

Greener Under Pressure? The Local Geography of Import Competition and Emissions in Swedish Manufacturing

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Abstract

We examine how local import competition — measured across different spatial dimensions within Sweden — affects the CO_2 emission intensity of manufacturing firms in Sweden. Leveraging detailed geographic data on the location of all Swedish manufacturing firms, we provide evidence that increased local import competition leads to lower emissions at the firm level, with the effect diminishing as the distance between producers and importers increases. Our findings indicate that relying on national-level measures of import competition may significantly underestimate the true environmental impact of trade shocks. We identify two primary mechanisms behind these reductions: (i) a pro-competitive efficiency-enhancing effect, where firms experience gains in total factor productivity, increasing value-added, lower marginal costs, and higher markups; and (ii) a product-mix effect, where firms reallocate production away from emission-intensive goods toward cleaner alternatives. Additionally, we find some evidence of firms relying on carbon offshoring as a response to import competition, as well as reliance on investment in pollution abatement, suggesting that firms adopt a mix of strategies to deal with increasing import competition.

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

JEL: F14, F18, Q56, Q58, R13

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1 Introduction

Firms contribute directly and indirectly to global warming and climate change through their greenhouse gas (GHG) emissions. With the urgency of addressing climate change, the environmental performance of firms is increasingly coming under scrutiny. It is common knowledge that firms are interconnected through complex global value chains (GVCs) such that some firms may choose to import their intermediate inputs instead of producing these in-house or sourcing them from local suppliers. This presents local upstream suppliers with import competition (**henceforth IC**) because they compete with imported products that they also produce. When faced with IC, local suppliers adjust in various ways, and their environmental behavior may be affected as a result. But how does IC affect the emissions of the firms that are subjected to it? Do they become greener under pressure, or otherwise?

To answer these questions, this paper examines the effect of spatially localized IC shocks on the environmental performance of local upstream producers in Swedish manufacturing. Specifically, we investigate how imports by Swedish manufacturers impact the CO₂ emission intensity (tons of CO₂ per unit output) of local upstream suppliers that produce the same products being imported. To further explain this, assume a Swedish car manufacturer (downstream Swedish firm) that outsources glass for its cars (see Figure A.1 for a graphical illustration). This car manufacturer can purchase glass from a (nearby) local producer, i.e. the Swedish upstream firm, or a foreign manufacturer. If the Swedish downstream car manufacturer decides to import the glass from a foreign producer, this represents IC for the Swedish glass manufacturer. How this firm responds to this competitive pressure is likely to affect its environmental performance, and specifically its emission intensity.

IC is usually measured at the national level with the assumption that competition increases symmetrically within an economy as soon as an imported product crosses the border (Lehr, 2025; Autor et al., 2013; Gullstrand and Knutsson, 2019). This, however, conceals the role of proximity in buyer-seller networks (see e.g. Bernard et al. 2019; Hillberry and Hummels 2008) and the spatial positioning of firms (see e.g. Syverson 2007). In addition, the literature has established a close relationship between GHG emissions and the position of industries in GVCs (see e.g. Shapiro 2021). Therefore, measures of nationwide IC can be imprecise when one estimates its effect on the firms' environmental performance.¹

This paper addresses these concerns by considering IC at the local level. Since we do not have information about the direct seller-buyer relationships, we use detailed spatial information from Sweden to model the exposure of upstream firms to IC shocks. The underlying assumption is that

¹Studies such as Anderson and Van Wincoop (2004), Autor et al. (2013) and Gullstrand and Knutsson (2019) show that the measurement of IC at a national level may not accurately reflect the influence of spatial frictions between and within countries.

manufacturers are ever more involved in fragmented supply chains where they supply intermediate inputs to one another and, therefore, trade shocks can have a more pronounced impact on producers in close proximity to importers. This is because trade shocks tend to be relatively contained within a region due to geographic and/or industrial frictions (Gullstrand and Knutsson, 2019).² The existing literature has explored the effects of IC on firm productivity, markups, and labor market outcomes. We are the first, as far as we are aware, to investigate the effects of IC on the CO_2 emission intensity of upstream firms. An important dimension of this paper is to explore the complex linkages between firms through their spatial distribution relative to each other when defining the exposure of the upstream producer to IC. By concentrating on Swedish producers (sellers) of intermediate goods that are simultaneously imported by manufacturing firms (buyers), we can spatially map the IC patterns of producers through the imports of manufacturing firms using detailed information about firm locations. Subsequently, we examine how IC shocks in different geographical market demarcations affect the local upstream firms' production and emissions. Another contribution of this study is to highlight the potential mechanisms through which IC may lead to a change in the firm's emission intensity, which draws on findings in the literature related to the effects of IC on the firms.

Theoretically, IC is expected to make the exposed upstream firm more productive because it increases the incentives for the competing firm to reduce slack under pressure from direct competition (Newman et al., 2023; Jabbour et al., 2019). Furthermore, more productive firms are more efficient, and thus, use less inputs, including less fossil fuel, in their production (Copeland et al., 2022). Therefore, more exposure to IC is expected to lower the emission intensity of upstream exposed firms. There is also evidence from the literature that firms respond to IC by upgrading their production as a means of further product differentiation (Newman et al., 2023; Antoniadou, 2015), focusing on the core products instead (Gullstrand and Knutsson, 2019), increasing the range of product scope (Goldberg et al., 2010), or dropping the low quality and often dirtier products (Antoniades, 2015). These responses often entail investing in new capital which tends to be more fuel-efficient, and this in turn leads to lower emission intensity.

To investigate these issues, we combine data on production and trade (at the 8-digit product level) with data on the energy use of Swedish manufacturing firms for the period 2005-2014. We start the analysis by defining the IC exposure faced by firms within small geographical units. Following Gullstrand and Knutsson (2019), we also use alternative measures of the firms' exposure to IC based on the nearest downstream importing firms. Because demand conditions in Sweden are expected to affect imports and producers' behavior simultaneously, we construct a firm-specific instrumental variable (shift-share instrument), which relies on the variation of world export supply as an exogenous shock for the firms' imports. We find evidence that IC leads to lower CO_2 emission

²Gullstrand and Knutsson (2019) find evidence for Sweden that upstream firms located near the buyers are more affected by IC compared to upstream firms that are located further away.

intensity and this result is robust to several IC measures defined at different geographic dimensions. We then proceed to examine the channels that explain this result. We find evidence that IC leads to an increase in firm productivity. Hence, emission intensity decreases because the firm becomes more energy-efficient through gains made in productivity. In addition, we find that the producing firm increases the production of its core product while also increasing markups. This suggests that the firm differentiates itself by upgrading the quality of its production whilst focusing on its core product. Because product upgrading is likely to involve cleaner capital investments, emission intensity also decreases.

This paper contributes to several strands of literature. We build on the growing body of literature that highlights the importance of proximity in buyer-seller networks ([Gullstrand and Knutsson 2019](#), [Bellone et al. \(2016\)](#), [Bernard et al. 2019](#), [Hillberry and Hummels 2008](#), [Autor et al. 2013](#)). A closely related paper by [Gullstrand and Knutsson \(2019\)](#) shows that the spatial dimension of IC matters for the firm’s efficiency in domestic production as marginal costs fall considerably. Several papers have also examined the role of the local economy and how it affects trade-induced changes in the economy. [Bellone et al. \(2016\)](#) consider both the spatial and quality dimensions of differentiation among firms and products and found that firm markups positively correlate with firm productivity while being negatively associated with local competition intensity and the extent of import penetration. [Autor et al. \(2013\)](#) assess the influence of IC from China on various labor market outcomes, such as employment and wages, utilizing U.S. labor market boundaries, whereas [Ding et al. \(2016\)](#) concentrate on the effects of import penetration on firm performance within Chinese provinces. Despite the local economy’s importance, little is known about IC at the local level and its effects on firms’ emissions and production processes. As we highlighted before, our paper is the first one to analyze the spatial dimension of the effects of IC on firm emissions.

Our findings make a novel contribution to the trade-environment literature (see [Copeland et al. \(2022\)](#) for a review) by quantifying the firm-level environmental impact of local IC and uncovering the critical role of geographic frictions in shaping emission outcomes. While previous studies, such as [Akerman et al. \(2024\)](#) and [Leisner et al. \(2023\)](#), have shown that importing intermediate inputs reduces emission intensity for importing firms in Sweden and Denmark, our paper shifts the focus to the firms facing intensified IC in their domestic product markets coming from the imports of other downstream firms. By doing so, we reveal that the environmental response to trade is not uniform but is shaped by regional frictions and market structures. Our findings highlight significant regional asymmetries, suggesting that studies relying solely on national-level trade measures may underestimate the environmental benefits of IC.

Lastly, we delve into the underlying mechanisms driving emission reductions, connecting our study to a substantial body of literature investigating the factors influencing firm-level productivity and abatement. Previous work has extensively analyzed how trade, competition, and market conditions

influence firm innovation and Hicks-neutral total factor productivity (TFP) (Newman et al., 2023; Bernard et al., 2019; Jabbour et al., 2019; Akerman et al., 2024; Forslid et al., 2018; Antoniadou, 2015), highlighting the crucial roles of technology adoption and product mix. Our findings complement and extend this literature by considering the effects of IC on firm behavior and outcomes. We also test the technological channel using firm-level abatement investment data. The results reveal a novel mechanism: IC exposure at the local level leads local producers - not just importers - to become relatively cleaner via productivity gains, product differentiation, and getting rid of periphery and often dirty products. On the other hand, there is some evidence that firms invest in emission abatement technologies. These results suggest that both the composition effect, driven by changing the product mix and product differentiation through quality upgrading as well as the technique effect or the technological channel are at play. This insight adds a new dimension to the ongoing debate on firms' emissions decomposition in response to trade shocks (Shapiro and Walker, 2018; Dussaux et al., 2023; Akerman et al., 2024; Leisner et al., 2023).

This paper proceeds as follows. Section 2 describes the data, sample construction, and measures of IC. Section 3 specifies the empirical strategy as well as the instruments. Section 4 provides the results and various robustness checks. Section 5 shows the channels at work and 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, m³ of natural gas etc.). CO₂ emissions can be calculated by using the fuel-specific CO₂ emission coefficients provided by SCB. Hence, CO₂ emissions are accurately calculated from fuel inputs. Our dependent variable will be emission intensity measured as emissions per Swedish Krona (SEK) of value-added.³ Table A.1 presents descriptive statistics for emissions and emission intensities of firms. On average, firms emit approximately 45,000 tons of CO₂ emissions annually, translating to about 0.017 tons of emissions per SEK value added. The median values of emissions and

³We also consider an alternative measures of emission intensity calculates 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 the alternative measure.

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 investments 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.⁴ 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 of the firm, we similarly merge several databases obtained from SCB. First, from the Production of Commodities and Industrial Services (IVP) database, we obtain annual information detailing the quantities and values of production at the 8-digit product levels of about 6,200 manufacturing firms in Sweden. Firms included in this database are private manufacturing firms employing a minimum of 20 employees. As the geographical information on plants and firms is incomplete before 2005, we restrict our sample to the period 2005–2014. 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. Third, the Structural Business Statistics database (FEK) provides a myriad of firm-level variables such as the number of employees, the industry, and balance sheet variables such as sales, assets, and investments.

The merged data from the above sources gives us detailed information about the production, trade, firm characteristics, and geographical location of all manufacturing plants and firms in Sweden.

⁴SCB 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>

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. Although we have geographical data at the plant level, our production and emission data for producers are recorded at the firm level. Consequently, for our empirical analysis, we focus on single-plant producing firms. Yet, in the case of importers, we distribute import flows based on plant size (using the number of employees) when allocating imports to the plants of multi-plant importers. This is because we cannot discriminate between locations when it comes to assessing the spatial impact of IC at the local level. We also restrict our sample to firms with energy and emission information, as well as those with positive sales volumes to eliminate inactive firms.⁵ We focus on intermediate goods producers who have the potential to sell locally to downstream manufacturing firms. Approximately 80% of all imports in our compiled sample are made by manufacturing firms. The goal is to match domestic producers of an intermediate good and potential buyers importing the same good while considering the geographic location of both parties and the distance between them. In part of the spatial analysis, we use a fine geographical division of Sweden called SAMS (Small Areas for Market Statistics). 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.

Table A.2 also presents a summary of production data and other firm-related information, including employment, markup, and sales. 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 65% 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).⁶

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

⁵We only include firms that are active with a maximum of 3 continuous years of inactivity during the sample period. As a result, we exclude firm exit as a possible outcome of the study.

⁶We obtain the markups for individual products produced by firms by dividing the output elasticity of materials by the materials share of total revenue.

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 the 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. 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.

2.3 Measuring Import Competition

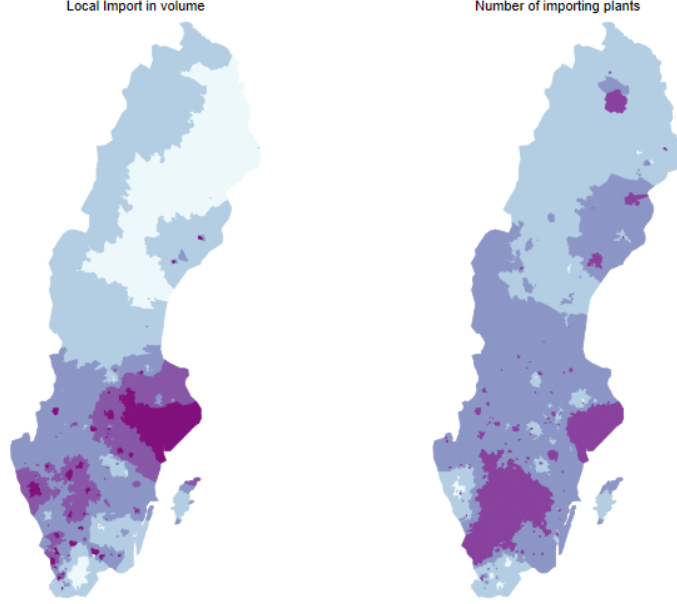
In this section, we present how we measure IC exposure faced by the upstream firm producing an intermediate input product that is simultaneously imported by the downstream manufacturer. First, we calculate total imports of all plants p belonging to firm f and importing an intermediate product j within a SAMS area s . We then make use of a spatial weight matrix (the inverse distance function) to construct a localized measure of IC giving a larger weight to importing activity in the proximity of the producers. Specifically, we use the dot product of the weight W_s with dimension $1 \times s$ and to generate IC as follows:

$$IC_{sit} = W_s \times IM_{sit} = \sum_{f \in \Omega_s, f \neq i} w_{sr} \times M_{fjt};$$

where M_{fjt} stands for the imports of product j by importing firm f , which is part of the set of firms located in the spatial dimension s (Ω_s) and i is the index of producing firms facing IC. This location-specific import measure does not include the producing firm i 's own import volume. The parameter w_{sr} , denotes the inverse distance function, d_{sr}^{-1} , measured in kilometers, between distinct SAMS areas indexed as s and r . Despite having detailed spatial divisions, there is still a possibility that these weights may be biased due to the aggregation method used, which can result in differences in the size of the SAMS areas. To address this issue, we apply row standardization to the weights (see e.g., El-Sahli et al. 2022). This means that the spatial weights for external distances ($s \neq r$) become $w_{sr} = d_{sr}^{-1} / \sum_{r \neq s} d_{sr}$. In a unique scenario where j and r are identical, we normalize the internal spatial proximity within each SAMS region to one, thereby implying a scenario where all industrial plants are assumed to be densely concentrated within a given SAMS region.

Figure 1 displays the spatial distribution of IC and the share of importing plants in the total

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

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:

$$EI_{it} = \beta_0 IC_{sit} + \theta_i + \theta_{bt} + \theta_{mt} + \epsilon_{it}; \quad (1)$$

where EI_{it} is the amount of emissions per SEK of value-added (in logs) of producing firm i in year t and IC_{sit} captures the IC (in logs) measured in the spatial dimension s faced by producing firm i at time t . 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.

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. Other sources of endogeneity are omitted variable bias and measurement error. 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.

To determine the relationship between imports and changes in the world export supply of a product, we create a specific instrument for each product and importing firm. Our identification strategy requires yearly data on world export supply from source countries, which we obtain from the UN COMTRADE database. These data, available at the 6-digit HS level, allows us to match them with our firm import data. First, we calculate the world export supply of the product, excluding the supply to Sweden and its immediate neighboring countries (Denmark, Finland, Germany, and Norway). We expect this variation in world export supply to be positively correlated with the imports of Swedish firms, as it reflects changes in the relative price and quality of the product in the exporting countries. To make the instrument specific to a particular importing firm and product at a particular time, we multiply the world export supply of the product by the pre-sample share of the product in total imports of the importing firm. The resulting firm-spatial-time specific instrument is calculated as follows:

$$IC_{sit}^{IV} = \sum_{f \in \Omega_s, f \neq i} w_{sr} \times sh_{fj} \times WX_{jt}; \quad (2)$$

where WX_{jct} is the world supply of product j at time t and sh_{fj} is the pre-sample share of product j imported by the domestic importing firm f . We use pre-sample shares to ensure that the input use of the importing firm is not influenced by current technology shocks. Since our IC measure is defined at the chosen spatial unit, the instrument IC_{sit}^{IV} will be the sum of world exports (excluding Sweden and neighboring countries) of product j that is imported by all firms f within the same

defined spatial dimension s as the producing firm i plus the firms in other spatial units with spatial decay determined by distance between the spatial units as discussed above.

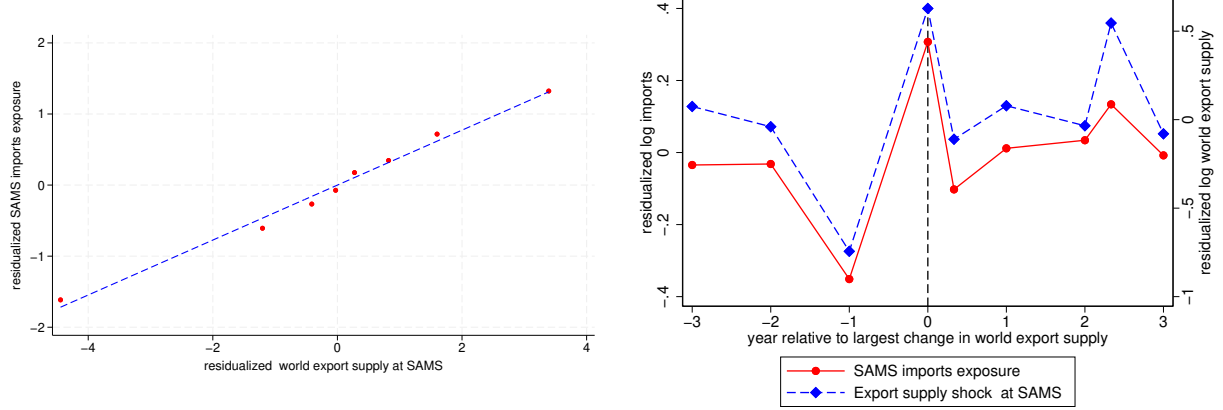
For the instrument to be valid, it should be highly correlated with the IC measure in the first stage of the instrumental variable (IV) estimation. In Figure 2, we investigate whether our instrument is strongly related with our local IC measure.⁷ The first graph provides evidence of a positive and robust relationship between the IC and the instrument, and further shows that the log-linear model fits the data well. Additionally, we validate the strength of the instrument using the Kleibergen-Paap F-statistic, which exceeds the conventional threshold of 10 across our main specifications. The event study in the second graph further complements this finding, showing that producers respond contemporaneously to changes in the world export supply of the products in which they face competition.

Our instrument should also satisfy the standard exclusion restriction: $\mathbb{E}[IC^{IV}\varepsilon] = \mathbb{E}[shWX\varepsilon] = 0$. This equation is immediately satisfied if the instrument is randomly assigned, but it does not require it. As explained in Goldsmith-Pinkham et al. (2020), Borusyak et al. (2022a) and Borusyak et al. (2022b), the exogeneity of instruments such as the one in our paper (aka shift-share instruments) can stem from the exogeneity of either the shares or the shocks. In the “shares view”, we would need to assume that unobserved determinants of imports and emissions are unrelated to the choice of initial product offerings of firms, conditional on industry trends. This assumption seems unlikely in our context. Indeed, any product-specific trend would violate the assumption. For instance, IC has been shown to increase productivity in Swedish manufacturing (Gullstrand and Knutsson, 2019). Thus, firms heavily specialized in products with low trade restrictions over the period would likely have grown faster than other firms, even without the supply shocks. Instead, we adopt the view that foreign supply shocks are as good as randomly assigned with respect to firm outcomes, after controlling for industry trends. This is a less restrictive requirement which simply argues that the instrument will be valid if the world export shocks are uncorrelated with the average firm-level characteristics that determine emissions (Borusyak et al., 2022b). The identifying assumption is that firms did not sort into industries such that the industry characteristics were correlated with the emissions and the import and export shocks. One example of problematic sorting would be if firms that increased their imports systematically, operated in sectors that experienced an increase in emissions and productivity. To address sorting of this kind, we include firm fixed effects (θ_i) and sector-year fixed effects (θ_{bt}). As robustness, we also add information on firm capital, employment, investment in machines, and the amount of emission rights purchased as additional controls.

Before moving to our main results, we present the relationship between our instrument and the log

⁷We follow Akerman et al. (2024) by residualizing both import exposure and export shock, i.e. we remove any variation that is already accounted for by firm-specific factors and five-digit industry-year fixed effects and isolate the residuals. This ensures that our estimates capture only the independent impact of trade shocks.

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

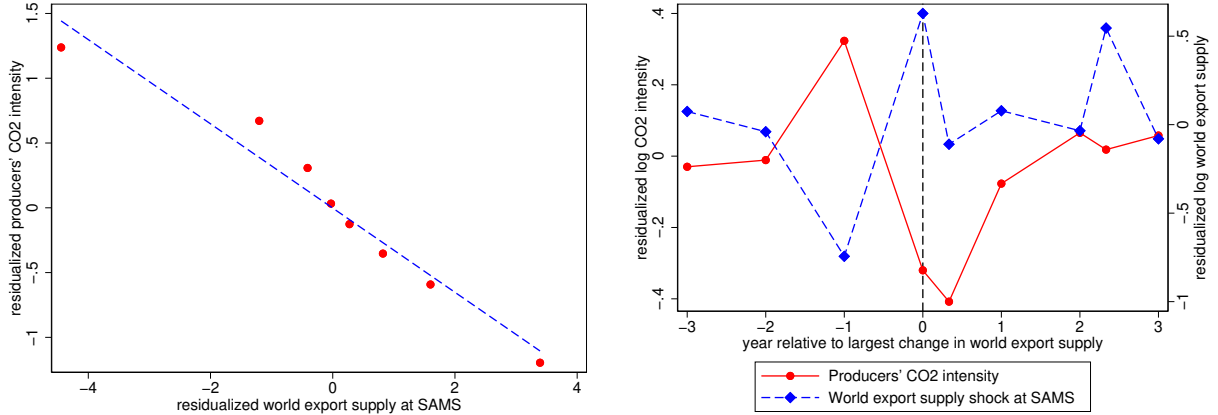


Note: The graph on the left depicts the estimated first-stage relationship between the log of the instrument (IC_{sit}^{IV}) and the log of IC exposure at SAMS level. The variables are residualized by regressing them on firm and five-digit industry-year fixed effects, with the residuals saved for plotting. 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.

of carbon intensity of producers in Figure 3 (in a similar fashion to Figure 2). The first graph of Figure 3 on the left shows a clear negative relationship between the instrument and carbon intensity, closely aligning with the log-linear regression model. Importantly, this relationship appears robust, with no indication that it is driven by potential outliers. To further validate our identification strategy, the second graph on the right of Figure 3 employs an event study approach to assess whether shocks to the instrument have an immediate effect on carbon intensity. Specifically, we track the mean residualized log carbon intensity and the mean residualized log instrument relative to the largest observed increase in the instrument, using an event time variable that normalizes the timing across producers. Since foreign export supply shocks occur at the SAMS level, the timing of the event (denoted as year zero) varies across producers. 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 1.⁸

⁸We do not rule out the possibility that the effect of IC on carbon intensity may unfold gradually, as firms may require time to adjust and undertake long-term investments in pollution abatement. To account for this, we extend our analysis by incorporating lagged measures of IC exposure as robustness check. We find that the effects remain significant even when allowing for a delayed response, suggesting that while the immediate impact is evident, there may be additional and gradual adjustments that firms may undergo in response to competitive pressures.

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.

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 1. In columns (1) and (5), 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 (6), we restrict the effect of IC to 500 km from the producing firm, while in columns (3) and (7), we consider IC that stems from SAMS regions that are 500-1000 km away. Finally in columns (4) and (8), 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. The results show that a 10 percent increase in local IC is associated with a statistically significant 5.6% percent decline in emission intensity (column (5)). The coefficient is economically larger than the analogous national-level IC estimate in Column (8), which is smaller in magnitude. The geographic nature of the effect is further clarified by the the distance-decay estimates. As shown in columns 6 and 7, the IV point estimates attenuate monotonically as we widen the distance bands (0–500 km vs 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 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

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
IC_{it}^{SAMS}	-0.235*** (0.020)				-0.569*** (0.050)			
$IC_{it}^{SAMS^{0-500km}}$		-0.142*** (0.017)				-0.454*** (0.040)		
$IC_{it}^{SAMS^{500-1000km}}$			-0.103*** (0.014)				-0.329*** (0.032)	
IC_{it}^{NAT}				-0.074*** (0.006)				-0.156*** (0.012)
Observations	7,924	7,924	7,924	7,924	7,924	7,924	7,924	7,688
Estimation Strategy	OLS	OLS	OLS	OLS	IV	IV	IV	IV
KP					143.93	335.38	212.67	214.83
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Municipal-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: IC_{it}^{SAMS} is the import competition measure weighted by the inverse distance function. We also use other distance band weights such as 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. For each estimation specification, we include firm fixed effects to control for time-invariant unobservable differences across producing firms. We account for sector-year fixed effect to purge the residual from all time-varying industry shocks. We also include municipal-year fixed effects to absorb shocks in municipal-level labor market dynamics. 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 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% annually between 2005 and 2014. Assuming Chinese exports, sometimes referred to as Chinese import penetration, are equivalent to IC in Sweden, our results suggest a decrease of around 12% on average in emission intensity in Swedish firms in response to this IC. While not directly comparable, Swedish GHG emission intensity (Kilotons CO_2 eq. per one Swedish Krona) dropped by around 20% between 2008 and 2014.⁹

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

⁹Source for this information is Statistics Sweden (SCB). No information is available before 2008. Source: [SCB Swedish emission intensities](#).

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 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 (5) of Table 1 to a host of robustness checks as follows.

Geographic Composition and Spatial Frictions. The baseline results indicate that localized import competition (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.

We begin by excluding Stockholm and Gothenburg, from the sample (Table B.1, 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.¹⁰ 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 statistically indistinguishable from zero. This result confirms that the IC effect is not driven exclusively by coastal firms.¹¹

¹⁰List of municipalities with ports are sourced from <https://www.searates.com/maritime/sweden>.

¹¹We 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

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.

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).

Across all of these specifications, the estimated effect of localized import competition on emissions intensity remains robust. These results demonstrate that our conclusions are not sensitive to alternative operationalizations of spatial frictions or regional composition, and they provide compelling evidence that the observed effects reflect genuine competitive pressures rather than geographic artifacts.

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 B.2 shows the coefficient estimates of IC from estimating equation 1 for the first 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

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.

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%.

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 a 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 B.2. 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 measure of emission intensity. 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 B.3 suggests that our benchmark estimate is qualitatively robust to this change, suggesting that firms reduce CO_2 emissions not just per unit of output but also relative to their economic contribution in response to IC.

Balanced Sample and Lagged effect. 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 B.3 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 B.3 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 CO₂ 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 B.3 (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 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 CO₂ 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 indicates 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% as much 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 import 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 2, 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.¹² 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 although importing firms benefit in terms of productivity gains from an increase in imports, so do non-importing producing firms through IC.

Table 2: 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)	0.014* (0.007)	-0.457*** (0.107)	0.208** (0.095)	0.633*** (0.119)	0.225*** (0.041)	-0.029* (0.015)	-0.018 (0.016)	0.719** (0.345)	0.032** (0.013)
$IC_{it}^{SAMS} \times \text{DirtyProdRank}$								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 estimate 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.

The productivity gains from IC are further reflected in other firm performance metrics, such as the firm’s value added which increased 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 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). Our findings, presented in columns (3-5) of Table 2, indicate that a 10% increase in exposure to IC indeed leads to an decrease of about 4.6% in

¹²Using an alternative method for measuring TFP by Levinsohn and Petrin (2003) yields a similar result.

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 2 column (6) shows that a 10% increase in IC exposure leads to approximately an 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 leads to a 0.29% lower probability that any product is produced. However, this result seems to be relevant to the dirtiest products in column (8). 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 2 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. 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 weight 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 CO₂ per unit of real output) of product p of sector j in sourcing country c , while $M_{ict,p \in j}$ is the imported quantity of firm i of products p of sector j from sourcing country. 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 2 column (10), suggests that import competition leads to an increase in offshoring activities with an elasticity of 0.032. Hence, both abatement and offshoring seem to be at play in the firm’s toolbox to respond to increasing IC pressure.¹³

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.

¹³The 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.

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 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.

References

- Abrell, J., Kosch, M., and Rausch, S. (2022). How effective is carbon pricing?—a machine learning approach to policy evaluation. *Journal of Environmental Economics and Management*, 112:102589.
- Akerman, A., Forslid, R., and Prane, O. (2024). Imports and the co2 emissions of firms. *Journal of International Economics*, 152:104004.
- Anderson, J. E. and Van Wincoop, E. (2004). Trade costs. *Journal of Economic literature*, 42(3):691–751.
- Antoniades, A. (2015). Heterogeneous firms, quality, and trade. *Journal of International Economics*, 95(2):263–273.
- Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The geography of trade and technology shocks in the united states. *American Economic Review*, 103(3):220–25.
- Barrows, G. and Ollivier, H. (2021). Foreign demand, developing country exports, and co2 emissions: Firm-level evidence from india. *Journal of Development Economics*, 149:102587.
- Bellone, F., Musso, P., Nesta, L., and Warzynski, F. (2016). International trade and firm-level markups when location and quality matter. *Journal of Economic Geography*, 16(1):67–91.
- Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2):639–688.
- Borusyak, K., Dix-Carneiro, R., and Kovak, B. (2022a). Understanding migration responses to local shocks. *Available at SSRN 4086847*.
- Borusyak, K., Hull, P., and Jaravel, X. (2022b). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1):181–213.
- Botta, E. and Koźluk, T. (2014). Measuring environmental policy stringency in oecd countries: A composite index approach.
- Copeland, R. B., Shapiro, S. J., and Taylor, M. S. (2022). Chapter 2 - globalization and the environment. *Handbook of International Economics*, 89(1):61–146.
- De Loecker, J., Goldberg, P. K., Khandelwal, A. K., and Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica*, 84(2):445–510.
- Ding, S., Jiang, W., and Sun, P. (2016). Import competition, dynamic resource allocation and productivity dispersion: micro-level evidence from china. *Oxford Economic Papers*, 68(4):994–1015.

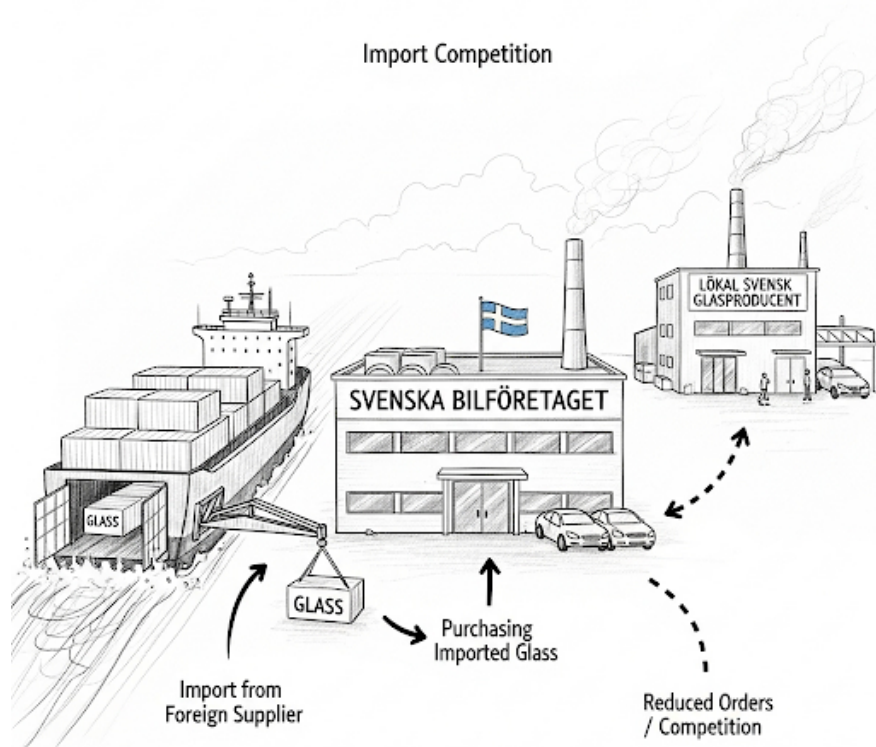
- Dussaux, D., Vona, F., and Dechezleprêtre, A. (2023). Imported carbon emissions: Evidence from french manufacturing companies. *Canadian Journal of Economics/Revue canadienne d'économique*.
- El-Sahli, Z., Gullstrand, J., and Olofsdotter, K. (2022). The external effects of offshoring on job security in smes. *Small Business Economics*, pages 1–28.
- Faber, B. (2014). Trade integration, market size, and industrialization: evidence from china's national trunk highway system. *Review of Economic Studies*, 81(3):1046–1070.
- Forslid, R., Okubo, T., and Ulltveit-Moe, K. H. (2018). Why are firms that export cleaner? international trade, abatement and environmental emissions. *Journal of Environmental Economics and Management*, 91:166–183.
- Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010). Imported intermediate inputs and domestic product growth: Evidence from india. *The Quarterly journal of economics*, 125(4):1727–1767.
- Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.
- Gullstrand, J. and Knutsson, P. (2019). *The Spatial Dimension of Import Competition*. Department of Economics, School of Economics and Management, Lund University.
- Hall, R. E., Blanchard, O. J., and Hubbard, R. G. (1986). Market structure and macroeconomic fluctuations. *Brookings papers on economic activity*, 1986(2):285–338.
- Hillberry, R. and Hummels, D. (2008). Trade responses to geographic frictions: A decomposition using micro-data. *European Economic Review*, 52(3):527–550.
- Hummels, D., Jørgensen, R., Munch, J., and Xiang, C. (2014). The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review*, 104(6):1597–1629.
- Jabbour, L., Tao, Z., Vanino, E., and Zhang, Y. (2019). The good, the bad and the ugly: Chinese imports, european union anti-dumping measures and firm performance. *Journal of International Economics*, 117:1–20.
- Lehr, J. (2025). Import competition and firm-level co2 emissions: Evidence from the german manufacturing industry. *Canadian Journal of Economics/Revue canadienne d'économique*.
- Leisner, J., Munch, J., Nielsen, A., and Schaur, G. (2023). The impact of offshoring and import competition on firm-level carbon emissions. *IZA Discussion Paper No. 16556*.

- Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341.
- Martinsson, G., Strömberg, P., Sajtos, L., and Thomann, C. J. (2022). Carbon pricing and firm-level co_2 abatement: Evidence from a quarter of a century-long panel. *European Corporate Governance Institute–Finance Working Paper*, (842).
- Newman, C., Rand, J., and Tarp, F. (2023). Imports, supply chains and firm productivity. *World Development*, 172:106371.
- Shapiro, J. S. (2021). The environmental bias of trade policy. *The Quarterly Journal of Economics*, 136(2):831–886.
- Shapiro, J. S. and Walker, R. (2018). Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade. *American Economic Review*, 108(12):3814–54.
- Syverson, C. (2007). Prices, spatial competition and heterogeneous producers: an empirical test. *The Journal of Industrial Economics*, 55(2):197–222.
- Ustyuzhanina, P. (2022). Decomposition of air pollution emissions from swedish manufacturing. *Environmental Economics and Policy Studies*, 24(2):195–223.
- Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters*, 104(3):112–114.

Appendix

A Descriptive Statistics and Miscellaneous Figures

Figure A.1: Graphical illustration of import competition



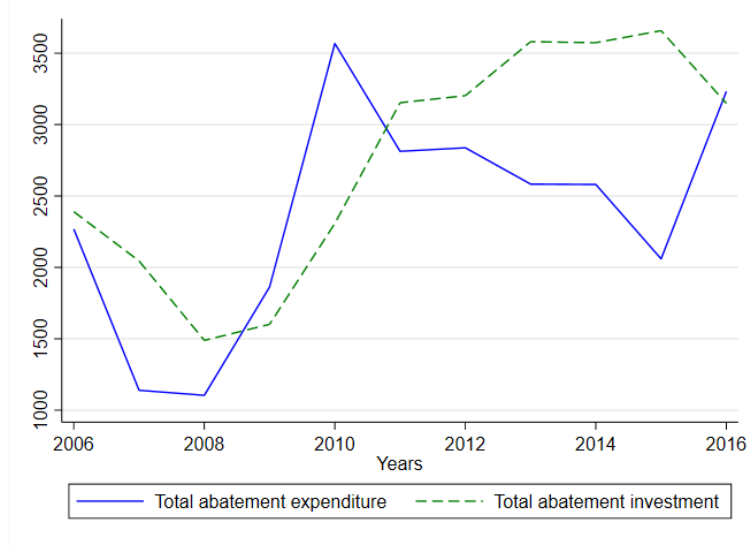
Note: Produced by the authors using AI (Google Gemini).

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)	0.017	0.077	9.11e-07	0.001	0.005	0.012	5.63

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 ^{<i>t=0</i>}	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

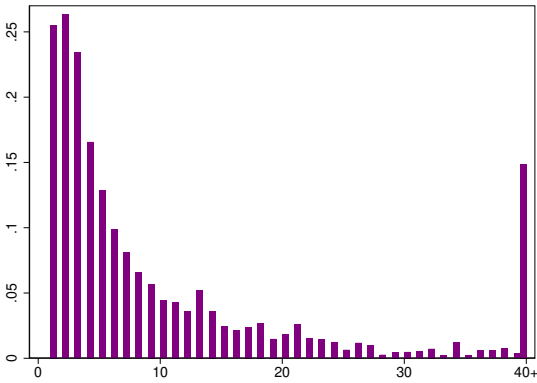
Note: Summary statistics for producing firms in terms of production, size, markup and sales. The left columns summarize the full sample set at firm-plant-product-year level in the database, and the right columns only at the firm-year level with our data restrictions. Our full sample contains 2,279 firms, 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

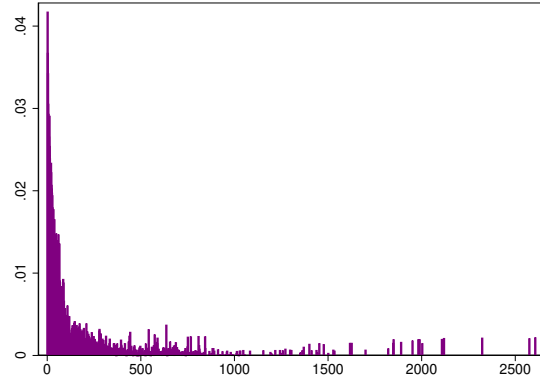
	Regression sample			
	Mean	SD	Min	Max
Import (million SEK):				
Total	190.50	1244.15	0.00	36681.45
SAMS	9.01	99.68	0	7076.78
1st nearest Neighbor	18.31	229.43	0.00	9517.50
2nd nearest Neighbor	17.10	222.86	0.00	9143.51
3rd nearest Neighbor	12.40	149.71	0.00	8738.09
Distance (KM):				
To 1st nearest Neighbor	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: 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*** (0.050)	-0.576*** (0.047)	-0.644*** (0.073)	-0.507*** (0.061)	-0.513*** (0.076)	-0.502*** (0.105)	-0.535*** (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, Sweden's two largest metropolitan areas, to ensure that the results are not driven by urban agglomerations. Column (3) restricts the sample to non-port municipalities, while Column (4) focuses on port municipalities, to assess whether proximity to international trade infrastructure alters the estimates. Column (5) interacts IC_{it}^{SAMS} with an indicator for coastal municipalities to test whether import competition has heterogeneous effects depending on coastal access. Column (6) restricts the sample to interior municipalities, and Column (7) interacts IC_{it}^{SAMS} with a measure of urban density to capture differential effects in more urbanized areas. All specifications are estimated using instrumental variables (IV), with the Kleibergen–Paap (KP) statistic reported for instrument strength. Each regression includes firm fixed effects to control for time-invariant heterogeneity, sector-by-year fixed effects to absorb sector-specific shocks and trends, and municipality-by-year fixed effects to account for 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 both the firm and SAMS levels to allow for arbitrary heteroskedasticity, serial correlation within firms, and spatial correlation within SAMS regions over time.

Table B.2: Robustness: 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	✓	✓	✓	✓	✓	✓

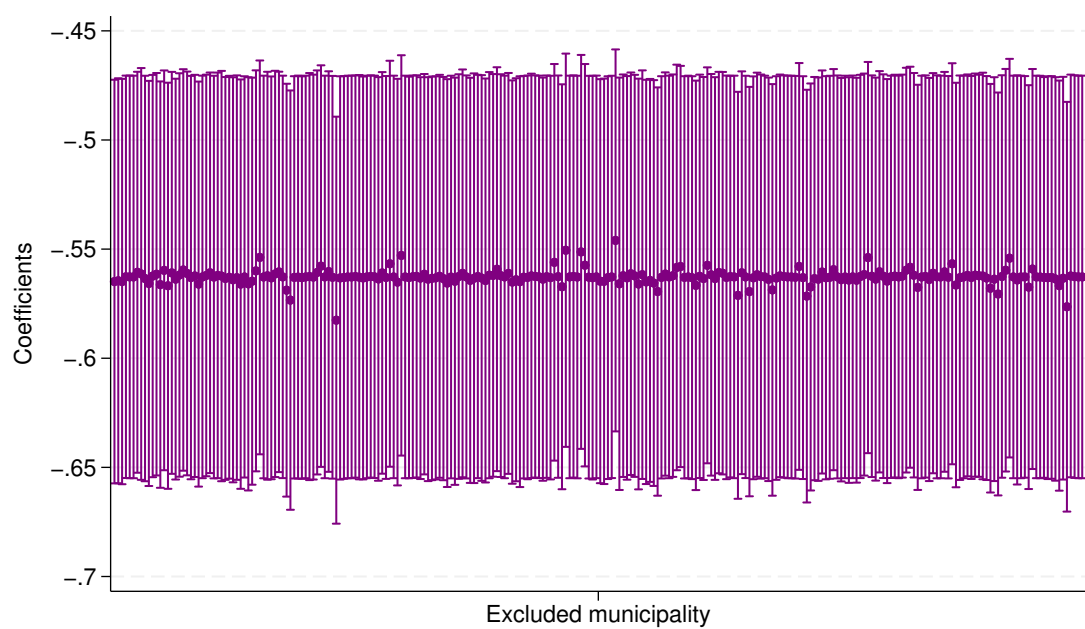
Note: IC_{it}^{xn} denotes import competition, measured as exposure to the x geographically closest neighbors. All specifications include a rich set of fixed effects: firm fixed effects to control for time-invariant firm characteristics, sector-by-year fixed effects to capture sector-specific shocks 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.

Table B.3: Robustness: Additional Controls

	Unit Output	Balanced Sample	Lagged Effect	Controls + Energy Price	Controls + Carbon tax
	(1)	(2)	(3)	(4)	(5)
IC_{it}^{SAMS}	-0.819*** (0.070)	-0.563*** (0.069)	-0.565*** (0.120)	-0.568*** (0.046)	-0.568*** (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 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.

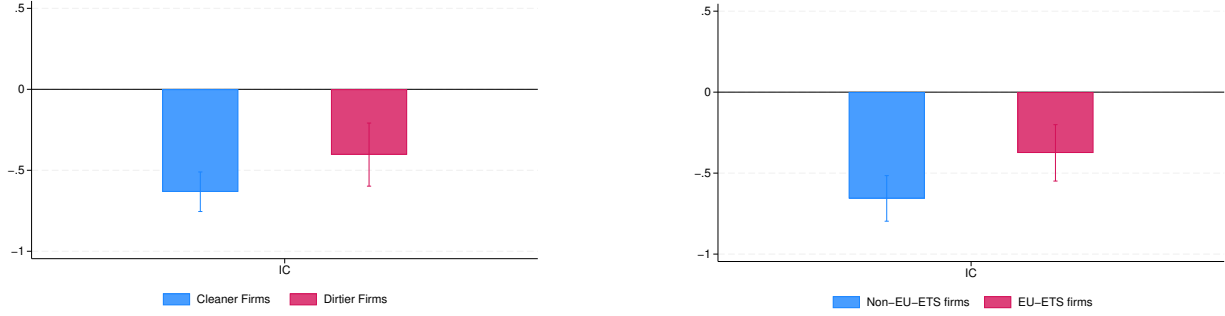
Figure B.1: Jackknife analysis by leaving out one municipality at a time.



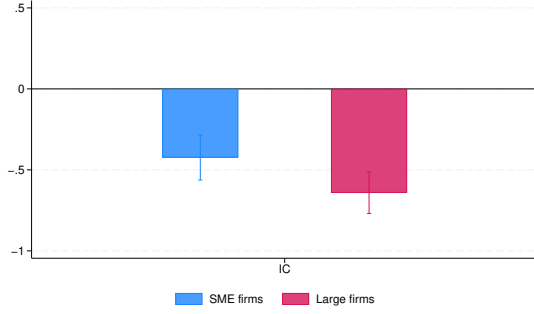
Note: Each point plots the coefficient estimate obtained by re-estimating the baseline specification after omitting the corresponding municipality from the sample (there are 254 municipalities). Vertical lines denote 95% confidence intervals based on two-way clustered standard errors at the SAMS and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

C Heterogeneity

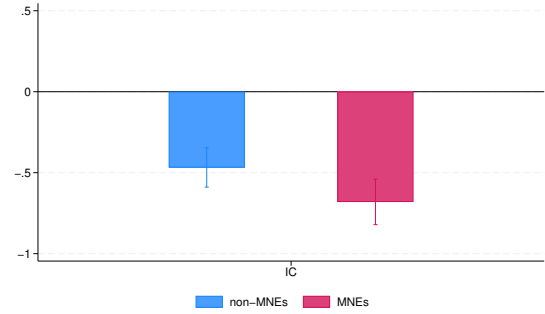
Figure C.1: **Heterogeneity:** IC effects on emission intensity



A. Clean vs Dirty firms

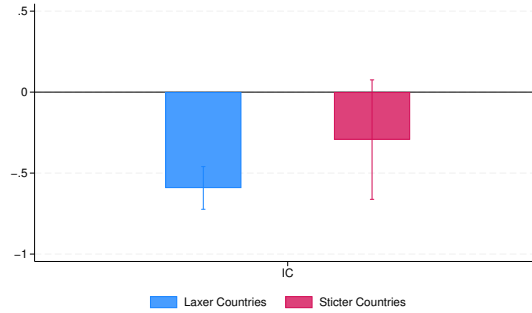


B. EU-ETS vs non-EU-ETS firms



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 1. 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.