Greener Under Pressure?

The Local Geography of Import Competition and Emissions in Swedish Manufacturing *

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Abstract

We examine how localized import competition — measured at fine geographic scales within Sweden — affects the CO_2 emission intensity of manufacturing firms. Using comprehensive administrative data on Swedish manufacturing firms linked to detailed geographic and trade records, we show that increased localized import competition significantly reduces firm-level CO_2 emission intensity, with effects that decay monotonically with geographic distance between producers and importers. Our findings indicate that national-level measures of import competition substantially understate the true environmental impact of trade shocks on upstream domestic suppliers. We identify two primary mechanisms: (i) a pro-competitive efficiency-enhancing effect, through which firms experience productivity gains, lower marginal costs, and higher markups; and (ii) a product-mix effect, through which firms exit emission-intensive peripheral products and concentrate on cleaner core activities. We also find evidence of increased pollution abatement investment and partial carbon offshoring, revealing that upstream producers draw on a broad adjustment toolkit in response to localized competitive pressure.

Keywords: Import competition, trade and environment, emissions, heterogeneous firms

JEL: F14, F18, Q56, Q58, R13

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1 Introduction

International trade reshapes domestic production networks. As firms increasingly rely on imported intermediate inputs and participate in global value chains (GVCs), trade shocks alter competitive pressures not only for direct importers but also for their domestic suppliers. These adjustments have potentially important environmental consequences. Yet, while a large literature studies how trade affects productivity, markups, and labor outcomes, much less is known about how trade-induced competitive pressure influences firms' environmental performance—particularly through indirect supplier linkages.

When a domestic manufacturer begins importing a product that was previously sourced locally, upstream domestic producers face intensified import competition (henceforth IC). In response, these firms may contract, exit, upgrade, or reorganize production. Each of these adjustments can alter emission intensity, or the amount of emissions per unit of output. On the one hand, competitive pressure may induce efficiency improvements, product upgrading, and adoption of cleaner technologies, thereby reducing emission intensity (Newman et al., 2023; Jabbour et al., 2019; Copeland et al., 2022). On the other hand, if firms operate under increasing returns to scale or face adjustment frictions, import competition could reduce output scale in ways that increase emission intensity (Shapiro and Walker, 2018; Cherniwchan et al., 2017). Whether firms become "greener under pressure" is therefore theoretically ambiguous and ultimately an empirical question.

While a growing literature examines how international trade affects emissions through changes in scale, composition, and technique, existing approaches implicitly assume that trade-induced competitive pressures are spatially uniform within countries (Akerman et al., 2024; Liu et al., 2023; Cherniwchan et al., 2017; Gutiérrez and Teshima, 2018; Simon and Prince, 2016). This assumption contrasts with well-established evidence that production networks are geographically localized: firms interact most intensively with nearby buyers and suppliers, and these linkages are shaped by strong spatial frictions (Bernard et al., 2019; Hillberry and Hummels, 2008; Syverson, 2007). If competitive pressures operate through such localized networks, then the environmental responses to trade are also likely to be spatially uneven, with exposure decaying in distance and concentrating within local production systems. In this setting, conventional aggregate measures of import competition may mischaracterize the true environmental transmission of trade shocks. This concern is particularly relevant for outcomes such as emission intensity, which depend on production technologies, supply chains, and local market structure (Shapiro, 2021). As a result, existing approaches may understate—or misinterpret—the environmental consequences of globalization.

To address this issue, we build on the spatial import-competition framework of Gullstrand and Knutsson (2019), who show that import competition in Sweden operates through geographically localized buyer–seller networks. Extending their approach, we construct firm-level exposure to localized import competition shocks using detailed spatial data on firm locations. Because direct buyer–seller linkages are not observed, we model upstream exposure based on the proximity between importing firms and domestic producers of the matched imported products, allowing competitive pressure to decay with distance.[1] While previous work has documented productivity gains and product reallocation in response to import competition, the environmental consequences of these adjustments among indirectly affected domestic suppliers remain largely unexplored. By quantifying these indirect environmental responses, we provide a more complete assessment of how trade shocks, specifically shocks related to IC, reshape domestic emissions.

Importantly, the upstream domestic producers in our estimation sample account for approximately 59% of total domestic manufacturing CO_2 emissions, confirming that the upstream channel is not a marginal phenomenon. While the trade–environment literature focuses largely on direct importers, production networks imply that competitive shocks propagate upstream through geographically concentrated supplier relationships. If supplier adjustments are environmentally significant, analyses that consider only importing firms may substantially underestimate the aggregate environmental impact of trade shocks.

To investigate these issues, we combine administrative data on Swedish manufacturing firms' production, trade flows (at the 8-digit product level), and energy use for the period 2005–2014. We construct a measure of firm-level exposure to localized import competition by linking product-level import flows to the geographic proximity between importing firms and domestic producers of the same goods. This generates variation in competitive pressure across firms, space, products, and time. A central empirical challenge is that domestic demand conditions may simultaneously affect both imports and firms' environmental performance. To address this concern, we implement a shift-share instrumental variable strategy that exploits plausibly exogenous variation in world export supply across products and source countries. The instrument interacts firms' pre-sample exposure shares with global supply shocks, thereby isolating the component of local import competition driven by foreign export growth rather than domestic conditions.

We find that increased local import competition significantly reduces CO_2 emission intensity, and that this effect is substantially stronger when exposure is measured at finer geographic scales rather than at the national level. These findings suggest that the environmental response to trade is strongly mediated by local production networks. Turning to mechanisms, we uncover a pattern that goes beyond the importer-level evidence in the existing literature. Local competitive pressure induces upstream domestic producers—not only direct importers—to become cleaner. We show that firms respond through productivity gains, product reallocation, and increased investment in pollution abatement. These adjustments point to a powerful technique channel reinforced by product reallocation. Strikingly, we also detect evidence of partial offshoring of more carbon-intensive production stages. While importer-focused analyses find

[1] As a concrete illustration, consider a Swedish car manufacturer (the downstream firm) that outsources glass. It can source from a nearby domestic producer or from a foreign manufacturer (see Figure A.1 for a graphical illustration). If the downstream firm imports glass from abroad, this constitutes IC for the domestic glass producer. How that producer responds to competitive pressure is likely to affect its emission intensity.

little role for pollution haven mechanisms, our results suggest that once one accounts for localized competitive spillovers and upstream linkages, task reallocation across borders becomes an economically meaningful margin of adjustment. In this sense, import competition does not merely clean firms internally—it reshapes the organization of production itself.

This paper makes four main contributions. First, we introduce a spatially granular measure of import competition — constructed at the level of small local labor market areas rather than industries or national aggregates — and use it to identify an upstream transmission channel through which trade shocks propagate to domestic producers. The existing trade–environment literature largely examines environmental responses among importing firms directly (Akerman et al., 2024; Leisner et al., 2023; Liu et al., 2023; Copeland et al., 2022), leaving the indirect effects on upstream domestic suppliers largely unexplored. By measuring competitive pressure from geographically proximate importers while controlling for firms' own import activity, we isolate an indirect channel that is causally identified, economically meaningful, and operates through the geographic structure of local production networks. This upstream channel is distinct from and complementary to the direct importer channel studied elsewhere in the literature.

Second, we contribute to the growing literature on the spatial organization of production networks (Gullstrand and Knutsson 2019, Bellone et al. 2016, Bernard et al. 2019, Hillberry and Hummels 2008, Autor et al. 2013) by demonstrating that the environmental consequences of trade shocks are fundamentally distance-dependent. Building on the spatial framework of Gullstrand and Knutsson (2019), who demonstrate that import competition operates through geographically localized buyer–seller networks, we extend their approach in three important ways. First, we adapt their product-level distance-weighted import competition measure to construct a firm-level exposure appropriate for environmental outcomes, aggregating across products using predetermined production shares. Second, we embed this spatial exposure in a shift–share IV design that isolates exogenous foreign supply shocks according to recent recommendations by Borusyak et al. (2025), and by explicitly eliminating mechanical own-import effects—an essential step when studying emissions. Third, whereas Gullstrand and Knutsson focus on costs, prices, and markups, we show that spatially localized import competition has economically large and previously unmeasured effects on firms' CO_2 emission intensity through productivity gains, product reallocation, pollution abatement investment, and partial offshoring. Our results show that the emission response to import competition declines sharply and monotonically with the geographic distance between importers and domestic producers. This finding is robust to alternative spatial weight structures — including band-limited and nearest-neighbor specifications — and confirms that proximity, rather than administrative boundaries, governs the transmission of competitive pressure (Bernard et al., 2019; Hillberry and Hummels, 2008; Autor et al., 2013; Bellone et al., 2016).

Third, we provide new evidence on the mechanisms through which localized competitive pressure reshapes upstream producers' environmental performance (Newman et al., 2023; Shapiro and Walker, 2018; Dussaux et al., 2023; Akerman et al., 2024; Leisner et al., 2023; Jabbour et al., 2019; Antoniades, 2015). We document a broad and simultaneous adjustment toolkit:

productivity gains and cost reductions consistent with a technique effect (Shapiro and Walker, 2018), systematic exit of emission-intensive peripheral products consistent with a composition effect, and increased investment in pollution abatement technology. Crucially, we also detect partial reallocation of carbon-intensive production stages abroad — an offshoring margin not visible in analyses of importing firms (Akerman et al., 2024) and one that carries direct implications for the design of carbon border adjustment mechanisms. While prior work emphasizes either the technique or the composition channel (Shapiro, 2021; Antoniades, 2015), our spatially explicit design reveals that upstream producers draw on both simultaneously.

Fourth, a few other studies examine import competition and firm-level environmental outcomes (Cherniwchan et al., 2017; Gutiérrez and Teshima, 2018; Liu et al., 2023; Simon and Prince, 2016). Some of these studies employ similar causal identification strategies and document comparable mechanisms in response to trade-induced competition. This paper contributes to this literature by bringing a finer geographical dimension.

The paper proceeds as follows. Section 2 describes the data, sample construction, and measures of IC. Section 3 specifies the empirical strategy and instruments. Section 4 presents the main results and robustness checks. Section 5 examines the channels. Section 6 concludes.

2 Data and Descriptive Statistics

2.1 Firm-level Emissions and Abatement

The data used in this paper originate from Statistics Sweden (SCB) and consist of several merged data sets with information about the population of Swedish manufacturing firms. The first database is the energy consumption database, which contains information on the energy consumption of all manufacturing plants with ten or more employees. Firms report detailed information about the annual consumption (with units) of different fuel types (e.g., liters of diesel, MWh of electricity, m^3 of natural gas etc.). CO_2 emissions can be calculated by using the fuel-specific CO_2 emission coefficients provided by SCB. Hence, CO_2 emissions are accurately calculated from fuel inputs. Our dependent variable will be emission intensity measured as emissions per Swedish Krona (SEK) of value-added.[2] Table A.1 presents descriptive statistics for emissions and emission intensities of firms. On average, firms emit approximately 45,000 tons of CO_2 emissions annually, translating to about 0.017 tons of emissions per SEK value added. The median values of emissions and emission intensity are consistently lower than the averages, indicating right skewness and a high concentration of emissions among a small number of firms.

Abatement stands for the activities by the firm to reduce pollution. We obtain annual abatement data from a survey conducted by SCB where firms report their abatement investments and expenditures (measured in thousands SEK). Specifically, firms are asked to report any in-

[2]We also consider alternative measures of emission intensity calculated as emissions per unit output (see e.g. Barrows and Ollivier 2021) and value of output (see e.g. Shapiro and Walker 2018). All results in this paper are robust to using these alternative measures.

vestments and expenditures they have made in machinery and equipment aimed at reducing pollution and emissions, as well as any expenses associated with investing in cleaner machines and technology.[3] The abatement data come from a semi-random sample of manufacturing firms, which includes all manufacturing firms with more than 250 employees, 50% of firms with 100–249 employees, and 20% of firms with 50–99 employees. Figure A.2 shows the trends in abatement expenditure and investment. We observe a notable increase in average abatement investment and expenditure after 2008. Nevertheless, the average abatement expenditure has seen a slight decline since 2010, hinting at a potential trade-off between expenditure and investment. This suggests that firms' commitments and allocation of funds for environmental expenditure and investment may vary.

2.2 Production, Trade, and Geography

On the production side, we merge several administrative databases, also obtained from SCB. First, we use the Production of Commodities and Industrial Services (IVP) database, which provides annual information on quantities and values of production at the 8-digit product level for approximately 6,200 Swedish manufacturing firms. The IVP covers private manufacturing firms employing at least 20 workers. Because geographic plant identifiers are incomplete prior to 2005, we restrict the analysis to the period 2005–2014, ensuring consistent firm-plant linkage throughout the sample.

Second, we obtain trade data from the International Trade in Goods (ITG) database. This database provides detailed country and product trade information for all Swedish firms, encompassing values and quantities of imports and exports at the 8-digit product level. ITG records the universe of Swedish firms' imports and exports, including transaction-level values and quantities at the 8-digit product level and by partner country. Product classifications are reported using time-varying Combined Nomenclature (CN) codes. To ensure comparability over time, we harmonize all transactions to a fixed CN8 classification, denoted $p \in \mathcal{P}$. Concretely, we map each raw code to a stable CN8 definition and restrict attention to products that are domestically produced according to the IVP production register. This restriction is economically and econometrically important. It ensures that our measure of import competition is defined over products with an active domestic counterpart, thereby capturing genuine competitive pressure rather than mechanical import exposure. It also mitigates attenuation bias arising from imports of goods that have no domestic production analogue.

Third, we draw from the Structural Business Statistics (FEK) database, which provides comprehensive firm-level information, data on employment, industry classification, sales, assets,

[3] SCB defines pollution abatement as capital expenditures for methods, technologies, processes, or equipment designed to collect and remove pollution after its creation, prevent its spread, and treat and dispose of pollutants generated by the company's operations. These include protection of ambient air and climate, waste(water) management, protection of soil and groundwater, among others. Some of these technologies such as thermal oxidizers and catalytic converters improve combustion efficiency and optimize fuel usage, which can indirectly reduce total CO_2 emissions from auxiliary fuel consumption. Source: https://www.epa.gov/air-emissions-monitoring-knowledge-base/monitoring-control-technique-thermal-oxidizer

investment, and other balance-sheet variables. FEK allows us to measure firm performance and control flexibly for observable firm characteristics.

Together, the IVP, ITG, and FEK databases form a comprehensive, transaction-level panel that links detailed product-level trade exposure to firm-level production and financial outcomes within a unified administrative framework. Of particular relevance to this paper, the data includes the location coordinates (latitudes and longitudes) of plants and firms within Sweden. This enables us to geo-locate all firms, producers and importers. In part of the spatial analysis, we use a fine geographical division of Sweden called SAMS (Small Areas for Market Statistics). SAMS cells are defined by SCB as the smallest functional economic units that capture market integration. SAMS divides Sweden's 290 municipalities into 9209 small areas, which allows us to create spatial variables without worrying about the unevenness of municipal borders. Each cell's centroid and coordinates are obtained from the SCB's GIS register. IC is *local* in the sense that we measure it at the SAMS level—the imports of other manufacturing producers located in the same or nearby SAMS cells—rather than at the industry or regional level.

Sample construction. Although customs records identify the importing firm, they do not report the physical location where imports are used. This presents a central measurement challenge: many firms operate multiple plants, and the geographic incidence of imported inputs or final goods may differ across establishments. To recover a credible measure of local import exposure, we merge firm-level trade records with establishment-level information from the Central Business Register (CFAR), which provides annual plant identifiers, employment, and precise geographic location (SAMS).

Let $\mathcal{J}(f,t)$ denote the set of plants j owned by importing firm f in year t, and let L_{fjt} denote plant employment. We allocate firm-level imports of product p from all origin countries o by the plant j using an employment-share rule that is deliberately conservative and transparent as follows:

$$\tilde{M}_{fjpt} \;=\; \sum_{o} M_{fpot} \times \omega_{fjt}, \qquad \omega_{fjt} \;=\; \frac{L_{fjt}+1}{\sum_{j\in\mathcal{J}(ft)}(L_{fjt}+1)}. \tag{1}$$

The $+1$ adjustment prevents undefined shares when employment is zero for small units and ensures all multi-plant firms are allocated strictly positive weights. We implicitly assume that all plants import the same products proportionally as the firm in the case of multi-product imports. Equation (1) yields plant- and product-level imports $\tilde{M}_{f,j,p,t}$ that respect firm totals by construction and place the geography of imports where the firm's economic activity is plausibly located. Importantly, the allocation step anchors trade exposure in the firm's physical production footprint, rather than attributing all imports to headquarters or to an arbitrary location. This is crucial for a design that seeks to measure localized competitive pressure.

On the upstream local producing firm side, emissions are recorded at the firm level. For multi-plant firms, the geographic unit of competitive exposure does not coincide with the unit at which outcomes are observed, introducing spatial mismatch. To eliminate this ambiguity, our estimation sample is restricted to single-plant producing firms, for which a single SAMS cell uniquely identifies both the firm's location and the competitive environment it faces. Importantly, this restriction applies only to *producing* firms — the units that face the IC shock whose emission intensity we study. The employment-share allocation rule in equation (1) continues to apply to *importing* firms in the neighborhood, which may operate multiple plants, ensuring that the SAMS-level import competition measure correctly attributes each multi-plant importer's competitive pressure to the appropriate geographic cells.

We further restrict the sample to active firms with energy and emissions information and positive sales, excluding firms with extended periods of inactivity. In addition, the analysis focuses on intermediate goods producers, who plausibly compete with imported intermediate inputs in local markets. Notably, manufacturing firms account for approximately 80% of total imports in the compiled sample, reinforcing the relevance of import competition within the manufacturing sector. The resulting estimation sample contains 1,497 single-plant producing firms, down from 2,279 firms in the full production database; the difference reflects excluded multi-plant producers and firms with incomplete emission or sales records.

Two implications of the single-plant restriction warrant explicit acknowledgment. First, single-plant firms account for approximately 66% of firms in the production database and roughly 59% of total domestic manufacturing CO_2 emissions, confirming that the estimation sample represents the large majority of Sweden's manufacturing carbon footprint. Second, the excluded multi-plant firms account for the remaining 41% of manufacturing emissions and may respond to competitive pressure partly through cross-plant reallocation of emission-intensive activities — a margin our single-plant design cannot detect directly. To the extent that such responses are environmentally important, our estimates capture the intensive-margin environmental response of geographically concentrated producers and may represent a lower bound on the aggregate environmental effect of import competition.

2.3 Measuring Import Competition

In this section, we present how we measure IC exposure faced by the upstream firm producing an intermediate input product that is simultaneously imported by the downstream manufacturer. The construction is designed to capture *the intensity of foreign competitive pressure in the local market environment surrounding the local producing firm*, allowing for spatial decay and market interaction across neighboring locations.

SAMS geography and the spatial structure of competition. We measure this environment at the level of SAMS, a high-resolution geographic partition designed to approximate economically meaningful neighborhoods. Let $s \in \mathcal{S}$ index SAMS areas, and let each plant j be located in $s(j)$ with centroid coordinates (x_s, y_s).

We begin by aggregating allocated plant imports to the SAMS–product–year level. Total imports of product p in SAMS s and year t are defined as:

$$M_{spt} = \sum_{j \in \mathcal{J}(ft); s(j)=s} \tilde{M}_{fjpt} \tag{2}$$

In equation (2), $\tilde{M}_{fjpt}$ is calculated according to equation (1).

Localized import competition. Competitive pressure is not confined within administrative borders. Producers compete with importers located in other SAMS areas, with competitive intensity declining in geographic distance. We therefore model exposure as a spatially weighted average of surrounding import activity. Let W denote a spatial weight matrix for the SAMS region satisfying $w_{ss'} \geq 0$, $w_{ss} = 0$, and row normalization $\sum_{s' \neq s} w_{ss'} = 1$. Our baseline specification uses inverse-distance weights, i.e. $w_{ss'} \propto d_{ss'}^{-1}$, where $d_{ss'}$ denotes the geographic distance between SAMS centroids. This structure allows competitive influence to decay smoothly with distance rather than discontinuously at arbitrary borders.[4]

Localized import competition facing the local producing firm i in product p and year t is therefore given by:

$$\mathcal{IC}_{ipt} = \underbrace{\sum_{s' \neq s(i,t)} w_{s(i,t)s'} M_{s'pt}}_{\text{External markets}} + \underbrace{M^{(-i)}_{s(i,t)pt}}_{\text{Same-area IC (excl. own)}} . \tag{3}$$

In equation 3, the first term measures competitive pressure arising from nearby markets, and the second captures competing imports within the same local area, net of the firm's own imports. Together, these components yield a measure of external competitive exposure that is geographically continuous and free from mechanical self-influence. The decomposition clarifies that competition operates both within narrowly defined markets and across adjacent regions. A key identification concern is that a producer's own imports should not mechanically inflate its measured exposure to import competition. To eliminate this reflection problem, we explicitly remove the producing firm's own imports from the local market environment.

To assess the spatial reach of competition, we additionally construct band-limited weight matrices isolating (i) 0–500 km and (ii) 500–1000 km neighbors, each row-normalized within band. These alternative weight structures allow us to decompose competitive pressure into near-market and mid-range components and assess how rapidly competitive pressure decays with distance.

[4]Row-normalization implies that $\mathcal{IC}_{spt}(W)$ measures the distance-weighted *average* import intensity in surrounding areas, rather than the total import mass within reach. This is a deliberate modeling choice: without row-normalization, firms located in regions surrounded by many SAMS areas (typically urban centers) would mechanically record higher IC than firms in sparsely populated regions, even if the average competitive intensity is the same. Row-normalization ensures comparability across SAMS areas of heterogeneous size and neighbor density. We verify that results are robust to unnormalized inverse-distance weights, which scale the measure by total surrounding import mass; the estimates are qualitatively similar.

From product-level exposure to firm-level competition. Finally, we aggregate product-level exposure to the firm level using predetermined product weights. Let θ_{ip0} denote firm i's baseline production share in product p in the set of products P, measured prior to the main sample window and held fixed over time. Firm-level IC is defined as:

$$\mathcal{IC}_{it}^{SAMS} = \sum_{p \in \mathcal{P}} \theta_{ip0} \, \mathcal{IC}_{ipt}. \tag{4}$$

This construction yields a firm-year measure of import competition that is (i) granular at the CN8 product level, (ii) localized through SAMS geography and spatial spillovers, and (iii) predetermined in composition through baseline product weights. The construction ensures that variation in exposure reflects external shifts in competitive pressure rather than endogenous adjustments in product mix or importing behavior.

2.4 Data Descriptives

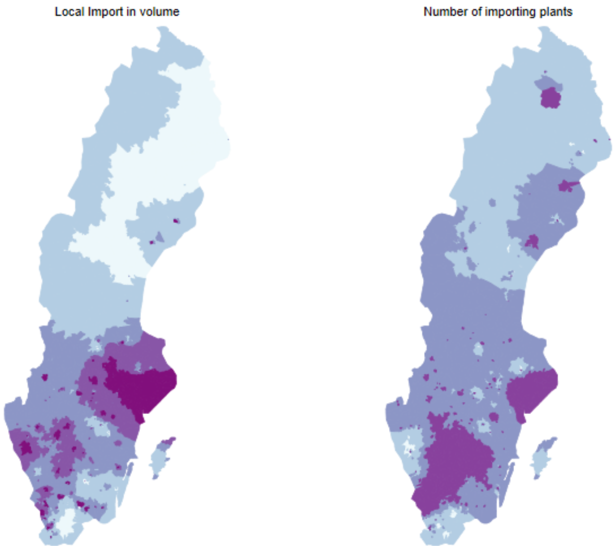
Table A.2 also presents a summary of production data and other firm-related information, including employment, markup, and sales. Recall that after restricting our sample to active firms operating a single plant and selling intermediate products locally, we end up with 2,279 manufacturing firms. However, within this sample, we have emission information available for only 1,497 firms (approximately 66% of the sample is retained). On average, the producing firm in our sample produces about 3 products with a maximum number of 68 products, and average sales of 930 million SEK. The average firm's sales from the core (main) product as a share of revenue is about 53% - a product is classified as a core product when it accrues more than 50% of the entire firm revenue. Moreover, the average share of products in the firm's total production exposed to IC pre-sample is about 67%. On average, about 59% of the firms' products are classified as a core product, whereas the rest are fringe products. We calculate the markup for both single-product and multi-product firms using techniques initially proposed by Hall et al. (1986) and further refined by De Loecker et al. (2016).[5]

Moreover, we present descriptive statistics about imports and the geographic location of importers vis-à-vis the local producers in Table A.3. The average import value for manufacturing firms across Sweden is around 190 million SEK, while at the SAMS level, it hovers around 9 million SEK, suggesting large concentrations of imports in some SAMS areas. Regarding the location of the producing firm relative to the nearest importing firms, we note that the average import value is higher for the first nearest importing firm compared to subsequent ones. This is a first indication that IC is on average more intense in the vicinity of the firm. Analyzing the distance between importers and producers, we find that the average distance from the first nearest importing neighbor is approximately 23.33 km, while the third nearest is almost twice that distance at 66.32 km. These distances have larger coverage than the average SAMS area, with a radius of around 2 km, and the average municipality, with an average radius of 18 km.

[5]We obtain the markups for individual products produced by firms by dividing the output elasticity of materials by the materials' share of total revenue.

Figure A.3 displays the distribution of producers and importers across SAMS regions. The distribution is skewed with most SAMS regions having fewer producers and importers, and a few having many.

Figure 1: Spatial distribution of import exposure



Note: The shading demarcates distinct regions into quintiles, with the darkest shade symbolizing the highest quintile and the faintest shade signifying the lowest quintile. All figures incorporate spatial lags, employing weight adjustments standardized by rows, which are determined by distance

Figure 1 displays the spatial distribution of IC and the share of importing plants in the total local (SAMS) number of manufacturing firms. In the left panel of the graph, we compute the import volume and number of importing plants for each SAMS area plus their spatial lags (with the spatial-weights based on distance). We observe a notable concentration of raw import volume along a corridor extending from Stockholm, reflecting the high degree of economic activity in these areas. In the right panel, we observe that the numbers of importing plants tend to cluster around Stockholm and in the central part of Southern Sweden.

3 Empirical Approach

To estimate the effect of localized IC exposure on the CO_2 emission intensities of producers, we consider the following specification:

$$EI_{it} = \beta_0 IC_{it}^{SAMS} + \theta_i + \theta_{bt} + \theta_{mt} + \epsilon_{it}; \tag{5}$$

where EI_{it} is the amount of emissions per SEK of value-added (in logs) of producing firm i in year t and IC_{it}^{SAMS} captures the IC (in logs) faced by producing firm i at time t as defined by equation 4. We condition import exposure on firm fixed effects (θ_i) to control for individual firm unobserved heterogeneity. Additionally, we control for industry-year fixed effects (θ_{bt}), with the industries being defined at the 3-digit industry (SNI) codes, to capture broad changes in demand, production, industry emission intensity levels, and imports by wholesalers of different goods. We further include municipality-year fixed effect (θ_{mt}) to control for shocks at the municipal level in labor markets as well as changes in environmental regulations, which are set at the municipal level in Sweden.

3.1 Shift–Share Identification

Our measure of IC, which largely depends on import demand of Swedish importers, may suffer from endogeneity issues. For example, firms may be encouraged to import intermediate goods if they are located close to low-productivity producers. Hence, changes in supply and demand conditions may feed into each other, which would lead to reverse causality. To mitigate these concerns and estimate the causal effects of IC exposure, we must isolate the supply-driven increase in imports (components that are caused by arguably exogenous increases in trade). Following Hummels et al. (2014) and recent discussions by Goldsmith-Pinkham et al. (2020), Borusyak et al. (2022a) and Borusyak et al. (2022b), we use global supply shocks directed to countries other than Sweden and its neighboring countries as instruments.

We obtain annual product-level world export data from UN COMTRADE at the HS6 level and harmonize these to our CN8 classification. For each product p and year t, we construct

$$WX_{pt} = \log\left(\text{ExportSupply}_{pt}^{(-SE^{+})}\right),$$

where the world export supply exclude flows to Sweden and its neighboring countries (Denmark, Finland, Germany, and Norway). These shocks capture changes in global supply conditions — such as productivity growth, trade liberalization, or technological upgrading in exporting countries — that affect the relative availability and price of product p independently of Swedish and neighboring countries' demand.

To translate global shocks into local competitive pressure, we follow the standard shift–share logic. For each importing firm f, we define the pre-sample import share of product p as:

$$\phi_{fp0} = \frac{M_{fp0}}{\sum_{p' \in P} M_{fp'0}},$$

where shares are measured prior to the estimation window and held fixed throughout. These predetermined shares capture firms' baseline exposure to each product category.

We then aggregate export shocks across importers using the same spatial structure that defines localized import competition in equation (3). Let Ω_s denote the set of importers located in SAMS s, and with $w_{ss'}$ as the inverse-distance weights, we define the product-level world supply shock to location s as:

$$Z_{spt} = \sum_{s' \neq s} \sum_{f \in \Omega_{s'}} w_{ss'} \phi_{fp0} WX_{pt} + \sum_{f \in \Omega_s} \phi_{fp0} WX_{pt}.$$

This expression mirrors the structure of localized import competition: global product supply shocks are transmitted through geographically proximate importers, with competitive influence decaying smoothly in space.[6]

For a producing firm i located in $s(i)$, the product-level instrument is $Z_{ipt} = Z_{s(i),pt}$. Aggregating across products using the firm's predetermined production weights θ_{ip0} yields the firm-level instrument:

$$IV_{it}^{SAMS} = \sum_{p \in P} \theta_{ip0} Z_{ipt}$$

The instrument therefore varies at the firm-year level through three sources: (i) exogenous product-level world export shocks, (ii) cross-sectional differences in baseline import exposure of geographically proximate importers, and (iii) predetermined product weights of the producing firm. Because world export growth is measured outside Sweden (and neighboring counrtries) and shares are fixed prior to the sample period, the identifying variation is driven by foreign supply shifts rather than domestic demand or contemporaneous firm adjustments. Following Borusyak et al. (2025), we apply the logarithmic transformation to world export supply prior to interacting with baseline shares, thereby avoiding the mechanical endogeneity that arises from logging the weighted sum.

Identification relies on the assumption that world export supply shocks are orthogonal to unobserved determinants of emission intensity in Swedish manufacturing, conditional on fixed effects and baseline exposure shares. Formally, the exclusion restriction requires that

$$\mathbb{E}\left[IV_{it}^{SAMS} \cdot \varepsilon_{it}\right] = 0,$$

where ε_{it} denotes the structural error in equation (6). Following the shift–share framework of Goldsmith-Pinkham et al. (2020), Borusyak et al. (2022a) and Borusyak et al. (2025), identification can in principle arise from exogeneity of either the shares or the shocks. In our setting, the "shares view" would require that firms' baseline product exposure θ_{ip0} and import shares ϕ_{fp0} are uncorrelated with future unobserved emission trends. Given the well-documented links between product specialization, productivity, and environmental performance, this assumption would be strong (Gullstrand and Knutsson, 2019; Akerman et al., 2024).

Instead, our identification relies on the "shifts view." We exploit variation in product-level world export growth occurring outside Sweden and its neighboring markets. These foreign supply shocks reflect changes in technology, trade costs, and productivity in exporting countries.

[6] Two clarifications on the construction of Z_{spt} are warranted. First, the exposure term $\sum_{f \in \Omega_{s'}} \phi_{fp0}$ aggregates importers by their product-mix composition (the within-firm share ϕ_{fp0} sums to 1 per firm), rather than by baseline import value. This design choice reflects the identification goal: we seek to isolate variation in the *composition* of exposure to global supply shocks, holding constant the importer set. Robustness to size-weighted exposure — replacing ϕ_{fp0} with $\phi_{fp0} \times \bar{M}_{f0}$, where $\bar{M}_{f0}$ is each importer's baseline total import value — yields qualitatively similar first-stage and reduced-form estimates. Second, when a producing firm i is also an importer, its own pre-sample shares ϕ_{ip0} enter the same-SAMS component of $Z_{s(i),pt}$, potentially creating a direct own-import channel for the world supply shock. To make sure this does not drive the results, we estimate using a leave-one-out version of Z_{spt} that excludes the producing firm's own shares from the same-SAMS term. This is to make sure that the instrument captures competitive pressure from *other* importers rather than the firm's own exposure.

Conditional on firm fixed effects, sector-year fixed effects, and municipality-year fixed effects, such shocks are plausibly unrelated to idiosyncratic emission dynamics of Swedish upstream producers.

Intuitively, the design compares firms that are differentially exposed to the same global product shock through predetermined import linkages. Because baseline shares are fixed prior to the sample window, and world export growth is measured in third markets, the identifying variation comes from foreign supply shifts rather than domestic demand conditions or contemporaneous firm adjustments. We further assess this assumption by conducting shift-level balance tests and event-study pre-trend analyses, following Borusyak et al. (2025). As robustness, we also add producer's own imports, information on firm capital, employment, investment in machines, and the amount of emission rights purchased as additional controls.

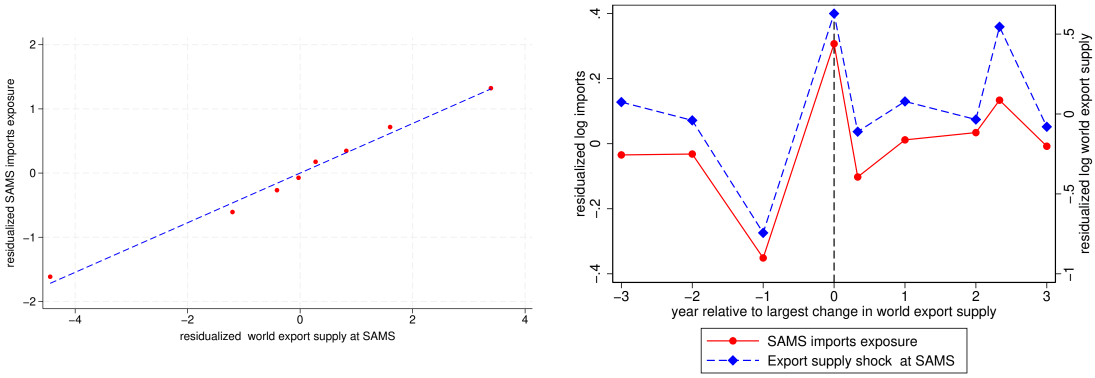
First stage and reduced-form evidence. Before turning to the structural estimates, we provide graphical evidence on both instrument relevance and reduced-form effects. Figure 2 examines the relationship between the instrument and localized import competition. Following Akerman et al. (2024), we residualize both the IC measure and the export shock with respect to firm fixed effects and five-digit industry–year fixed effects, isolating the variation that identifies our specification. The left panel shows a clear and monotonic positive relationship, consistent with the first-stage regression. Across specifications, the Kleibergen–Paap F-statistic exceeds the conventional threshold of 10, indicating strong instrument relevance. The event-study panel in Figure 2 further illustrates that localized import competition responds sharply and contemporaneously to large export-supply shocks. The absence of pre-trends supports the interpretation that variation in IC is driven by foreign supply shifts rather than underlying local trends.

Figure 3 presents the corresponding reduced-form relationship between the instrument and producers' log carbon intensity. The left panel shows a stable negative association, closely mirroring the model specification in Table 1 and indicating that global export shocks translate into cleaner production outcomes. The event-study in the right panel traces emission intensity around the timing of the largest export shock faced by each producer. By construction, the mean log world export supply exhibits a sharp increase at time zero, reflecting the largest shock in the instrument. We find that an increase in export shocks correlates with a nearly immediate decline in firms' emission intensity. Thus, our assumption of contemporaneous effect of local IC and emission intensity seems tenable and appropriate for our model in equation 5.

Figure 4 presents an IV event study that directly traces the dynamic response of emission intensity to instrument-induced shocks in localized import competition. We observe no statistically significant pre-trends, and emission intensity declines sharply in the event year. The effect partially attenuates in subsequent years but remains negative on average, consistent with competitive pressure inducing both immediate operational adjustments and gradual technology adoption.[7]

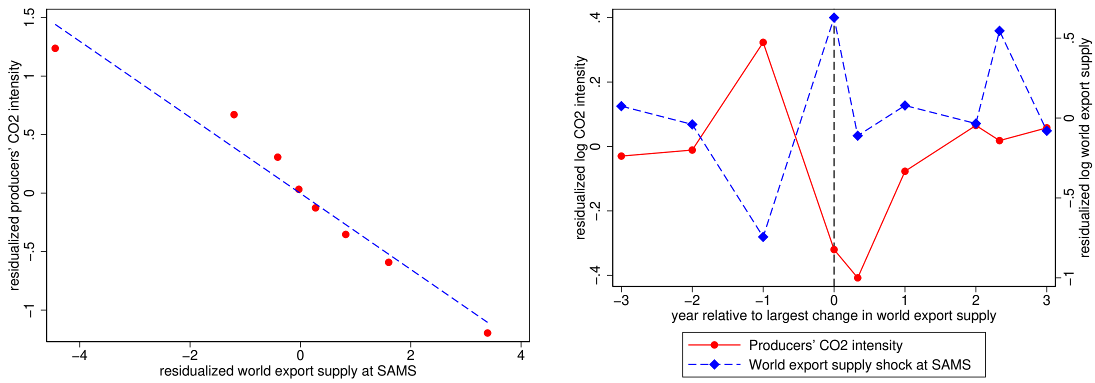
[7] To account for the possibility that some adjustments unfold over time, we also estimate specifications with lagged IC exposure as a robustness check. Results remain statistically significant and economically

Figure 2: Export Supply Shock at SAMS level and Local IC



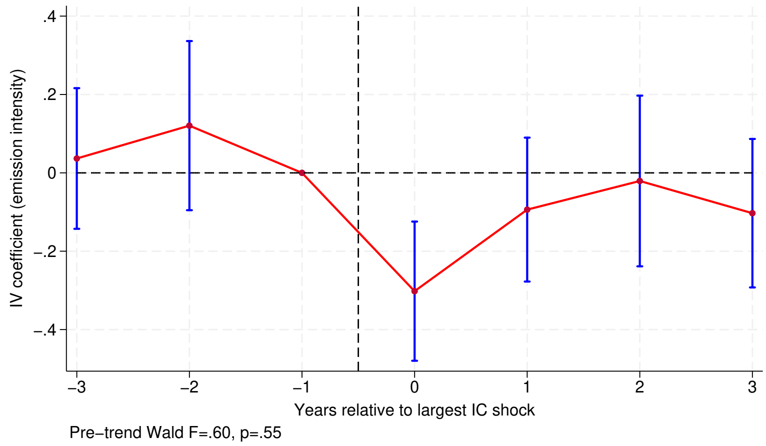
Note: The graph on the left depicts the estimated first-stage relationship between the log of the instrument (IV_{it}^{SAMS}) and the log of IC exposure at SAMS level. The variables are residualized by regressing them on firm and five-digit industry–year fixed effects, with the residuals saved for plotting. The data is grouped into eight bins based on the residualized instrument, ensuring each bin contains an equal number of firms. The graph on the right shows the trend of the average log of the instrument and the average log of IC relative to an event-time variable. This event-time variable is set to zero in the year in which each firm experiences its largest increase in the export supply shock at the SAMS level. The analysis is limited to firms with data available for three years before and after the largest observed increase in the instrument.

Figure 3: Export Supply Shock at SAMS level and Producer's CO_2 Intensity



Note: The graph on the left presents the estimated (intention-to-treat) relationship between the log of the instrument (IC_{sit}^{IV}) and the log of carbon intensity of producers. As with the Figure 2, the two variables are residualized by regressing them on firm and five-digit industry–year fixed effects, with residuals saved for analysis. The firms are then grouped in 8 equal bins based on the residualized instrument. The graph on the right shows the trajectory of the average log of the instrument and the average log of carbon intensity relative to an event-time variable. This event-time variable is set to zero in the year in which each firm experiences its largest increase in the instrument. The analysis is restricted to firms with available data spanning three years before and after the largest observed increase in the instrument.

Figure 4: Dynamic Effect: Export Supply Shock and Producer's CO_2 Intensity



Note: This figure plots IV event-time coefficients of log CO_2/value added relative to the year in which each firm experiences its largest instrument-induced increase in localized import competition (event time 0). The dashed vertical line denotes the event year. Coefficients are estimated relative to $t = -1$. Blue bars represent 95% confidence intervals. The pre-trend Wald test fails to reject joint insignificance of the leads (F=0.60, p=0.55), indicating no evidence of differential pre-trends. Emission intensity declines sharply at the time of the shock, consistent with a contemporaneous competitive response.

4 Results

4.1 Main Results

We begin by investigating the spatial impact of IC defined at the SAMS level on the emission intensity of producing firms. Table 1 shows the results of both the OLS and IV (instrumental variable) estimates for estimating equation 5. In columns (1) and (4), we measure IC without any restrictions on the distance between the SAMS region of the producing firm and importing firms in all other SAMS regions in Sweden. In columns (2) and (5), we divide the IC effect across two distance bands 0-500 km and 500-1000 km from the producing firm. Finally in columns (3) and (6), we measure IC at the national level, i.e. IC is measured as the sum of imports from all firms importing the products that are simultaneously produced by the local producing firm within Sweden. Focusing on the IV estimations, the results show that a 10 percent increase in local IC is associated with a statistically significant 5.7% percent decline in emission intensity in the IV estimation in column (4). The coefficient is economically much larger than the analogous national-level IC estimate in column (6). The geographic nature of the effect is further clarified by the the distance-decay estimates. As shown in column (5), the IV point estimates attenuate monotonically as we widen the distance bands from 0–500 km to 500–1000 km. This clear decay with distance provides direct evidence that proximity matters: competitive pressures from geographically nearby importers exert the strongest influence on upstream producers' emission intensity. These results confirm that localized measures of import competition generate larger estimated reductions in firm-level emissions than national measures, consistent with local

meaningful.

proximity amplifying competitive pressure. The consistently strong Kleibergen-Paap (KP $>$ 10) statistics indicate that the instruments are sufficiently strong and relevant for our analysis (as discussed above), and strengthen the causal interpretation of the findings.

Table 1: Main Results

	Dep. var: log (CO_2 per value added)					
	(1)	(2)	(3)	(4)	(5)	(6)
IC_{it}^{SAMS}	-0.235***			-0.569***		
	(0.020)			(0.050)		
$IC_{it}^{SAMS^{0-500km}}$		-0.102***			-0.299***	
		(0.017)			(0.061)	
$IC_{it}^{SAMS^{500-1000km}}$		-0.054***			-0.147***	
		(0.013)			(0.047)	
IC_{it}^{NAT}			-0.074***			-0.156***
			(0.006)			(0.012)
Observations	7,924	7,924	7,924	7,924	7,924	7,688
KP				143.93	98.89	214.83
Estimation Strategy	**OLS**	**OLS**	**OLS**	**IV**	**IV**	**IV**
Firm FE	√	√	√	√	√	√
Sector-Year FE	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√

Note: IC_{it}^{SAMS} is the import competition measure weighted by the inverse distance function. In columns (2) and (5), we use distance bands: 0-500km ($IC_{it}^{SAMS^{0-500km}}$) and 500-1000 km ($IC_{it}^{SAMS^{500km-1000km}}$). IC_{it}^{NAT} is producer i's IC exposure measured for at the national level in Sweden (i.e., IC from all firms in Sweden importing the same products produced by producer i. The regressions sample contains 1,497 producing firms in Sweden. In all estimations, we include firm, sector-year, and municipal-year fixed effects. Statistical significance levels are denoted by * for p<0.10, ** for p<0.05, and *** for p<0.01. Standard errors are clustered at the firm and SAMS level to account for heteroskedasticity and within-firm correlation over time.

To put this in context, Chinese exports to Sweden grew by an average of 21% per year between 2005 and 2014. Treating Chinese import growth as a proxy for the average annual change in localized IC, our estimate of -0.57 implies that a year in which Chinese IC rises by 21% is associated with an approximately $0.56 \times 0.21 \approx 12\%$ reduction in emission intensity for exposed upstream producers relative to the no-growth counterfactual. While not directly comparable, Swedish emission intensity (Kilotons CO_2 eq. per one Swedish Krona) dropped by around 20% between 2008 and 2014.[8]

Overall, the findings indicate that as we widen the geographical scope from the SAMS area demarcations to the national level, the relationship between imports and the firm's emission intensity weakens. Therefore, studies evaluating the environmental effects of trade may have underestimated such effects by only considering national-level measures. Our results align with Gullstrand and Knutsson (2019) who found that IC does not significantly affect the firm's marginal costs when measured at the national level, but rather has a significant impact at the local (SAMS) level. This is expected because it is likely that trade shocks will have a more pronounced impact on producers in close proximity, and the effects of these shocks are likely to falter with distance. In terms of production efficiency, the results suggest IC across specific

[8]Source for this information is SCB. No information is available before 2008. Source: SCB Swedish emission intensities.

spatial areas will make firms more energy efficient with better production decisions and techniques. We investigate such possible mechanisms in section 5. Before that, we test our results for robustness next.

4.2 Robustness and Heterogeneity

We subject our benchmark result in column (4) of Table 1 to a host of robustness checks as follows.

Geographic Composition and Spatial Frictions. The baseline results indicate that localized IC reduces emission intensity. Furthermore, our analysis in section 2.3 suggests that there is geographic concentration of importing activities around the industrial centers of Stockholm and Gothenburg. A natural concern, therefore, is that these estimates may reflect geographic composition rather than true competitive pressures. Specifically, if cleaner industries are disproportionately located near industrial hubs, ports, or coastal cities, the observed IC effect could simply capture differences between coastal and interior regions. To address this concern, we implement a set of robustness checks that account for port proximity, coastal status, importer-side geography, and alternative nearest-neighbor definitions of IC.

Table 2: Robustness I: Geographic Location

	Baseline	Drop Stockholm/Gothenburg	Non-Port Municipality	Port Municipality	Coastal Interaction	Interior Sample	Urban Density
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IC_{it}^{SAMS}	-0.569***	-0.576***	-0.644***	-0.507***	-0.513***	-0.502***	-0.535***
	(0.050)	(0.047)	(0.073)	(0.061)	(0.076)	(0.105)	(0.083)
$IC_{it}^{SAMS} \times Coastal$					0.012		
					(0.013)		
$IC_{it}^{SAMS} \times Urbanization$							-0.015
							(0.031)
Observations	7,924	7,611	5,245	2,534	4,508	2,828	7,924
Estimation Strategy	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**
KP	143.93	152.80	79.70	74.65	24.23	20.95	55.98
Firm FE	√	√	√	√	√	√	√
Sector-Year FE	√	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√	√

Note: This table reports robustness checks of the baseline specification to alternative geographic samples and interactions. Column (1) reproduces the baseline results; column (2) excludes firms located in Stockholm and Gothenburg; column (3) restricts the sample to non-port municipalities; column (4) restricts the sample of port municipalities only; column (5) interacts IC_{it}^{SAMS} with an indicator for coastal municipalities; column (6) restricts the sample to interior municipalities; and column (7) interacts IC_{it}^{SAMS} with a measure of urban density. All specifications are estimated using instrumental variables (IV), with the Kleibergen–Paap (KP) statistic reported for instrument strength. Each regression includes firm fixed effects, sector-by-year fixed effects, and municipality-by-year fixed effects. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Standard errors are clustered at both the firm and SAMS levels.

We begin by excluding Stockholm and Gothenburg, from the sample (Table 2, column 2). The results remain virtually unchanged relative to the baseline, indicating that these hubs do not drive our findings. Next, we compare firms located in port municipalities with those in non-port municipalities (columns 3 and 4 respectively). The estimated effects are similar across both groups, with non-port municipalities exhibiting a slightly larger effect of 6% compared to 5.1% in port municipalities.[9] This comparison suggests that proximity to seaports does not dominate the IC channel. We then interact import competition with proximity to coastal areas, defined as producers within 50 kilometers of a seaport, and find the interaction effect to be small and

[9]List of municipalities with ports are sourced from https://www.searates.com/maritime/sweden.

statistically indistinguishable from zero (column 5). This result confirms that the IC effect is not driven exclusively by coastal firms.[10] We further examine an interior-only sub-sample, defined as firms located more than 50 kilometers from the nearest port, and re-estimate the instrumental variable specification (column 6). The interior-only estimates continue to show a sizable and somewhat similar negative effect. This pattern reinforces that the mechanism underlying IC is not confined to coastal regions. We also interact IC with the degree of urbanization and find no significant effects, suggesting that urban concentration does not drive the results (column 7).

Finally, we perform a jackknife analysis across municipalities, sequentially omitting each municipality from the sample. We find that the coefficient estimate is very stable in this exercise, suggesting no single municipality drives the results, further confirming the robustness of our findings (Figure B.1).

Nearest Neighbor. One reservation about using the spatial units defined by the SAMS regions may be that their geographical demarcations (administrative borders) are somewhat arbitrary. Hence, an importing firm just within the SAMS border is given a higher weight than a firm just outside the border although proximity to the local producer is the same. This may introduce some bias to the IC measure. Also, recall that we set the internal distance within a SAMS region equal to 1 km, which may underestimate the internal distances within a SAMS area. To overcome the potential bias from the previous measure, we consider alternative definitions of IC based on the x nearest importing firms to the local upstream producer as follows:

$$IC_{it}^{xn} = \sum_{f \in \Omega_{x,f \neq i}} Import_{fjt};$$

where the IC faced by the upstream producer IC_{it}^{xn} is the sum of all imports of product j imported by the importing firms f, which are part of the set of the x nearest importing firms Ω_x. We use various counts of nearest neighbors. To explore how IC behaves as we consider higher x^{th} nearest neighbors, Table 3 shows the coefficient estimates of IC from estimating equation 5 for the $1st$ up to the $4th$ nearest importing firm. We observe that the magnitude of this coefficient drops significantly after the third nearest neighbor. In other words, it seems that IC introduced by potential buyers that are nearest to the producing firms makes the latter more energy efficient and this effect dies out the further out the importing firm is from the upstream producer. Quantitatively, we find that for a distance of about 50 km between importer and producer (an average distance for two-nearest neighbors), a 10% increase in IC can reduce the producers' emission intensity by approximately 2.4%.

[10]We hand-collect all coordinates (latitudes and longitudes) of ports in Sweden from https://www.searates.com/maritime/sweden. We then calculate the nearest distance of each firm's production facility to the ports using STATA's `geonear` command. The resulting variable, *distance to port*, is measured in kilometers and denotes the minimum distance from each producer to the closest port. To capture coastal proximity, we define a binary indicator, *Coastal*, equal to 1 if the facility is located within 50 km of a port, and zero otherwise. This threshold follows common practice in the trade-transport literature (see Faber 2014 for a similar approach) and is varied in robustness checks (25 km and 75 km) to ensure absence of sensitivity.

Table 3: Robustness II: Nearest Neighbor

	$x=1$	$x=2$	$x=3$	$x=4$	$x\leq 5$	≤ 10
	(1)	(2)	(3)	(4)	(5)	(6)
IC_{it}^{xn}	-0.536**					
	(0.245)					
IC_{it}^{xn}		-0.243***				
		(0.090)				
IC_{it}^{xn}			-0.289			
			(0.189)			
IC_{it}^{xn}				-0.155*		
				(0.089)		
IC_{it}^{xn}					-0.336**	
					(0.144)	
IC_{it}^{xn}						-0.229**
						(0.097)
Observations	7,559	7,559	7,469	7,391	7,776	7,776
KP	11.57	38.47	8.70	24.90	12.41	16.85
Firm FE	√	√	√	√	√	√
Sector-Year FE	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√

Note: IC_{it}^{xn} denotes import competition, measured as exposure to the x geographically closest neighbors. All specifications include a rich set of fixed effects: firm fixed effects to control for time-invariant firm characteristics, sector-by-year fixed effects to capture sector-specific shocks and trends, and municipality-by-year fixed effects to absorb local demand or policy shocks at the municipal level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Standard errors are clustered at the firm level, which accounts for arbitrary heteroskedasticity as well as serial correlation in outcomes within firms over time.

As part of this robustness exercise, we consider different aggregations of the nearest importing neighbors. We first consider the five nearest neighbors ($x \leq 5$), and then the 10 nearest importing neighbors ($x \leq 10$). If a producer has multiple importers that are equally distant, we select the largest of these importers. In most instances, the distances to the nearest neighbors encompass a larger area than the SAMS administrative boundaries, which suggests that the SAMS regions may be somewhat restrictive as spatial units. When we compare the total import value of the five nearest importing manufacturing firms to the total import within an administrative border, the sum of the five closest importers exceeds the import value at the SAMS level in 77% of cases, and in 67% of cases when using municipalities. We present the results of the 5 and 10 nearest importing neighbors in columns (5) and (6) respectively of Table 3. The results show that a 10% increase in IC stemming from the five nearest importers reduces emission intensity by the emitting producer by about 3.4%. This effect decreases to about 2.3% if the 10 nearest neighbors are considered. Hence, these alternative definitions complement our SAMs-based and distance-band measures and allow us to trace the distance decay of IC effects in a high-resolution setting. Together, these tests directly address the possibility that our findings reflect geographic composition rather than localized competition.

Alternative Outcome, Balanced Panel, and Lagged Effects. Table 4 presents three additional checks. First, we investigate the robustness of our benchmark result to changing the dependent variable to emissions per unit of output. The result in column (1) of Table 4 suggests that our benchmark estimate is qualitatively robust to this change, suggesting that firms reduce CO_2 emissions not just per unit of value-added but also relative to their economic contribution in response to IC.

Another potential concern is that the observed decline in emissions intensity may reflect firm entry and exit in response to import competition, which would make the estimates sensitive to changes in firm composition. To address this, column (2) of Table 4 reports results for a balanced panel of firms present throughout the sample period. The estimates remain largely unchanged, indicating that our findings are not driven by sample composition or entry and exit dynamics.

While our main specification captures the immediate response to import competition, column (3) of Table 4 allows for lagged effects to account for potential gradual adjustments that firms might undertake, such as process improvements or incremental technology adoption. The coefficient increases modestly, consistent with adjustment over time.

Role of Swedish environmental policy. Sweden has one of the highest CO_2 tax rates in the world and is part of EU emissions trading scheme (ETS). This raises a natural concern: rather than improving productivity, firms facing stronger import competition might instead switch to cheaper but dirtier modes of production, with Sweden's environmental policies merely constraining the extent of such behavior. To address this, we implement a series of robustness checks that directly test whether our findings are sensitive to energy prices or Sweden's carbon pricing regime. The results, reported in Table 4 (columns 4-5), show that our baseline effect is highly robust. Column (4) extends the specification to include firm-specific energy prices. We also include additional firm-level controls such as producer's own import, capital, employment, investment in machinery, and ETS allowances purchase. If the effect were explained by a shift to lower-cost, higher-emission fuels, the inclusion of energy costs would substantially reduce the coefficient. Instead, the estimate remains nearly unchanged (–0.568), directly contradicting the "dirty production" hypothesis. Subsequently, we account for Sweden's evolving carbon pricing policies. Following Martinsson et al. (2022), we construct a firm-year measure of the effective marginal CO_2 tax rate, which incorporates statutory tax schedules, sectoral exemptions, revenue-share thresholds (0.8% before 2011, 1.2% thereafter), and EU ETS participation. Column (5) includes this measure as an additional control. The coefficient remains highly stable (–0.568), indicating that our results are not mechanically driven by differential exposure to carbon taxation.

Heterogeneity. We also subject our results to several heterogeneity checks. The coefficient estimates produced from this series of estimations are plotted in Figure C.1. First, we examine whether exposure to IC affects firms differently based on the emission intensity of their production. Specifically, we analyze whether the impact of IC varies depending on the emission intensity of the firms. To this effect, firms are classified as dirty (clean) if their energy use is above (below) the median values of the sample. The results in panel A show that both clean and dirty firms observe lower emission intensity, but this effect is larger for cleaner firms. This indi-

Table 4: Robustness III: +Additional Controls

	Unit Output	Balanced Sample	Lagged Effect	Controls +Energy Price	Controls + Carbon tax
	(1)	(2)	(3)	(4)	(5)
IC_{it}^{SAMS}	-0.819***	-0.563***	-0.565***	-0.568***	-0.568***
	(0.070)	(0.069)	(0.120)	(0.046)	(0.046)
Observations	7,924	2,634	3,887	7,924	7,924
KP	143.93	101.38	16.62	39.45	37.96
Firm FE	√	√	√	√	√
Sector-Year FE	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√

Note: Column (1) reports results where emission intensity is defined as emissions per unit of output. Column (2) restricts the sample to a balanced panel of firms, thereby excluding entry and exit dynamics and ensuring that the estimates are not driven by compositional changes in the firm population. In Column (3), import competition is lagged by one period to mitigate potential simultaneity concerns. Columns (3) and (4) further examine the role of energy prices and the Swedish carbon tax in shaping firm-level emissions. Columns (4) and (5) additionally control for firm-level characteristics, including domestic firm's own imports, capital stock, employment, machinery investment, and purchases of emission trading rights (ETS), to capture heterogeneity in production capacity, labor intensity, and compliance behavior. Statistical significance levels are denoted by * for p<0.10, ** for p<0.05, and *** for p<0.01. Standard errors are clustered at the firm and SAMS level to account for heteroskedasticity and within-firm and SAMS correlation over time.

cates that environmentally proactive firms respond more positively to competitive pressures by further reducing their emissions, possibly through enhanced efficiency and adoption of cleaner technologies as well discuss later.

Second, we examine differences between firms subjected to the EU-ETS and those that are not. We split the sample into two, one for non-ETS firms and another for ETS firms respectively. Estimating the baseline specification with the two samples separately yields a larger coefficient estimate for non-ETS firms (panel B). This suggests that while ETS compliance may reduce emissions, it also narrows the scope for further improvements from non-price stimuli such as IC. This result aligns with studies such as Abrell et al. (2022), who have shown that regulated firms under the EU-ETS often operate closer to their abatement frontier, and additional policy shocks, such as higher carbon prices, yield smaller marginal reductions in carbon intensity.

Third, we check the heterogeneity of our results along the firm size. We estimate the baseline specification separately for small- and medium-sized enterprises (SMEs) with less than 250 employees on the payroll, and large firms with 250 or more employees. The coefficient estimates (panel C) suggest that while both types are affected similarly by IC, larger firms reduce their emission intensity by around 50% more following a given increase in IC. This is expected because larger firms tend to be more productive and possess more financial space to respond to shocks. A similar exercise attempts to differentiate between MNEs (multinational enterprises) and non-MNEs (panel D). The coefficient estimate is larger for MNEs and reflects the larger adjustment capacity of MNEs in the face of IC shocks.

Finally, we investigate whether IC coming from countries with less strict environmental regulation has a bearing on the firm's emission response. For example, IC from cheaper and often high emission-intensive products may trigger a different response from the local producer in Sweden than IC stemming from countries with similar environmental stringency as Sweden. To conduct this exercise, we use the OECD's Environmental Policy Stringency (EPS) index, a composite index derived from indicators of about 15 market-based and non-market environmental policy instruments in 28 countries, including 4 non-OECD countries (Botta and Koźluk, 2014). This indicator ranges from 0 (most lax policies) to 6 (most stringent policies). Using this indicator, we construct a dummy variable that takes the value of one for countries with an average EPS index that is lower than Sweden's score (less strict) between 1991 and 2014, and zero otherwise. The result in panel E indicates that the reduction in emission intensity applies to IC from countries with laxer environmental policies, with the coefficient from the estimation for the sample of countries with stricter environmental code being statistically not different from zero.

5 Channels at Work

While the results demonstrate that IC reduces firms' emission intensity, the precise mechanisms driving these reductions remain an open question. Several potential channels merit further investigation. First, reductions in emission intensity could stem from overall increase in firms productivity which leads to fewer inputs (e.g fuel) per a given output. Second, firms may respond to competitive pressure by adopting cleaner technologies, investing in energy-efficient production processes, or shifting toward lower-carbon inputs. Third, firms might outsource pollution-intensive activities to third-party suppliers or relocate production to regions with less stringent environmental regulations.

Efficiency and Pro-Competitive Effect. First, we assess the impact of localized IC exposure on the productivity of surviving firms. Existing research has established that low competition tends to diminish the firm's incentives to streamline its production processes and increase efficiency (Jabbour et al., 2019). Thus, we hypothesize that increased localized IC exposure can lead to a reduction in slack among surviving producing firms and enhance within-firm productivity (Newman et al., 2023). This boost in firm productivity will result in fewer inputs required to produce a given output (Copeland et al., 2022); therefore, the amount of fuel needed will be less. We put this to the test by regressing our first IC measure on the firm's productivity. In Table 5, column 1, using firm total factor productivity (TFP) as measured by Wooldridge (2009), we find a positive and significant impact of IC on the productivity of the upstream producer's productivity; a 10% increase in IC leads to an increase of 0.25% in firm productivity.[11] When comparing this estimate to the estimate produced by Akerman et al. (2024) in their study on the effects of direct importing on the productivity of Swedish manufacturing firms, our estimate is smaller in magnitude. This suggests that while importing firms benefit in terms of productivity gains from an increase in imports, so do local producing firms through IC.

The productivity gains from IC are further reflected in other firm performance metrics, such as the firm's value added which increases by about 0.14% in response to an increase of 10% in IC. We further test the hypothesis that the firm's response to IC can lead to *pro-competitive effects* by (i) decreasing their marginal cost, which arises from efficiency gains and reallocating

[11]Using an alternative method for measuring TFP by Levinsohn and Petrin (2003) yields a similar result.

Table 5: Potential Channels of Transmission

	TFP	VA	MC	P	MU	Core Product	Prob(Product Exit)		Abatement	Offshoring
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IC_{it}^{SAMS}	0.025*	0.014*	-0.457***	0.208**	0.633***	0.225***	-0.029*	-0.018	0.719**	0.032**
	(0.014)	(0.007)	(0.107)	(0.095)	(0.119)	(0.041)	(0.015)	(0.016)	(0.345)	(0.013)
IC_{it}^{SAMS} × DirtyProdRank								0.003***		
								(0.001)		
Observations	7,721	7,986	7,334	8,028	7,334	8,029	8,029	8,029	879	8,503
KP	63.59	136.47	62.35	71.77	62.35	43.76	43.76	19.68	41.04	63.07
Firm FE	√	√	√	√	√	√	√	√	√	√
Sector-Year FE	√	√	√	√	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√	√	√	√	√

Note: All regression specifications includes firm fixed effects (Firm FE), Year fixed effects (Year FE), sector-year fixed effects (Sector-Year FE), and municipal-year fixed effects (Municipal-Year FE). TFP stands for Total factor productivity and is estimated using the method by Wooldridge (2009). VA, MC, P, and MU denote the firm's value added, marginal cost, price and markup respectively. We estimates MC and MU based on De Loecker et al. (2016). Firms report abatement investments and these include the installation of pollution control equipment in factories, the development of renewable energy projects, or the implementation of waste management systems. We only have abatement data for a subset of the firms in our sample. Statistical significance levels are denoted by * p<0.10, ** p<0.05, and *** p<0.01. Standard errors are clustered at the firm level to account for heteroskedasticity and within-firm correlation over time.

resources to more productive firms, and/or (ii) improving their ability to charge higher prices due to various factors that enable the producing firms to set their products apart (potentially contributing to their productivity improvements) (Antoniades, 2015). We estimate markups following closely the estimation approach of De Loecker et al. (2016).[12] Our findings, presented in columns (3-5) of Table 5, indicate that a 10% increase in exposure to IC indeed leads to an decrease of about 4.6% in the firm's marginal cost and an increase of 2.1% prices. These dual effects – lower marginal costs and higher prices – culminate in a significant increase in markups. Notably, markups increase by 6.3% in response to a 10% rise in IC, suggesting that firms capitalize on productivity improvements to differentiate their products and command higher prices. This aligns with the pro-competitive effects described by Antoniades (2015), where firms enhance product quality or reduce marginal costs to sustain profitability under competitive pressures (Newman et al., 2023; Goldberg et al., 2010; Gullstrand and Knutsson, 2019). Generally, these channel may indicate that firms become more productive and profitable, which reflects positively on their emission intensity through more efficient production and potentially further quality upgrading.

Product-Mix Effect. Furthermore, and as mentioned earlier, there is the possibility that, beyond simply streamlining operations, domestic producers may change their product mix. Namely, domestic producers may increase production of their core products (Gullstrand and Knutsson, 2019), or drop their low quality (and often dirty) products (Antoniades, 2015) as a strategic response to compete with imported goods. We explore these mechanisms by considering how localized IC impacts (a) the production of core products, and (b) the probability of dropping dirty products. Table 5 column (6) shows that a 10% increase in IC exposure leads to

[12] Markups are entered as log markup in all regressions. To address the well-documented sensitivity of ratio-based markup estimators to extreme input-revenue shares — our data record markups as high as 98,092 and as low as 0 (Table A.2) — we winsorize markups at the 1st and 99th percentiles prior to estimation. Results are robust to winsorization at the 5th/95th percentiles and to the exclusion of observations with markups below 0.1 (implying marginal costs exceed price by more than tenfold).

around 2.3% increase in the firm's core product output. However, when we condition exposure on more emission-intensive products using product-survival analysis, we find that firms tend to phase out their low-quality (dirty) products. In columns (7), we run a regression where the dependent variable is the probability that a product is no longer produced (product exit), and in column (8), we interact the IC variable with a rank indicator where the products are sorted into quartiles in terms of their energy use; a rank of zero is given to the products in the bottom quartile, and a rank of 3 is given to the products in the top quartile (i.e., to the dirtiest products). We estimate that a 10% increase in IC raises the probability of product exit by 0.29 percentage points — i.e., a product that faces stronger localized IC is more likely to be dropped from the firm's portfolio. The interaction result in column (8) suggests that this pro-exit effect is concentrated among emission-intensive products: the positive coefficient on $IC \times$ DirtyProdRank implies that the exit probability increases more steeply for higher-ranked (dirtier) products, consistent with firms selectively shedding their most polluting product lines. This aligns with the trade literature on the composition effect of trade, where multi-product firms can adjust their product mix towards low-energy-intensive and low-marginal-cost products (Shapiro, 2021; Copeland et al., 2022; Leisner et al., 2023).

Abatement vs Offshoring Effect. Another interesting mechanism for emission reduction at the firm level is whether IC induces producing firms to increase investment in pollution abatement and/or are just offshoring dirty part of their production abroad. We analyze annual abatement data from SCB to investigate this mechanism. Importantly, we gather information on the firms' investment in abatement technology. Examples of pollution abatement investments include the installation of pollution control equipment in factories, the development of renewable energy projects, or the implementation of waste management systems. The regression results for this mechanism are presented in Table 5 column (9). We observe that IC has a significant and positive effect on abatement investment. Hence, the producing firm responds further to competitive pressures by investing in reducing emissions, which would further differentiate the firm and help it reduce its environmental footprint costs.

It is also conceivable that producing firms facing IC offshore may offshore some of their production as a means to reduce production costs and regain competitiveness. This would in turn reduce emission intensity at home, especially if the firm offshores its relatively more emission-intensive inputs. In other words, IC can lead to the composition of production to shift towards cleaner production by driving an increase in imports of dirty goods that are not produced in-house. To investigate this channel, we follow the study by Dussaux et al. (2023) to calculate the emissions embodied in imports (also see e.g. Liu et al. 2023) . To account for the carbon content of import, we first compute the emission intensity of each sector in the source countries using data on total emissions and production from the Eora Global Supply Chain Database (EGSCD). We then calculate the emissions embodied in imported inputs as the sum of emissions weighted by the firm's imports. That is,

$$CarbonImport_{it} = \sum_{p} \sum_{c} M_{ict,p \in j} EI_{ct,p \in j}$$

where $EI_{ct,p\in j,}$ is the total emission intensity (i.e., tons of CO_2 per unit of real output) of sector j in sourcing country c at time t, while $M_{ict,p\in j}$ is the real import value of firm i for products p belonging to sector j from sourcing country c, deflated to constant prices using product-level import price deflators from SCB and expressed in the same real-output units as EI.[13] In this exercise, we focus on imported intermediate goods, classified at the 3-digit level according to the 5th revision of the Classification by Broad Economic Categories (BEC). The estimated coefficient of this exercise, reported in Table 5 column (10), suggests that import competition leads to an increase in offshoring activities with an elasticity of 0.032. We acknowledge that an increase in the absolute level of carbon imports could partly reflect a scale effect: since IC also raises firms' value added (Table 5, column 2), total input demand — including imported carbon-intensive intermediates — may rise mechanically with output expansion. To partially address this concern, we verify that the elasticity *relative to domestic output* also rises with IC, consistent with a compositional shift toward imported inputs rather than a pure scale effect; this ratio-based check similarly yields a positive and statistically significant coefficient. Hence, both abatement and offshoring seem to be at play in the firm's toolbox to respond to increasing IC pressure.[14]

Conclusively, our study suggests that efficiency gains via IC extend to firms' environmental behavior. Trade exposure at different locations can enhance environmental efficiency via increased productivity growth, product up-scaling and differentiation, and adoption of sustainable production practices, thereby contributing to a greener and more responsible global supply chain.

6 Conclusion

The classical examination of the impact of IC on various firm outcomes, including environmental performance, typically considers IC at the national level, assuming that competition is symmetric nationwide. Using detailed geographical information about the locations of all manufacturing firms in Sweden during the period 2005–2014, we explore the effects of IC in a spatial

[13] To ensure dimensional consistency, CN8-level import values are deflated using annual product-level price indices and then mapped to ISIC sectors to align with the EORA MRIO real-output basis. The resulting units of $M_{ict,p\in j}$ are millions of constant-price SEK, directly comparable to the real-output denominator in $EI_{ct,p\in j}$. The product $M_{ict,p\in j} \times EI_{ct,p\in j}$ therefore yields tons of CO_2 equivalent embodied in the firm's intermediate imports from country c.

[14] The finding that both the technique effect and the composition effect are at play contributes to the ongoing debate on firms' emissions decomposition. While studies such as Shapiro and Walker (2018) emphasize the dominance of the composition effect, others — including Dussaux et al. (2023), Akerman et al. (2024), Ustyuzhanina (2022), and Leisner et al. (2023) - highlight the primacy of the technique effect. Our results highlight a novel mechanism: the competitive pressure from imports induces local firms to adopt strategies that combine the two effects.

framework on the CO_2 emissions of local producing firms. Considering different spatial definitions to measure IC, we find evidence that IC from local importers has a significant negative impact on the emission intensity of domestic upstream producers. However, this effect seems to wane as the distance between the producers and importers increases. We also find evidence of improved productivity, increased investment in pollution abatement, product differentiation, and the reduction of energy-intensive products among producing firms in response to localized IC.

In summary, our findings reveal a positive globalization impact on the environment coming from increased IC. Consequently, our results underscore the possibility that prior empirical studies might have undervalued the environmental and productivity gains derived from trade. This lends empirical support to the theoretical arguments presented by Autor et al. (2013), emphasizing the role of local economy in playing a significant part of identifying trade-induced changes in the economy.

By extension, the study highlights that trade's effect on the environment could be positive. This does not, however, consider the possibility of carbon leakages. In fact, import competition often entails carbon leakage as we have alluded in this paper because firms may be outsourcing some of their intermediate input to foreign agents that are dirtier than their Swedish counterparts. This means that while our study suggests that IC may have positive effects on the environment in Sweden, we can not say that the total effect is positive on aggregate after accounting for carbon leakages. To deal with carbon leakages, the EU is planning to introduce the Carbon Border Adjustment Mechanisms (CBAM) in 2026. This involves levying taxes on carbon-intensive imports to mitigate the carbon offshoring effect. Additionally, the creation of a certification system is recommended to ensure that products meet specific eco-friendly criteria, fostering cleaner production methods on a global scale. Another policy implication of our study is the need for strategic investment in green technologies. Directing local resources towards R&D and sustainable production methods can foster innovation in green technologies and stands to benefit both domestic and imported goods, contributing to more sustainable development.

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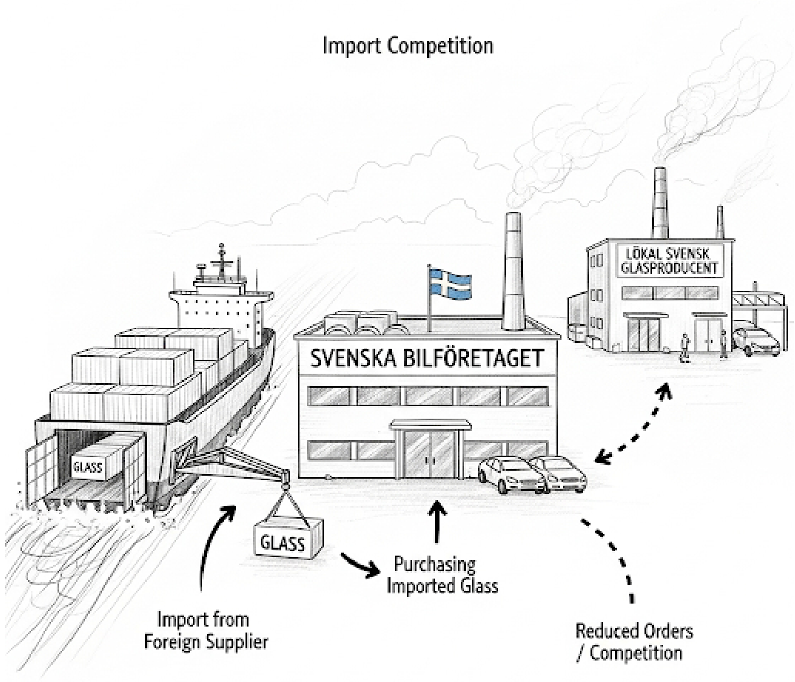
Appendix

A Descriptive Statistics and Miscellaneous Figures

Figure A.1: Graphical illustration of import competition



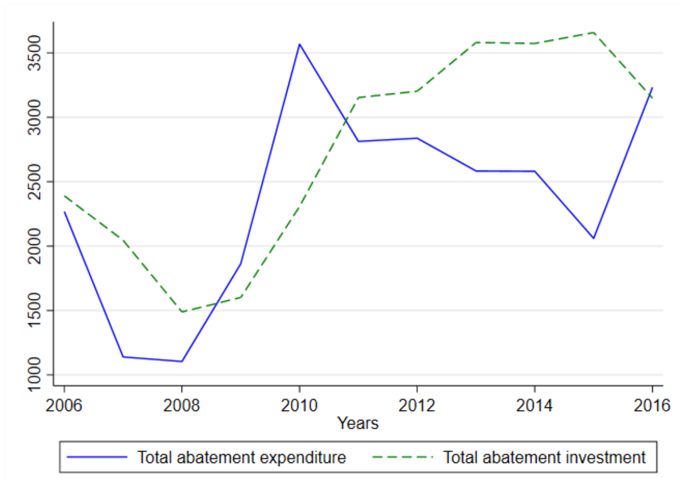
Note: Produced by the authors using AI (Google Gemini).

Table A.1: Descriptive statistics on emissions

	Mean	SD	Min	10th perc.	**Median**	75th perc.	Max
CO_2(1000 tons)	45	189.05	0.003	0.39	2.73	10.05	2378.67
CO_2(tons)/value added (SEK)	0.00017	0.0077	9.11e-07	0.0001	0.0005	0.0012	0.563

Note: The sample comprises 1,497 producing firms with more than 20 employees, observed over the period 2005–2014, which constitutes the regression sample used in the analysis.

Figure A.2: Trend of abatement expenditure and investment (SEK, thousands)



Note: The sample consists of large firms with more than 50 employees. Abatement investments are typically long-term in nature and often require significant capital expenditures upfront. Examples of abatement investments include the installation of pollution control equipment in factories, the development of renewable energy projects, or the implementation of waste management systems. Abatement expenditure, on the other hand, refers to the actual costs or expenses incurred in carrying out abatement measures. It represents the financial outlays associated with implementing and maintaining environmental protection initiatives. Abatement expenditures can include a wide range of costs, such as operational expenses, maintenance costs, monitoring and compliance costs, research and development expenses, or fees paid for environmental permits or licenses.

Table A.2: Descriptive statistics for production, and firm characteristics

	Full sample				Regression sample			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Number of products	9.39	12.84	1	68	2.80	4.30	1	68
Product share in firms revenue	0.28	0.36	0	1	0.53	0.41	0	1
Core product	0.35	0.48	0	1	0.59	0.49	0	1
Product share in firm production$^{t=0}$	0.37	0.39	0	1	0.67	0.40	0	1
Markup	15.9	938.94	0	98092.45	17.31	1148.65	0	98092.45
Employment	547.98	1737.33	20	20492	230.12	931.50	20	20492
Output (various units)/1000	399.78	7259.41	0	450874.09	724.13	11403.84	0	450874.09
Sales (million SEK)	2407.36	9006.02	0	120555.02	930.08	5274.52	0	120555.02

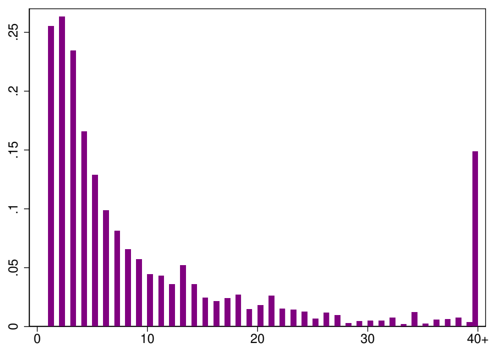
Note: Summary statistics for producing firms in terms of production, size, markup and sales. The left columns summarize the full sample set at firm-plant-product-year level in the database, and the right columns only at the firm-year level with our data restrictions. Our full sample contains 2,279 firms, whereas our regression sample contains 1,497 firms. All observations have a year dimension. Sales and employment are calculated at firm level using the FEK database. Core products are products with shares in firms revenue exceeding 50%. Currency values are millions of current year SEK

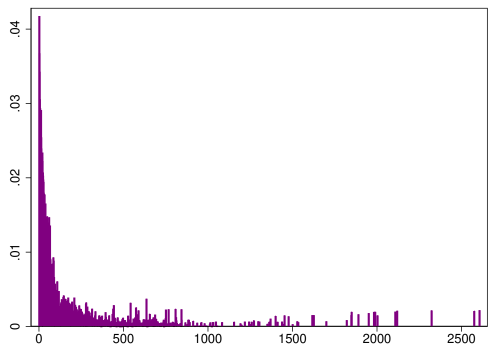
Table A.3: Descriptive statistics: Imports and geography

	Regression sample			
	Mean	SD	Min	Max
Import (million SEK):				
Total	190.50	1244.15	0.00	36681.45
SAMS	9.01	99.68	0	7076.78
1st nearest Neighbor	18.31	229.43	0.00	9517.50
2nd nearest Neighbor	17.10	222.86	0.00	9143.51
3rd nearest Neighbor	12.40	149.71	0.00	8738.09
Distance (KM):				
To 1st nearest Neighbor	34.33	63.71	0.00	1027.16
To 2nd nearest Neighbor	52.89	82.99	0.00	1157.26
To 3rd nearest Neighbor	66.32	92.80	0.00	1296.15
Import Competition				
IC^{SAMS}	10.8	2.44	0	17.48

Note: Summary statistics for producing firms in terms of imports (million SEK) and distance (km) from the producer to nearest importing firm . A distance of zero means the nearest neighbor is in the same SAMS area as the producing firm. Import competition measure is in logs. All observations have a time dimension.

Figure A.3: Distribution of Number of producers and importers





A. Number of Producers

B. Number of Importers

Note: The graph shows the distribution of the number of producers (panel A) and importers (panel B) within the SAMS regions of Sweden.

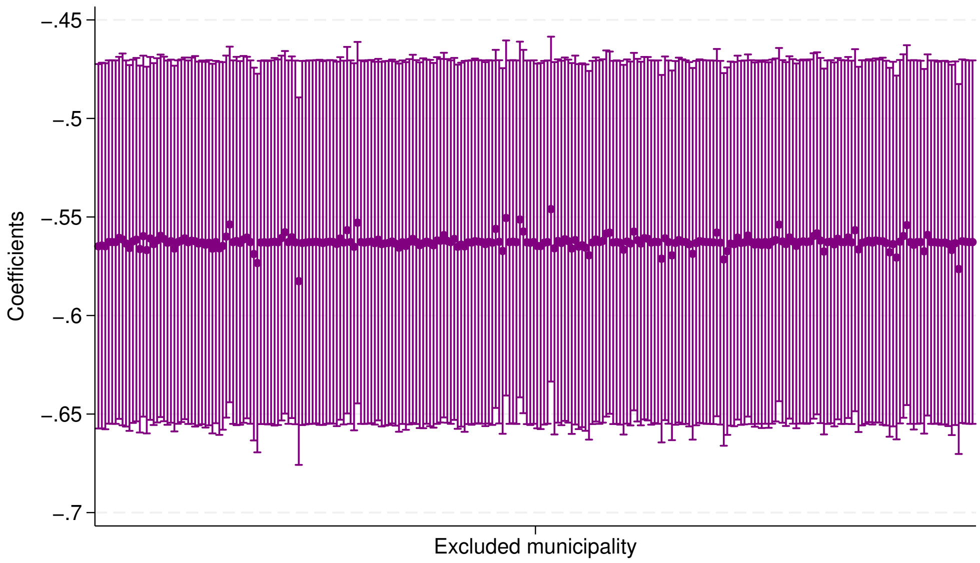
B Robustness Checks

Table B.1: Robustness: Exposure Robust Standard Errors

	(1) Prod×Yr cluster	(2) Double cluster	(3) 3 Way Clustering
$IC^{S}AMS$	-0.569***	-0.569***	-0.569***
	(0.036)	(0.049)	(0.047)
Observations	7,924	7,924	7,924
KP	257.17	140.90	156.86
Firm FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Municipal-Year FE	Yes	Yes	Yes

Note: Statistical significance levels are denoted by * for p<0.10, ** for p<0.05, and *** for p<0.01. We cluster the standard errors at different exposure level. Column 1 using product-year clustering, column 2 includes firm levels clustering and column 3 includes the municipal-year clustering

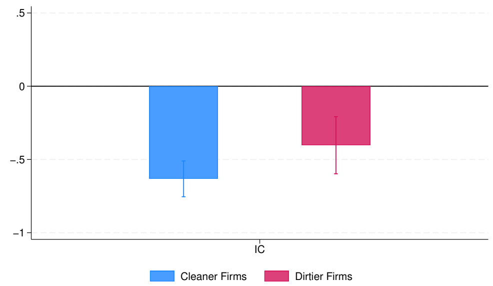
Figure B.1: Jackknife analysis by leaving out one municipality at a time.



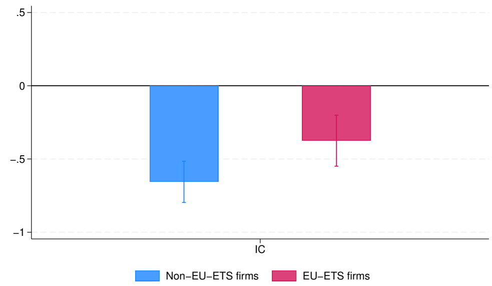
Note: Each point plots the coefficient estimate obtained by re-estimating the baseline specification after omitting the corresponding municipality from the sample (there are 254 municipalities). Vertical lines denote 95% confidence intervals based on two-way clustered standard errors at the SAMS and firm level.

C Heterogeneity

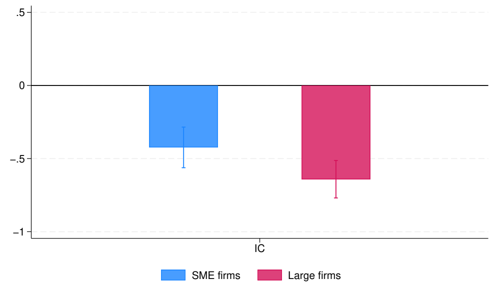
Figure C.1: **Heterogeneity:** IC effects on emission intensity



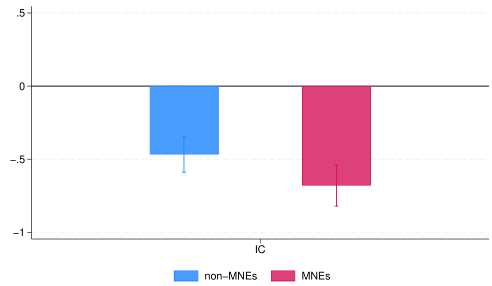
A. Clean vs Dirty firms



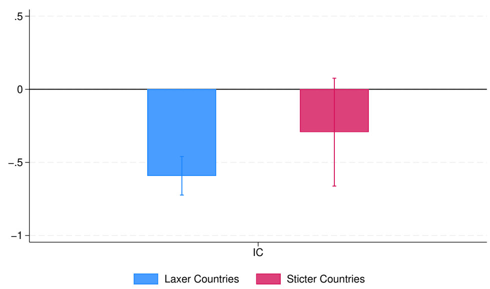
B. EU-ETS vs non-EU-ETS firms



C. SMEs vs Large Firms



D. MNEs vs non-MNEs



E. IC from Laxer vs Stricter Countries

Note: The Figure reports the estimated coefficients β_0 for the different groups defined in equation 5. The vertical axis displays the point estimates, while the bars represent the associated 95 percent confidence intervals. The coefficients are obtained from instrumental variables regressions, where local import competition is instrumented using export supply shocks weighted by pre-sample import shares and the sectoral energy mix. Standard errors are clustered at the SAMS level. In all cases, the Kleibergen–Paap statistics indicate that the instruments satisfy the conventional thresholds for relevance.