing Plant Project	2024	Green	Batteries	BATTERY-INDIA-PLI-ACC	v2-retrieval	221
Kalatalav Chemical Complex Expansion Project	2010	Green	Inorganic chemicals	INORG-CHEMS-BIPOLAR-MEMBRANE	v2-retrieval	108
Purnia (North-East Bihar) Cement Plant Project	2024	Green	Cement	CEMENT-RENEW-CAPTIVE-SOLAR-WIND	v2-retrieval	85
Paradeep Uranium Seperation Plant Project	2017	Green	Mining	MINING-TAILINGS-REPROCESSING	v2-retrieval	75
Tapukara Plant Capacity Expansion Project	2015	Green	Electric vehicles	EV-BEV-PASSENGER-CAR	v2-retrieval	63
Mathura-Kasganj-Kalyanpur Railway Electrification Project	2016	Green	Transport / logistics	TRANS-RAIL-ELECTRIFICATION-INDIA	v1	48
Devarapally Aluminum Alloy Ingots & Aluminum extrusions Expansion Project	2010	Green	Aluminium	ALU-SECONDARY-SCRAP-REMELT	v2-retrieval	41
Vadodara Blade Manufacturing Project	2011	Green	Power equipment	PWREQ-WIND-DIRECT-DRIVE-PMSG	v1	41
50 MW (NTPC's 1,200 MW Auction) ISTS-Connected Solar PV Power Project	2024	Green	Electricity	ELEC-SOLAR-PV-UTILITY	v1	35
Dhanej Nano Urea Manufacturing Plant Expansion Project	2021	Green	Fertilizers	FERT-4R-NUTRIENT-STEWARDSHIP	v1	28
Ichalkaranji Mega Powerloom Cluster Project	2012	Green	Textiles	TEXTILE-AIR-JET-WEAVING	v2-retrieval	24
Udupi Dairy Plant Project	2011	Green	Food, beverage, consumer	FOOD-INDIA-ICAR-NDDB-FSSAI-AGRO	v2-retrieval	22
Kallakal Steel Plant Expansion Project	2018	Transition	Steel	STEEL-IRON-INDUCTION-FURNACE	v2-retrieval	22
Khurda PET preform, Bottles and Caps Recycled Flakes and Pellets Plant Project	2024	Green	Organic chemicals	ORGCHEM-MECHANICAL-RECYCLING	v1	19
Haldia Smelting Unit Project	2016	Green	Non-ferrous metals	NONFE-PB-SECONDARY-RECYCLING	v2-retrieval	16
Manjhiladih Ferro Alloy Plant Expansion project	2018	Green	Ferro alloys	FERROALLOY-WASTE-HEAT-ELECTRICITY	v2-retrieval	15
Bhavnagar EWS Package I (Housing for All) Residential Project	2018	Green	Real estate / construction	BLDG-INDIA-ECBC-PMAY-SuryaGhar	v1	11
NCR Resource-Efficient Bricks Unit Project	2011	Green	Glass and ceramics	CERAMICS-LOW-C-CLAY-MIXES	v2-retrieval	9
Sullurpet (Nellore) Rubber Reclaim Division Expansion Project	2018	Green	Plastics conversion	PLASTICS-RUBBER-RETREADING	v1	7
Manderdisa Bamboo Industrial Park Project	2019	Green	Pharma / paints / other	WOOD-FSC-SUSTAINABLE	v2-retrieval	7
Noida Solar Pumping Systems Manufacturing Plant Project (Phase 1)	2023	Green	Industrial machinery	INDMACH-SOLAR-PUMP-KUSUM	v1	2

(F) Validation Lastly, I validate the indicator on a hand-labeled random sample. I draw a sample stratified by sector and by the model's *green* call, and label each project as genuinely *green* or not from its description, product list, and retrieved text, blind to the model's coding. Table D.9 reports agreement by sector: precision, the share of model-green projects confirmed green, is high where evidence is concrete and the confidence floor screens the marginal cases, while misses concentrate in projects with thin descriptions.

Table D.9: Manual validation of the green indicator, by sector

Sector	N	Accuracy	Precision	Recall
Electricity	24	100%	100%	100%
Food, beverage, consumer	24	100%	100%	100%
Organic chemicals	24	100%	100%	100%
Other	24	100%	100%	100%
Pharma / paints / other	24	96%	92%	100%
Real estate / construction	24	92%	83%	100%
Steel	24	100%	100%	100%
Textiles	24	88%	75%	100%
Transport / logistics	24	75%	50%	100%
All	216	94%	89%	100%

D.1.4 *ProwessDx* database processing

***ProwessDx* description** *ProwessDx* is a database that contains financial and other information for firms, both standalone (single-entity accounts) as well as consolidated (parent plus subsidiaries). It draws from annual reports and financial statements, and also includes information on labor spending, costs of goods sold, sales, CSR spending, various types of fixed assets, among other variables.

***ProwessDx* geolocation** In the case of *ProwessDx*, geocoding is simpler than for *CapexDx*. After importing all firms, I retain unique addresses and feed them to the API of *Google Maps*. Table D.10 presents descriptives on the geocoding process, including the unique addresses queried through the API, the ones that were successfully geocoded, and the ones that were successfully geocoded and found to be within India. Overall, 99.86% of all unique addresses were correctly geocoded and found to be within India.

Table D.10: *ProwessDx* geolocation summary

Step	Count
Unique addresses attempted	51,862
Successfully geolocated addresses	51,848
Addresses located within India	51,789
Geolocation success rate (%)	99.97
Within India (% of attempted)	99.86

D.2 *S&P Global Panjiva Supply Chain Intelligence* database

D.2.1 *Panjiva* database processing

Panjiva is a database that includes records on the shipment level, showing the exporter, consignee, addresses and names on both sides, internal IDs for both sides, as well as information on the product code, amounts, units of measure and shipment values. Data for India is available from 2016 until 2025. To work with *Panjiva*, I begin by splitting the data for each year into 2 million observation chunks. Subsequently, I create datasets of unique exporter *Panjiva* IDs, addresses, and names. There are a total of 589,447 unique IDs, 438,994 unique addresses, and 377,307 unique names across all available years.

Unit harmonization and weight imputation. Panjiva records the physical quantity of each shipment in the unit chosen by the filer, so the same HS6 code appears with quantities in kilograms, metric tons, pieces, square meters, liters, and other units, often within the same HS6 code. Raw quantities are therefore not additive. This section describes how I harmonize units before collapsing the shipment-level data to the exporter $\times$ HS6 $\times$ destination panel used in the analysis, as well as the procedure I follow to express non-weight products in tons for CBAM emission cost calculations.

I first map each raw unit code into one of seventeen unit families (weight, count, length, area, volume, etc.). Within each family, I define a reference base unit and a multiplicative conversion factor to it. For example, weights convert to kilograms, areas to square meters, volumes to liters, and counts, lengths, sets, pairs, and the remaining families to their natural base unit. A shipment's quantity in the base unit is its reported quantity times the conversion factor.

Given that a single HS6 code can be measured in several incompatible units, I assign a dominant family to each HS6 code, defined as the unit family accounting for the largest share of the code's shipments over the full 2016-2025 sample. When collapsing, I retain only shipments whose unit family matches the HS6's dominant family and drop the remainder, which cannot be expressed in a common metric. Importantly, customs value in USD is retained for all positive-value shipments regardless of unit. Only the *quantity* aggregates are restricted to the dominant family, so that the value-based exposure measures are unaffected by this restriction. Quantities of the retained shipments are converted to the base unit and summed to the exporter $\times$ HS6 $\times$ destination level.

The CBAM emission cost measure requires shipment weight in tons, but for HS6 codes whose dominant family is not weight (for example, products customarily counted in pieces) tonnage is not directly observed. For each such code I recover an implied price per kilogram from the minority of its shipments that are nonetheless reported in a weight unit. I then compute USD per kilogram on each weight-family shipment, trim values below the first and above the ninety-ninth percentile to remove data-entry outliers, and take the median across the remaining shipments as the code's reference price per kilogram (with an HS4-level fallback for codes with too few weight observations). Tonnage for a non-weight shipment is then imputed as its customs value divided by this reference price per kilogram, divided by one thousand. These imputed weights enter only the CBAM emission cost calculation. The baseline panel in my analysis uses the harmonized within-family quantities described above.

Exporter geolocation. The *Panjiva* database includes the full address of shippers, without any information on specific coordinates. To most efficiently map shippers to districts, I utilize the API service provided by *Google Maps* and query all unique addresses. Overall 99.20% of all addresses were successfully geolocated within India.

Table D.11: Panjiva geolocation summary

Step	Count
Unique addresses attempted	447,837
Successfully geolocated addresses	444,947
Addresses located within India	444,264
Geolocation success rate (%)	99.35
Within India (% of attempted)	99.20

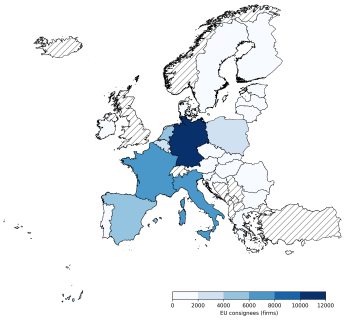
Consignee processing. I assign every consignee to a world region using a country-region reference table, and retain the unique consignees located in the EU-27 in each year. Beyond consignees physically located in the EU, I identify consignees that are *owned* by EU firms, since an EU multinational's foreign subsidiary activity is relevant in terms of capturing potential responses to the regulation. Using *Capital IQ*, I (i) select all companies headquartered in an EU-27 country as candidate ultimate parents, (ii) link them to their

subsidiaries through *Capital IQ*'s point-in-time ultimate-parent table, which records, for each company, its top-of-chain parent and the start and end dates of the relationship, so a firm is captured whether it is a direct subsidiary or is held through intermediate (possibly non-EU) holding companies, (iii) construct active-year indicators from the ownership dates, and (iv) crosswalk the subsidiaries to *Panjiva* identifiers. Intersecting this set with the consignee universe, by region and year, yields the consignees that are subsidiaries of EU parents and the years in which that ownership was active.

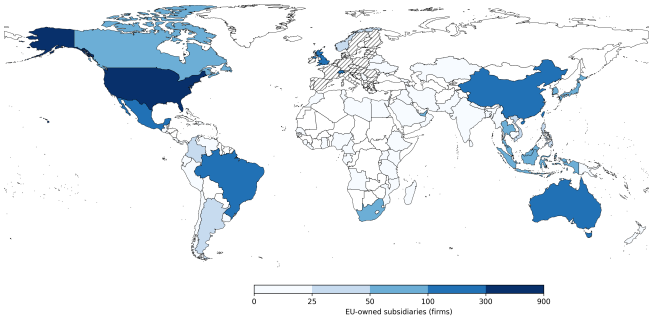
I combine the directly-located EU consignees with the EU-owned subsidiary consignees into a single annual dataset, flagging each consignee as a direct EU buyer or as an EU subsidiary. Where a firm qualifies on both grounds, the ownership (subsidiary) classification takes precedence. This yields, for each year, the set of *Panjiva* consignees of Indian exports that are subject to, or owned within, the EU. Figure D.5 displays the spatial distribution of the two sets of consignees.

Figure D.5: Locations of consignees and subsidiaries in 2022

(a) Consignees in the E.U.



(b) Subsidiaries of E.U. firms



Symmetrically, I flag which Indian *shippers* are themselves subsidiaries of EU-27 ultimate parents, by intersecting the shipper identifiers with the same EU-ownership crosswalk. Because the *Capital IQ*-*Panjiva* crosswalk covers roughly one third of unique Indian shippers, predominantly the larger, internationally-visible firms, these flags are a lower bound within the matchable set. Shippers that cannot be matched are treated as not EU-owned.

Table D.12 reports the construction of the *Panjiva* firm universe and its exposure to the European Union. On the export side, the records contain 443,755 unique Indian exporters, of which 148,680 (33.5%) are matched to *Capital IQ*; the unmatched two-thirds are smaller or unlisted firms outside its coverage. Among matched exporters, EU ownership is rare, only 1,487 (1.0% of matched, 0.3% of all) have an ultimate parent in the EU-27, confirming that Indian exporters are overwhelmingly domestically owned. On the buyer side, the data contain 1,811,435 unique consignees with a recorded country, roughly four times the number of exporters, reflecting the fragmentation of foreign demand (a typical exporter ships to many distinct buyers). Of these, 311,331 (17.2%) are located in the EU-27 and 92,262 (5.1%) are owned by an EU-27 ultimate parent (located anywhere). The ownership channel is substantial relative to location: EU-owned consignees number about 30% as many as EU-located ones, indicating that EU corporate reach extends materially beyond the bloc's borders. Because ownership is identified through *Capital IQ*, the EU-ownership figures are restricted to matched firms and are therefore lower bounds; the consignee total excludes shipment records with no recorded consignee country.

Table D.12: *Panjiva* consignees and shareholders

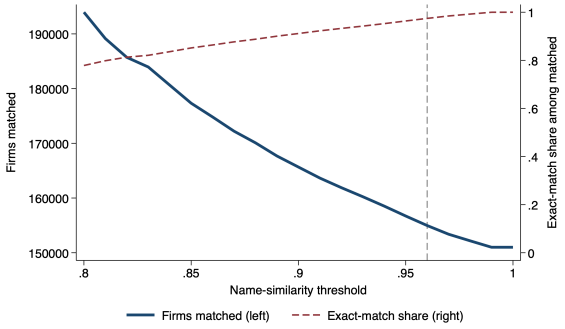
Step	Firms	Share
Exporters (Indian shippers)		
Unique exporters	443,755	100.0%
matched to *Capital IQ*	148,680	33.5%
EU-owned (ultimate parent)	1,487	0.3%
Consignees (foreign buyers)		
Unique consignees (with country)	1,811,435	100.0%
located in EU-27	311,331	17.2%
owned by EU-27 parent	92,262	5.1%

D.2.2 Recovery of Corporate Identification Numbers (CINs) for *Panjiva* firms

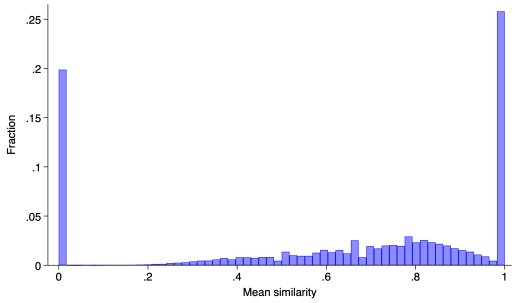
As with the *CapexDx* firms, I use firm names to recover Corporate Identification Numbers (CINs). For each of the 391,253 unique exporter names in *Panjiva*, I query *QuickCompany* and score every returned company name against the searched name using a token-set similarity ratio. Figure D.6 presents descriptive statistics of this process before filtering: panel (a) plots the relationship between a candidate's order in the returned list and its similarity score, while panel (b) presents the distribution of match similarity at the same stage. As before, I retain only the top five candidates per name, keep matches with a similarity of at least 0.96, and select the first (highest-scoring) remaining candidate as the match.

Figure D.6: Descriptive statistics on the matching process with CINs

(a) Matched firms and exact-share vs. threshold



(b) Distribution of match similarity



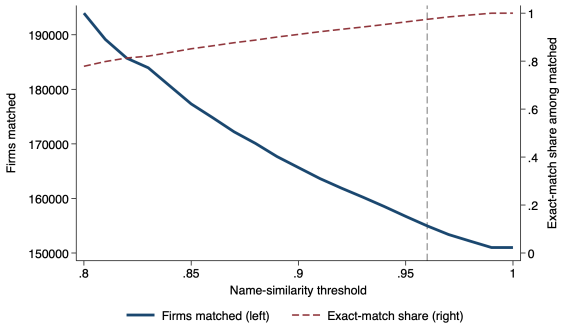
This procedure recovers CINs for 162,642 unique exporter names, 41.6% of those searched, of which more than 97% (158,366) achieve a perfect similarity score of 1 with the name returned by *QuickCompany*. These names correspond to 160,460 unique exporter identifiers in the trade data, which I carry forward to link *Panjiva* exporters to the firm panel. To assess robustness, Table D.13 reports the precision of a manually validated random sample of matches.

To link trade flows to firm-level investment and balance-sheet data, I match *Panjiva* exporters to *CapexDx* and *ProwessDx* firms through two complementary channels: (i) an identifier-based channel, which recovers Corporate Identification Numbers (CINs) for *Panjiva* exporters and intersects them with the CINs of the firm databases, and (ii) a name–location channel, which fuzzy-matches exporter names to firms with geolocated *CapexDx* projects in the exporter's vicinity. The two channels are constructed independently, which allows me to cross-validate them on the set of exporters matched by both.

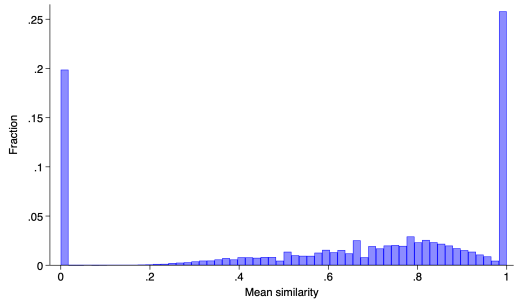
Channel 1: recovering CINs. Mirroring the procedure used for *CapexDx* firms (Section D.1.2), I query the 391,253 distinct exporter names on *QuickCompany*, retain the first five candidates per query, and keep candidates with a name similarity of at least 0.96. Figure D.7(a) shows how the number of matched exporters and the exact-match share respond to the similarity threshold; Figure D.7(b) displays the similarity distribution among retained candidates. Keeping the most similar candidate per exporter yields 162,642 recovered CINs (41.6% of the names searched), of which 97.4% are exact normalized-name matches. The lower recovery rate relative to *CapexDx* firms reflects the nature of the underlying records: *Panjiva* shipper names are transcribed from customs documents and include sole proprietorships and trading houses absent from the corporate registry. As before, I manually verify a stratified random sample of 100 matches: 92.1% identify the correct firm (Table D.13).

Figure D.7: Descriptive statistics on the CIN matching for *Panjiva* exporters

(a) Matched exporters and exact-share vs. threshold



(b) Distribution of match similarity



Panel (a) plots the number of exporters matched (left axis) and the share of matches that are exact normalized-name matches (right axis) as a function of the similarity threshold; the vertical line marks the 0.96 cutoff. Panel (b) shows the distribution of similarity scores among retained candidates. *Source: QuickCompany.in* and *Panjiva*.

Table D.13: Manual validation of recovered CIN matches (*Panjiva* exporters).

	Checked	**Correct**
Exact-name matches (similarity $= 1$)	50	92.0%
Near matches ($0.96 \leq$ similarity < 1)	50	94.0%
Population-weighted overall		92.1%

Intersecting the recovered CINs with those of the firm databases links each exporter to its *CapexDx* and *ProwessDx* records. Table D.14 reports the size of each CIN universe and the resulting overlap: 17.2% of *CapexDx* and 18.1% of *ProwessDx* CINs appear among *Panjiva* exporters, consistent with the fact that most domestic firms do not export directly.

Table D.14: CIN-based firm-to-firm matching

Step	**Count**
Unique CINs in *CapexDx*	18,185
Unique CINs in *ProwessDx*	56,277
Unique CINs in *Panjiva*	106,862
Share *CapexDx* found in *Panjiva* (%)	15.12
Share *ProwessDx* found in *Panjiva* (%)	15.74

Channel 2: name–location matching. The second channel requires no identifier. For every geolocated exporter, I collect at least one geolocated project within 10 km, compute a fuzzy similarity score between the exporter and firm names, and retain pairs with a name score above 96 located within 5 km of each other. Table D.15 traces the exporter universe through each stage of this funnel, and Table D.16 shows the number of retained matches under alternative name-score and distance thresholds, demonstrating that the retained set is stable in the neighborhood of the chosen cutoffs.

Final crosswalk and coverage. I combine exporter-to-firm crosswalk, taking the union of matched pairs. Table D.17 reports its coverage over the universe of exporters active in the CBAM baseline period. Matched exporters account for 6.8% of firms but 53.8% of total export value and 86% of CBAM-product exports to the EU, reflecting the concentration of trade among larger firms.

Table D.15: Name–location matching funnel

Step	**Count**	**% of exporters**
Unique geolocated *Panjiva* exporters	373,560	100.0
with ≥ 1 *CapexDx* project ≤ 10 km	372,955	99.8
best-match name score > 96	9,842	2.6
and within 5 km (retained)	8,500	2.3
Unique *CapexDx* firms matched (`co_code`)	6,064	

Table D.16: Name–location matches retained under alternative thresholds

Name score	< 1 km	< 2 km	< 5 km	< 10 km
> 90	7,371	9,360	13,791	18,836
> 94	6,073	7,281	9,286	11,032
> 96	5,710	6,808	**8,500**	9,842
> 98	5,531	6,606	8,254	9,555
$= 100$	5,451	6,510	8,133	9,419

Table D.17: Final crosswalk: matched exporters and trade-value coverage (2023Q1–Q3)

	Firms	**% firms**	**% export value**	**% CBAM–EU value**
Matched (either channel)	9,687	6.8%	53.8%	86.0%
CIN only	5,507	3.8%	16.4%	30.3%
name–location only	1,644	1.1%	21.1%	28.1%
both channels	2,536	1.8%	16.3%	27.6%
Unmatched	133,783	93.2%	46.2%	14.0%
All active exporters	143,470	100.0%	100.0%	100.0%

Notes: Universe: exporters active in 2023Q1–Q3. Value weights are average quarterly export value; the last column weights by CBAM-product exports to the EU-27. CIN matches from *QuickCompany* recovery; name–location matches require a name score above 96 within 5 km.

D.3 Firm emissions

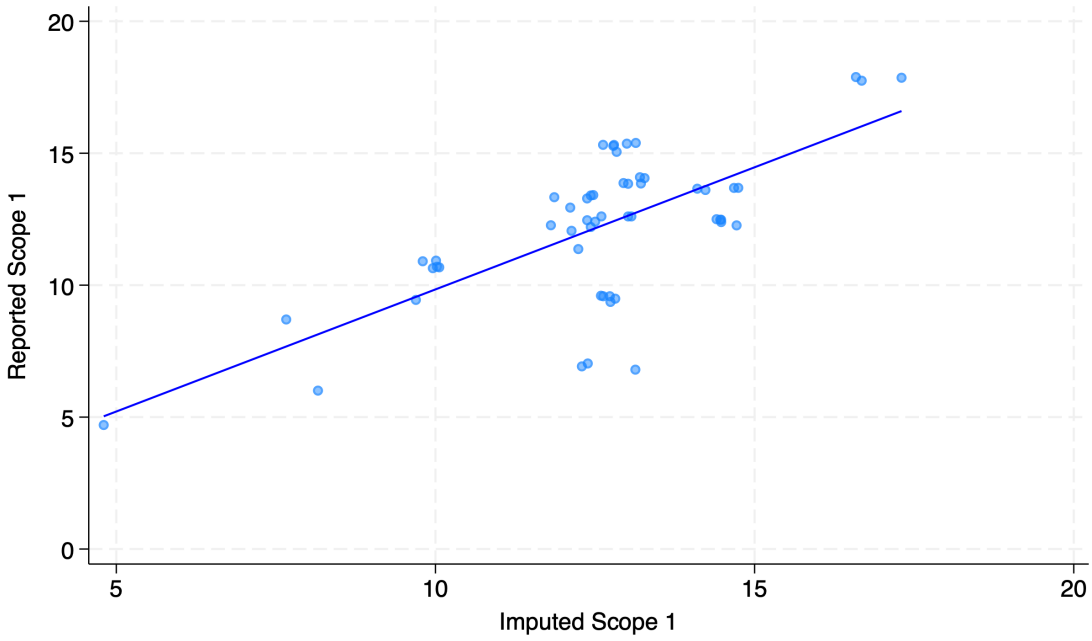
D.3.1 Emissions imputation

Table D.18: CO_2 emission factors

Energy source	kg CO_2/unit	Unit	kg CO_2/MMBTU
Acetylene	0.1053	scf	71.61
Agricultural Byproducts	974.9	short ton	118.17
Anthracite	2597.82	short ton	103.54
Biogas (Captured Methane)	0.0438	scf	52.07
Coke	2530.59	short ton	102.04
Coke Oven Gas	0.0281	scf	46.85
Distillate Fuel Oil No. 1	10.18	gallon	73.25
Distillate Fuel Oil No. 2	10.21	gallon	73.96
Electricity	0.951	kWh	278.00
Fuel Gas	0.0819	scf	59.00
Kerosene	10.15	gallon	75.20
Kraft Black Liquor	1131.11	short ton	94.42
LPG	5.79	gallon	62.98
Lignite	1369.28	short ton	96.36
Lubricants	10.69	gallon	74.27
Motor Gasoline	8.78	gallon	70.22
Naptha	8.5	gallon	68.02
Natural Gas	0.0545	scf	53.02
Petroleum Coke (Liquid)	14.64	gallon	102.41
Petroleum Coke (Solid)	3072.3	short ton	102.41
Propane (Liquid)	5.59	gallon	61.46
Residual Fuel Oil No. 6	11.27	gallon	75.10
Solid Byproducts	2725.32	short ton	105.51
Wastewater Treatment Biogas			52.07
Waxes	9.57	gallon	72.60
Wood and Wood Residuals	1442.64	short ton	93.80

Notes. Source: U.S. EPA 2012 Climate Registry Default Emission Factors (Table 12.1), as used in Barrows and Ollivier (2021). Electricity is the average Indian grid factor (951 g CO_2/kWh, 2000–2010). Biomass sources (agricultural byproducts, wood, black liquor, biogas) are assigned combustion factors following these authors rather than zeroed. Column 2 is used where reported units can be matched; column 4 (per MMBTU) is the fallback.

Figure D.8: Imputed versus reported Scope-1 emissions



Notes. Each point is a firm-year for which both imputed and an externally reported Scope-1 figure are available (22 firms, 76 firm-years, 2018-2025). The horizontal axis is the log of CO_2 emissions imputed from Prowess fuel-consumption data (direct combustion, Scope-1); the vertical axis is the log of reported Scope-1 emissions, harmonized from the Net-Zero Data Public Utility (Net-Zero Data Public Utility, 2026) and Climate TRACE (Climate TRACE, 2026) and matched to firms by name. The dashed line is the 45-degree line and the red line a linear fit; the correlation is 0.69. Agreement is strongest in combustion-driven sectors and weaker where process emissions dominate (e.g. cement, steel), which the combustion-based imputation does not capture.