DISCUSSION PAPER SERIES

DP16090

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INTERNATIONAL TRADE AND REGIONAL ECONOMICS

CEPR

ISSN 0265-8003

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Discussion Paper DP16090
Published 30 April 2021
Submitted 27 April 2021

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JEL Classification: F12, F15, F61, O33

Keywords: international trade, importing, Carbon Emissions, Carbon leakage

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Acknowledgements
Anders Akerman gratefully acknowledges research funding from the Torsten Söderberg Research Foundation, the Jan Wallander and Tom Hedelius Research Foundation and the Swedish Research Council. Rikard Forslid is grateful for research funding from the Jan Wallander and Tom Hedelius Research Foundation and the Swedish Research Council. Ossian Prane is grateful for research funding from the Jan Wallander and Tom Hedelius Research Foundation.

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Abstract

In this paper we explore how importing of intermediate goods affect the carbon intensity of firms in the Swedish manufacturing sector. By exploiting exogenous shocks in foreign export supply of intermediate goods, we estimate that a 10 percent increase in imports causes a 5 percent reduction in carbon intensity. Contrary to popular beliefs, we also find that most of this effect cannot be explained by offshoring of dirty stages of the production process. Instead, a mediation analysis suggests that the productivity-enhancing effect of importing is a more important driver of the reduction in firms' carbon intensity. To account for general equilibrium effects we also develop a model in which heterogeneous firms make endogenous decisions regarding production, importing and emissions. A calibration of this model based on our empirical results suggests that the elasticity of aggregate carbon emissions with respect to import trade costs is about 0.17.

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*Anders Akerman gratefully acknowledges research funding from the Torsten Söderberg Research Foundation, the Jan Wallander and Tom Hedelius Research Foundation and the Swedish Research Council. Rikard Forslid is grateful for research funding from the Jan Wallander and Tom Hedelius Research Foundation and the Swedish Research Council. Ossian Prane is grateful for research funding from the Jan Wallander and Tom Hedelius Research Foundation.

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1 Introduction

Policy-makers and the international community emphasize the importance of international trade in the transition to a more environmentally sustainable world economy.[1] At the same time, there is no consensus in the research literature on whether further trade liberalization is likely to reduce the emissions of greenhouse gases. Apart from higher emissions generated by cross-border transportation of goods, which comprise about 7 percent of global carbon emissions (World Bank, 2020), growth in trade can lead to higher levels of emissions by expanding economic activity. This effect can be partly or fully offset however if trade liberalization also induces a shift towards cleaner and more efficient production technologies (Grossman and Krueger, 1991; Copeland and Taylor, 1994; Cherniwchan et al., 2017). A critical task for economists is therefore to empirically assess if and to what extent trade participation causes firms to become cleaner.

In this paper we use detailed Swedish plant and firm-level data to explore how importing of intermediate goods causally affects the carbon intensity of manufacturing firms. Trade in intermediate goods has risen sharply since the 1980s as a result of the expansion of global value chains and the increased specialization by firms in specific tasks. Currently over half of total world trade is in intermediate goods.[2] There are also good reasons to believe that this type of trade affects the environmental performance of firms in somewhat different ways than trade in final goods. Nevertheless, the existing causal evidence is scant, in particular on the effect of imports, since most studies focus on the environmental performance of exporters (e.g. Batrakova and Davies, 2012; Cui et al., 2016; Forslid et al., 2018; Halladay, 2008). Our data cover the Swedish manufacturing sector. This sector emits a large share of total Swedish emissions and trade heavily in intermediate goods.[3]

There are in principle two mechanisms by which importing can make firms cleaner. The first is that importing affects the technology of the firm by giving it access to better and more specialized inputs, and we present a formal model that speaks to this case. The second mechanism is that importing firms may offshore dirty stages of the production process. This could happen if the home country has costly environmental standards or if foreign countries have a comparative advantage in these stages. For instance, in high-wage countries, the latter would be the case if dirty production stages are also labor intensive.

[1] For example, the UN resolution "Transforming our world: the 2030 Agenda for Sustainable Development" lists promoting international trade as a mean for achieving the agenda's goals (including combating climate change) (United Nations, 2015).

[2] World Bank (2020).

[3] In 2019, 26 percent of total Swedish greenhouse gas emissions came from the manufacturing sector (Swedish Environmental Protection Agency, 2020). In the U.S., this share was 22 percent (Environmental Protection Agency, 2021).

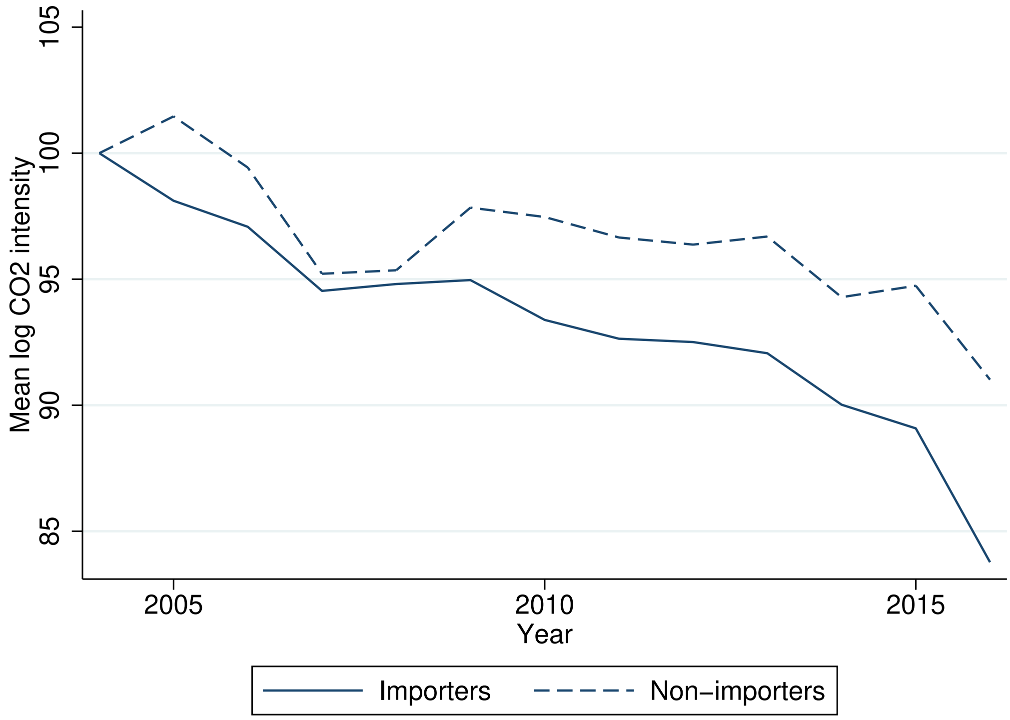


Figure 1. Evolution of mean log carbon intensity among importers and non-importers.

Notes: The figure is based on the 47,563 firm-year observations in the Swedish manufacturing sector for which we have data on carbon emissions. The sample includes all manufacturing firms operating at plants with 10 or more employees (see Section 2 for details). 31,691 observations are associated with positive imports and 15,872 with zero imports. Carbon intensity is measured as total carbon emissions (kg) over real value added measured in SEK 2004 prices. The plots show the percentage decline in the mean log carbon intensity relative to the 2004 values which are normalized to 100.

Figure 1 shows the percentage decline in the average log carbon intensity among a sample of importers and non-importers in Swedish manufacturing. On average, the group of importers experienced a 7 percentage point larger decline between 2004 and 2016.

However, Figure 1 does not establish a causal relationship between importing and carbon intensity. The pattern may be explained by other factors determining both the import decision of firms and their emission intensity. To identify a causal effect, we construct a shift-share instrument similar to that in Hummels et al. (2014). This instrument captures variation in imports of Swedish firms caused by foreign export supply shocks in intermediate goods. Specifically, we use Swedish administrative data on pre-sample firm-level import patterns by product (at the HS-6 digit level) and source country to compute shock exposure weights. We then match these weights with yearly data from UN Comtrade on world export supply at the country-product level. The result is an instrument that varies at the firm-year level and that is able to predict import levels solely based on foreign supply shocks. Because the import data is so detailed, a majority of the imported intermediates is sourced by a unique firm, creating large cross-firm variation in the instrument.

To give an example, suppose Canadian producers of steel bolts experience an idiosyncratic shock to their export supply. The instrument will then only respond to this for the few Swedish firms (if not a single) that have a pre-sample record of importing steel bolts from Canada. If the shock affects the import level of the firms, but is uncorrelated with other factors affecting their emission intensity, then we can use this variation to estimate a causal effect of importing. Several measures are taken to ensure the validity of the instrument. For example, we exclude all exports to Sweden to avoid the risk of domestic import demand affecting the shocks. We also take full advantage of the panel structure of our data and include firm and year fixed effects in our specifications. Lastly, we perform a battery of robustness checks to challenge our results.

Consistent with Figure 1, our results show that importing clearly reduces the emission intensity of manufacturing firms. In our baseline model, a 10 percent increase in imports reduces the emission intensity by 5 percent. An event-study shows that this effect is rapid – the largest drops in the firms' emission intensities coincide in time with the largest positive shocks to their predicted levels of importing. We also find that our results are robust to the inclusion of industry-specific and regional time trends, the exclusion of inputs for which Swedish import demand is relatively large, changes in the pre-sample year, and controlling for potential pre-trends in emission intensity. A potential concern is that this effect is weaker in the industries that pollute the most and therefore not environmentally significant. Investigating this, we find that the effect is even more negative for firms in the five most emission intensive industries.

The next step in the analysis is to explore the importance of the two mechanisms discussed above. If importing reduces firms' emission intensity mainly because they offshore dirty production stages to countries with less stringent regulation, then the net effect on total emissions may still be positive. If, on the other hand, cleaner production primarily stems from increased productivity or abatement, then trade in intermediate goods may reduce total emissions. Our analysis cannot say anything definitive about the effect on total emissions, however, since this would require emission data on the exporters in foreign countries. But we do take important steps forward by providing evidence that shows that the productivity link appears more important for the manufacturing firms in our sample.

We start by exploring whether the estimate remains negative and significant if we exclude all trade flows with non-OECD countries. Developed countries generally have more stringent environmental regulation in place. Thus, if the effect was driven by offshoring to low-wage and weakly regulated countries we should expect this to significantly alter our point estimate. What we instead see is a slightly more negative effect suggesting that carbon leakage to less developed countries is not the main mechanism. This result is consistent with a number of studies finding little evidence for the so called Pollution Haven Hypothesis (e.g. Levinson, 2009; Hanna, 2010).[4]

Offshoring of dirty production to other developed countries may still be what drives the effect however. To investigate this, we exclude all imports of goods that belong to the firms' own NACE 3-digit industry. If, for example, a firm is a steel manufacturer (NACE 24.1) we remove all imports of basic iron, steel and ferro-alloys produced by this industry. For the median firm in our sample, within-industry goods account for 20 percent of total imports. Moreover, if the main mechanism is that firms move parts of their core production to foreign countries, disregarding these imports should have a significant impact on our results. Instead, we find that the estimate is unaffected by this.

Having found that offshoring of dirty production is unlikely to be the main mechanism, we seek to quantify the importance of productivity. In a mediation analysis similar to that in Heckman et al. (2013), we first estimate the causal effect of importing on firms' productivity using our shift-share design.[5] We find that a 10 percent increase in importing enhances the productivity of firms by 2.4 percent. We then estimate how productivity relates to carbon intensity and decompose the total effect of importing on emission intensity into an explained component and an unexplained component. Our results suggest that about 11 percent of the total effect is due to the induced change in firm-level productivity while about 5 percent is due to a shift in the products firms' produce.

We proceed by incorporating the productivity channel into a standard trade model with features from environmental economics. This allows us to study general equilibrium effects on aggregate emissions using our reduced form estimates. The model shows that an increase in productivity can result in an increase in consumption rather than a reduction in emissions. If, however, a policy maker uses carbon taxation to hold the utility from consumption fixed, the model predicts that the elasticity of aggregate emissions with respect to import tariffs is 0.17. A trade liberalization of 10 percent on imports would then imply a 1.7 percent decrease in emissions with no loss in utility from consumption.

Our paper relates to several strands of literature. Methodologically, it relates to a growing number of studies using shift-share designs to identify causal effects (e.g. Kovak, 2013; Autor et al., 2013; Acemoglu et al., 2020) and a few recent papers using mediation analysis to explore the mechanisms of causal effects (e.g. Fagereng et al., 2021). But we are the first (to our knowledge) to implement these methods to explore the causal effect of importing on firm-level carbon intensity. While the trade-environment nexus has received

[4]The Pollution Haven Hypothesis predicts that dirty industries will increasingly locate in countries with relatively weak environmental regulation as a response to trade liberalization (Copeland and Taylor, 2003).

[5]We follow the method proposed by Levinsohn and Petrin (2003) to estimate firm-level productivity. For further details, see Appendix A.

considerable attention both theoretically and empirically[6], the body of well-identified microlevel research is very thin, with Cherniwchan (2017) being a rare example. He uses a triple difference design to study how the NAFTA trade liberalization between the U.S. and Mexico affected emissions of particular matter and sulfur dioxide in U.S. manufacturing plants. Consistent with our results, he finds large negative effects of increased access to Mexican inputs, but he does not assess the role of productivity, and instead finds that offshoring appears to be the main mechanism.

Our results also relate to the findings in Levinson (2009) and Shapiro and Walker (2018) studying the substantial reduction in air pollution from U.S. manufacturing since the 1980s. Using statistical decomposition methods, both papers find that cleaner technology explains the bulk of this reduction, i.e. lower emission intensity at the industry and product level, but attribute this technology shift to stricter environmental regulation rather than increases in international trade. A potential concern is that these studies do not fully incorporate within-firm adjustments to trade and therefore classify some of the trade-induced changes in emission intensity as policy-induced changes (Cherniwchan, 2017; Cherniwchan et al., 2017). We provide causal evidence of this trade-induced channel, and thus corroborate this concern.

Finally, our paper complements a large number of studies showing that exporters are cleaner than non-exporters (Batrakova and Davies, 2012; Cui et al., 2016; Forslid et al., 2018; Halladay, 2008). We also contribute to the burgeoning literature on the relationship between imports of intermediate goods and firm productivity (e.g. Amiti and Konings, 2007; Amiti and Wei, 2009; Amiti and Davies, 2011; Schwörer, 2013; Halpern et al., 2015). The bulk of this evidence is consistent with our result that importing increases productivity.

The rest of the paper is structured as follows. Section 2 describes the data and discusses patterns of trade and emission intensity among the firms in our sample. Section 3 describes our shift share design and Section 4 presents our main results. In Section 5 we implement the mediation analysis and in Section 6 we develop our theoretical model. Section 7 concludes.

[6]For a recent survey of this literature, see Cherniwchan et al. (2017).

2 Data

2.1 Data sources

The firm- and plant-level data used in this study is collected by Statistics Sweden – the government agency responsible for official statistics in Sweden. Our data on economic variables at the firm level such as value added, wages and other production costs comes from the Swedish Tax Authority. It covers the universe of private-sector firms in Sweden (about 1 million in total) over the period 1997-2016 and is based on administrative registries of the firms' balance sheets. The reliability and quality of this data is regarded as very high since misreporting is punishable by law. We also use this data to estimate the total factor productivity of firms following the method proposed by Levinsohn and Petrin (2003). The details of this method is described in Appendix A.

Our data on CO2 emissions is based on information collected by Statistics Sweden on the usage of energy from all manufacturing plants with 10 or more employees. It covers around 4,000-5,000 plants per year over the period 2004-2016. As the energy statistics include all types of fuel use, we are able to compute the plants' CO2 emissions by using fuel-specific CO2 emission coefficients provided by Statistics Sweden. Importantly, CO2 emissions are accurately calculated from fuel inputs since the technology for capturing CO2 at the pipe is not yet operational. Aggregating this data to the firm-level gives us around 3,500-4,500 firm observations per year. For 0.35 percent of the plant-level observations, two or more firms operate at the same plant. In these cases we use the firms' share of employees at the plant to approximate for their respective shares of total plant emissions. In addition, Statistics Sweden reports for a subset of firms, around 750 per year, how much they spend on pollution abatement and we have access to this data for the years 2000-2013.

Our firm-level data on imports is collected by Statistic Sweden through two statistical systems. The first system (Extrastat) concerns trade flows with countries outside the EU and is based on administrative data from the Swedish Customs Authority. The second system (Intrastat) provides statistics on trade flows with other EU countries and is based on monthly statistical surveys developed by the EU to mirror customs based data. While Extrastat covers the universe of firms engaged in non-EU trade, small firms with trade flows below a certain cutoff are excluded from Intrastat.[7] The trade data is highly detailed and provides us with information on what products firms import and from what countries at the 8-digit Harmonized System (HS) product classification level. We aggregate these

[7]The Intrastat survey covers firms with yearly exports to other EU countries of at least 4,500,000 SEK or with yearly imports from other EU countries of at least 9,000,000 SEK.

Table 1. Summary statistics

Variable	Median	Mean	Standard Deviation	Minimum	Maximum	Observations
Revenues (millions)	174.2	944	4,096	8.15	83,119	7,930
Value added (millions)	54.52	293.7	1,384	0.41	36,599	7,930
TFP (millions)	0.01	0.02	0.09	1e-06	2.38	7,856
Employees	87	304.8	1,020	8	19,751	7,930
Imports (millions)	23.91	221.3	1,410	8e-07	42,677	7,930
Exports (millions)	51	524	2,775	0	59,154	7,930
CO2 emissions (tons)	260	30,030	239,854	0.24	7,035,907	7,930
CO2 intensity (kg/SEK)	0.005	0.64	0.28	8e-07	10.34	7,930

Notes: The sample is balanced and covers the years 2004-2016. CO2 intensity is calculated as total CO2 emissions over value added. Total factor productivity (TFP) is calculated using the method outlined in Levinsohn and Petrin (2003). We lack estimates of TFP for 74 observations due to missing values on the use of intermediate inputs and capital which are needed in the estimation procedure. All nominal variables are in SEK and 2004 prices.

flows to the 6-digit HS level which over the years 1997-2017 includes imports of 4,971 product classification from 260 countries (or trade related geographic entities). This level of detail in the import data is what enables us to construct the shift-share instrument (see Section 3). Our identification strategy also requires yearly data on world export supply from source countries and we obtain this from the UN Comtrade database on bilateral trade. Since this data is available at the 6-digit HS level we can easily match it with our firm-level import data.

2.2 *Sample and summary statistics*

The base sample we create is a balanced panel comprising 610 manufacturing firms over the years 2004-2016 which amounts to 7,930 firm-year observations in total. All NACE 2-digit manufacturing industries (C10-C33) are represented in the sample and their respective shares in terms of output roughly correspond to their shares in the full set of manufacturing firms. Moreover, 32 percent are small firms (less than 50 employees), 45 percent are medium-sized firms (50-250 employees), and 23 percent are large firms (more than 250 employees). The common denominator is that the firms are large enough to be included in Statistic Sweden's annual survey on energy use and that they have imported goods on a yearly basis between 2003 and 2016, where 2003 is the pre-sample year used in the construction of our instrument.

Table 1 reports summary statistics on some important variables characterizing the firms in our sample. We see that the median is below the mean for each variable reflecting that

Table 2. Sourcing patterns

	50*th* Percentile	90*th* Percentile	99*th* Percentile	Observations
Country-input-year level				
Number of firms that import from each country-input-year cell	1	4	15	271,245
Firm-year level				
Number of source country-inputs	32	149	827	7,930
Number of source countries	11	23	48	7,930
Import share of non-offshoring	0.80	1	1	7,930
Import share of narrow offshoring	0.49	0.97	1	7,930
Import share of OECD imports	0.98	1	1	7,930
Import share of European imports	0.98	1	1	7,930
Import share of top 2 country-inputs	0.57	0.94	1	7,930
Import share of top 5 country-inputs	0.83	1	1	7,930

Notes: The sample is balanced and covers the years 2004-2016. Non-offshoring imports are defined as all product categories that are not produced within the firms' own 3-digit NACE industry. Narrow offshoring is defined as product categories that are produced within the firms' own 2-digit NACE industry. OECD imports are defined as imports from countries that became members of the Organization of Co-operation and Development (OECD) prior to 2004. European imports are defined as imports from Europe and Central Asia according to the World Bank regional categorization of countries.

the distributions are skewed to the right. This is explained by a few firms operating at a much larger scale than the rest of the importers. The standard deviations also reveal a significant degree of heterogeneity among the firms. Table D.1 in Appendix D shows how a larger set of variables (here expressed in logs) have evolved over the sample period. There are no sharp changes in the mean for any of the variables. However, we observe an increase in imports and a reduction in emission intensity by 0.22 and 0.74 log points, respectively.

Some facts about the firms' sourcing patterns are displayed in Table 2. The first row reports how many of the firms in our sample that import a particular input – differentiated by source country, HS-6 product category, and year – at the 50th, 90th and 99th percentile. A majority of the imported inputs are sourced by a single firm and only four firms import the input at the 90th percentile. We also see that the median firm imports 32 different country-inputs and source from 11 countries in a given year suggesting that the import patterns are highly heterogeneous and that most of the firms have zero or just a few imported inputs in common.

Table 2 also sheds light on other characteristics of the firms' import patterns. We follow Feenstra and Hanson (1999) and separate imports based on whether the goods belong to the same industry as the importing firms. In particular, we distinguish between non-offshoring imports and narrow offshoring where the former refers to imported inputs produced outside the firms' own 3-digit industry and the latter refers to imported inputs produced within their own 2-digit industry.[8] The idea is that the inputs which fall under the non-offshoring category are less likely to have ever been produced by the firms themselves as they are not within the firms own area of specialization. For instance, Feenstra and Hanson (1999) argue that imports of automobile parts by an automobile producer is normally viewed as offshoring while imports of steel by that same company is not. For the median firm-year, 80 percent of all imports are categorized as non-offshoring imports while 49 percent are categorized as narrow offshoring. In addition, Table 2 shows that most of the firms almost exclusively source inputs from other OECD and European countries and that the value of imports is concentrated in just a few country-inputs.[9]

In Appendix D, Table D.3, we also present statistics at the industry level on the output share, the import intensity, and the emission intensity for the top five industries (in terms of each variable) in our base sample. These statistics are then compared with the corresponding statistics in the full sample of manufacturing firms. We see that they roughly correspond to each other but with a few exceptions. The ranking of the dirtiest industries in our sample – which due to data limitation cannot be compared with the full sample of manufacturing firms – is particularly noteworthy and reveals significant cross-industry heterogeneity in emission intensity. In the analysis, we explore whether the firms belonging to these dirty industries are more or less affected by importing than the firms in less polluting industries.

3 Empirical model and identification

Our empirical strategy is motivated by two objectives. The first objective is to assess whether importing of intermediate goods has a causal effect on the carbon intensity of manufacturing firms. Theory suggests that importing could cause firms to become cleaner both by increasing their productivity and by inducing them to offshore dirty production to other countries. The second objective is to explore the importance of these two mechanisms.

We approximate the structural relationship between carbon intensity and imports by the following log-linear regression model,

[8] This implies that some import flows fall into both categories. The use of 3-digit industries in forming the non-offshoring category was necessary to ensure a minimum sample size in our analysis of the effect of this type of trade flows on emission intensity (see Section 4).

[9] Table D.2 in Appendix D displays which industries and countries the firms in our sample primarily source from. Germany is the largest import partner comprising 21 percent of all in-sample imports while NACE C28 (Machinery and equipment n.e.c) is the largest import industry.

$$\log E_{it} \;=\; \beta \log M_{it} \,+\, \delta^{'} W_{it} \,+\, \varepsilon_{it}, \tag{1}$$

where E_{it} is the carbon intensity of firm i in year t, measured as total CO2 emissions over value added; M_{it} is the total value of imports; W_{it} is a vector of controls including a constant and firm and year fixed effects; and ε_{it} is the residual containing all other unobserved shocks affecting the firms' emission intensity.

The inclusion of firm and year fixed effects purge the residual from all time-invariant factors and aggregate shocks affecting emission intensity. It also isolates within-firm variation in the level of imports over time. Estimating equation (1) with OLS should nonetheless be expected to yield biased estimates of β. The most obvious concern is perhaps firm-level shocks to productivity which are likely to affect both the emission intensity and the import demand of firms. A second concern is that investments in abatement aimed to reduce emissions may act as a substitute for offshoring, as argued in Cole et al. (2014). While productivity shocks are expected to create a downward bias (reinforcing the negative effect of importing), abatement shocks are expected to create an upward bias. This renders the OLS estimate of β hard to interpret as the omitted variable bias could go in either direction.

It may be tempting to add measures of productivity, abatement investment and other covariates to equation (1) in order to alleviate these concerns. However, this could do more harm than good if importing has a causal effect on these variables. Indeed, our theoretical framework predicts that importing can increase both the productivity of firms and their investments in abatement (see Section 6) suggesting that the true effect of importing would be underestimated if we included these variables.

To identify a causal effect we instead follow Hummels et al. (2014) and construct a shift-share instrument that captures quasi-experimental variation in the firms' import levels. The instrument is based on two insights. The first is that changes in other countries' export supply of intermediate inputs that are not due to changes in the import demand of Swedish firms are likely to be orthogonal to unobserved firm-level characteristics. The second insight is that changes in other countries' export supply of intermediate inputs reflect changes in the desirability of purchasing these inputs. For example, an increase in country c's export supply of input p may reflect a change in the production cost or quality of that input. In either case, firms that use input p from country c benefits from this, and may respond by increasing their imports of that input. Firms that do not use input p, on the other hand, should not be affected by this change in cost or quality. It is this causal link between the foreign export supply of intermediate goods and the import levels of firms sourcing these intermediate goods that our instrument is intended to capture. To measure each firm's exposure to changes in the supply of different country-inputs, (c,p), we use information on the firms' pre-sample import patterns.

Formally, our instrument is defined by,

$$Z_{it} = \sum_{c \in N_c} \sum_{p \in N_p} s_{icp} X_{cpt}, \tag{2}$$

where N_c and N_p denote the sets of all countries and HS-6 digit products, respectively; s_{icp} is firm i's import share of input p from country c in a pre-sample year (2003); and X_{cpt} is the total world export supply of input p in year t from country c, except exports to Sweden.

The validity of the instrument requires that the following full-data moment condition is satisfied,

$$\mathbb{E}\left[\sum_{i \in N_i} \sum_{t \in N_t} Z_{it} \varepsilon_{it}\right] = \mathbb{E}\left[\sum_{c \in N_c} \sum_{p \in N_p} \sum_{t \in N_t} X_{cpt} \varepsilon_{cpt} s_{cp}\right] = 0. \tag{3}$$

It states that the instrument is orthogonal with the residual in expectation over realizations of $\{Z_{it}, \varepsilon_{it}\}$ for all $(i,t) \in N_i \times N_t$, where N_i and N_t denote the sets of firms and years in our sample, respectively. If this condition holds and there is a first stage relationship between the instrument and importing, then β in equation (1) can be identified (see Appendix B for a derivation). The second equality follows by definition of Z_{it}, where $\varepsilon_{cpt} = \frac{\sum_i s_{icp} \varepsilon_{it}}{\sum_i s_{icp}}$ is an exposure weighted average of the residuals and $s_{cp} = \frac{1}{|N_i|} \sum_i s_{icp}$ is the average pre-sample exposure to supply shock (c,p).

There are two main approaches to ensure that equation (3) is satisfied. The first is to assume that the shock exposure weights, s_{icp}, are exogenous, the data is identically and independently distributed, and the shocks, X_{cpt}, are non-random, as shown by Goldsmith-Pinkham et al. (2020). The second approach, developed by Borusyak et al. (forthcoming), is to instead treat the shocks as random variables and assume that these are exogenous conditional on the shock-level residuals, $\varepsilon = \{\varepsilon_{cpt}\}$, and the exposure weights, $s = \{s_{cp}\}$. We motivate our instrument based on this latter approach, i.e. we allow the lagged import decisions of the firms to be endogenous and rely on the exogeneity of the foreign export supply shocks. Because the import shares are fixed in a pre-sample year and sum to one for each firm, the inclusion of firm and year fixed effects implies that it is sufficient to assume that changes in the world export supply, specific to each country-input (c,p), are as-good-as-randomly assigned to Swedish firms.[10]

[10]For a discussion on the role of fixed effects in shift-share designs, see Borusyak et al. (forthcoming).

In Appendix B we provide a more formal description of our shift-share design, the identifying assumptions, and proofs that these assumptions are sufficient to satisfy the condition in equation (3).

3.1 Mechanisms

We use two approaches in this paper to empirically assess potential mechanisms explaining the effect of importing on firm-level emission intensity. The first approach relates to whether the effect is due to firms offshoring more carbon intensive components of their production. Specifically, we exclude all imported intermediates from non-OECD countries in one specification, and all imported intermediates produced by the same industry as that of the importing firm in another specification. If the effect is driven by offshoring to developing countries with weak environmental regulation, or outsourcing of core production, these specifications should generate point estimates that are significantly different from our baseline estimate.

The second approach is a so called mediation analysis, described in detail in Section 5, which under additional assumptions allows us to quantify how much of the causal effect of importing that is attributed to changes in productivity and how much that is attributed to a shift in production towards cleaner products.

3.2 Threats to identification

Our shift-share design hinges on that unobserved shocks affecting the emission intensity of firms are uncorrelated with changes in the foreign export supply of intermediate goods. A threat to this assumption is potentially endogenous shocks to the Swedish import demand. Fortunately, we can deal with this rather effectively by excluding all exports to Sweden in the world export supply variable, X_{cpt}. This entails that changes in the import demand of Swedish firms do not have a direct effect on the instrument. However, for inputs that are primarily sourced by Swedish importers, shocks to the import demand may also have an indirect effect on X_{cpt}, by affecting the price of these inputs. We account for this potential source of endogeneity in Section 4.4.

A second threat to identification is that Swedish importers and their foreign suppliers could be affected by the same shocks. For example, secular trends in productivity or demand may be common to these firms if they belong to the same industry. Moreover, such trends would render our instrument endogenous if they influence the emission intensity of Swedish importers as well as the world export supply of the inputs they source. We address this issue in several ways in Section 4.4.

4 Empirical results

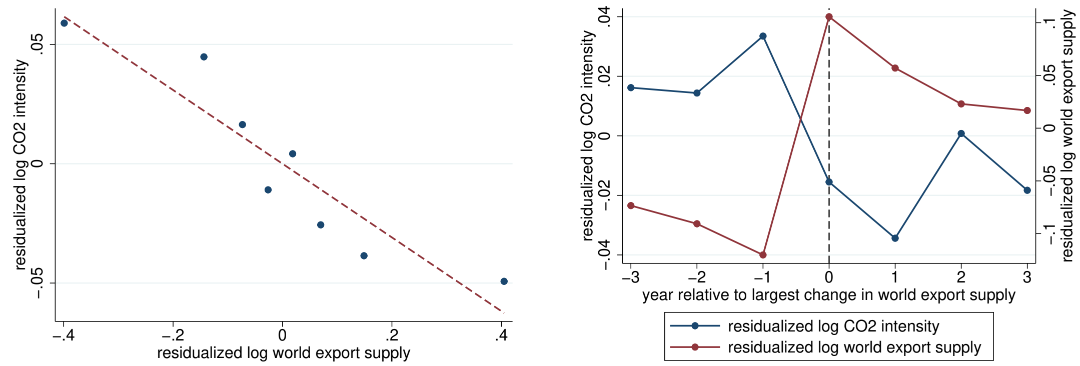
In this section we present causal evidence on the effect of importing (at the intensive margin) on the carbon intensity of firms using our shift-share IV design. The results suggest that an increase in importing makes firms cleaner and that this effect is both statistically and environmentally significant. We also find that the causal impact of importing remains significant when we exclude intermediate inputs that are associated with offshoring (i.e. inputs from non–OECD countries or from a firm's core area of production) and that the effect is robust to various specifications addressing potential endogeneity issues. We end the section with results showing that the effect of importing is even larger among manufacturing firms within dirty industries.

4.1 First stage and reduced form

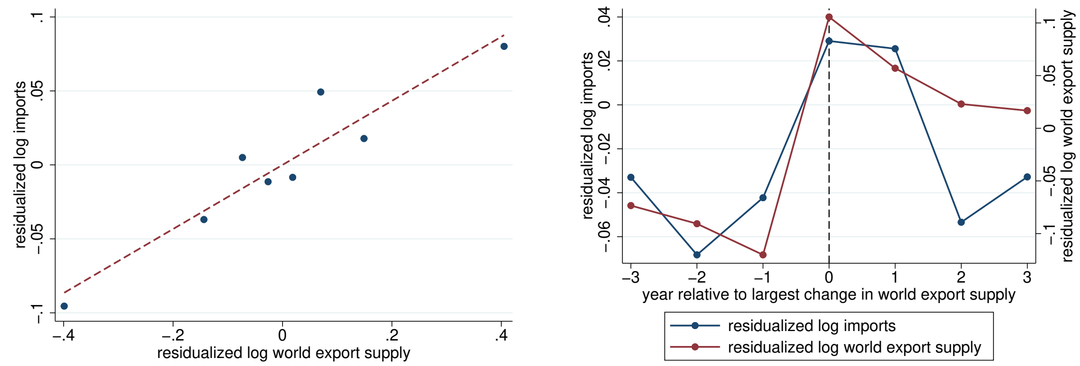
We begin by analyzing the first stage and the intention-to-treat relationships to establish how the shift-share instrument is associated with firm-level imports and carbon intensity. Recall that the instrument is a weighted average of the world export supply of country-inputs with firm-specific weights determined by pre-sample import patterns. We will henceforth refer to this instrument as world export supply.

In the left-hand graph of panel (a) in Figure 2 we illustrate the relationship between the log world export supply and the log carbon intensity in a scatter plot. For ease of exposition we have grouped the data into 8 bins and added the OLS regression line. Both variables are residualized, i.e. they are purged from all variation absorbed by the firm and year fixed effects in the regression. We see that the relationship is negative and well approximated by our log-linear regression model. It also seems that it is not driven by potential outliers. The result from running this regression is reported in column 2 of Table 3. The point estimate is highly significant and equal to -0.11, i.e. a 10 percent increase in the world export supply of intermediate goods is on average associated with a 1.1 percent reduction in the carbon intensity of firms.

In our specification of the intention-to-treat relationship we assume that shocks to the instrument have a contemporaneous effect on carbon intensity. To explore if this assumption is appropriate we conduct an event study illustrated in the right-hand graph of panel (a) in Figure 2. More specifically, we plot the mean residualized log carbon intensity and the mean residualized log instrument over an event time variable defined as years relative to the largest increase in the instrument. Since each firm is affected by different foreign export supply shocks, it follows that the time of this event, which we denote by zero, corresponds to different years for different firms. By construction, the mean log



(a) Intention-to-treat relationship



(b) First stage relationship

Figure 2. Illustration of the intention-to-treat and first stage regressions

Notes: The sample is balanced and covers the years 2004-2016. The left-hand graphs in panel (a) and (b) illustrate the estimated intention-to-treat and first stage relationships between the log of the instrument and the log carbon intensity and the log of imports, respectively. The instrument (world export supply) is defined as in equation (2). The graphs are constructed as follows: we regress each variable on firm and year fixed effects, save the residuals from these regressions, and plot them against each other in two scatter diagrams in which the data is grouped into 8 bins. The right-hand graphs in panel (a) and (b) illustrate the evolution of the average log of the instrument, log carbon intensity and log of imports, respectively, over an event-time variable defined to be zero in the year in which each firm experiences its largest increase in the instrument. All variables are residualized by regressing them on firm and year fixed effects and saving the residuals from these regressions. We confine the analyses to firms on which we have data three years before and three years after the largest observed increase in the instrument.

world export supply increases substantially at time zero. However, the figure also shows that this coincides with the largest drop in the mean log carbon intensity. This supports our modeling assumption that the effect on the firms' emission intensity is primarily contemporaneous in nature, although it should be noted that we also observe a smaller drop at time 1, suggesting some durability in the effect.

The first stage relationship between the log world export supply and the log of imports is illustrated in panel (b) of Figure 2. The left-hand graph shows that this relationship is positive throughout the entire support of the instrument and that our log-linear model fit the data well. The event study on the right-hand side of panel (b) is consistent with the event study of the intention-to-treat relationship. Specifically, it shows that the importers tend to respond contemporaneously to changes in the world export supply of the inputs they source. In column 4 of Table 3 we see that the point estimate of this effect is equal to 0.2 and highly significant, i.e. a 10 percent increase in the world export supply causes a 2 percent increase in imports on average. Furthermore, the Kleibergen-Paap F-statistic is 15.3 indicating that we do not have to be concerned about weak-instrument-bias in our IV estimator.

4.2 Main result

Our primary objective in this paper is to identify the causal effect of importing on the carbon intensity of manufacturing firms. Column 3 of Table 3 reports our baseline IV estimate of this effect. We see that it is highly significant and equal to -0.55. That is, a 10 percent increase in the import volume of firms causes a 5.5 percent reduction in their carbon intensity on average. This effect is significantly larger (in absolute value) than the effect estimated by OLS reported in column 1. However, as we discuss in Section 3, several factors are likely to confound the OLS estimate, although the sign of the bias was ex-ante ambiguous.

To add meaning to this result we can do a simple back-of-the-envelope calculation of how much of the average decline in carbon intensity in 2004-2016 that is attributed to imports. In Table D.1 in Appendix D we see that imports have increased on average by 0.22 log points over this period which by our IV estimate has caused a 12 percent reduction in the average carbon intensity. The total reduction in the average carbon intensity is also reported in Table D.1 and equal to 0.74 log points. Thus, our result suggests that roughly 16 percent of this decline is explained by an increase in imports. If we based this calculation on the OLS estimate instead we would erroneously predict that imports only accounted for about 1 percent of the observed fall in emission intensity.[11]

4.3 The importance of offshoring

Having established that importing causally affects the environmental performance of firms, we are now interested in understanding why this is the case. A potential mechanism is that increases in imports are associated with offshoring of dirty parts of the firm's production process. According to the Pollution Haven Hypothesis (PHH), firms in developed countries have an incentive to outsource emission intensive production to less developed countries

[11] Table D.1 shows that the average import level increased between 2004 and 2010 by 0.28 log points and then experienced a slight decline between 2010 and 2016. If we account for this and only base our calculation on the 2004-2010 sub-period we find that the increase in importing explains approximately 57 percent of the total decline in the average emission intensity in 2004-2010. This number is similar in magnitude to the result obtained by Cherniwchan (2017) who finds that NAFTA can explain about two-thirds of the reductions of particular matter (PM10) and sulfur dioxide emitted by U.S. manufacturing between 1990 and 2008.

Table 3. The effect of importing on CO2 intensity

	OLS	ITT	IV	First stage
Dependent variable:		log carbon intensity		log imports
	(1)	(2)	(3)	(4)
log imports	-0.045***		-0.553***	
	(0.008)		(0.208)	
log world export supply		-0.111***		0.201***
		(0.030)		(0.051)
N	7,930	7,930	7,930	7,930
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
F-statistic				15.3

Notes: The sample is balanced and covers the years 2004-2016. Columns (1) reports the result of the OLS regression in equation (1) while column (2) reports the result of the intention-to-treat regression. Column (3) reports the 2SLS regression of equation (1) and column (4) reports the result of the first stage regression. The dependent variable in columns (1)-(3) is the log carbon intensity, i.e. the log of CO2 over value added. All regressions include year and firm fixed effects. The reported F-statistic is the first-stage Kleibergen-Paap F-statistic. Robust standard errors are in parentheses. *** 1%, ** 5% and * 10%.

with weak environmental regulation. To test the importance of this channel, we exclude all imports of intermediate goods from non-OECD countries in our shift-share regression framework and check whether this significantly alters our point estimate. Because some firms in some years only import from developing countries we loose a few observations in this exercise. To account for potential selection effects we re-estimate our baseline model on this smaller sample to serve as our point of comparison. The result is reported in columns 1 and 2 of Table 4. We see that the estimate in column 2 of the causal effect of imports from other OECD countries is significant and even more negative than the baseline estimate in column 1. However, the two estimates are not significantly different from each other.

To test the importance of offshoring more generally, we distinguish between imports that are more likely to substitute for in-house production and imports that are less likely to do so based on whether the imported intermediates are produced by the same industry as the importing firm and estimate the causal effect of these two types of import flows separately. In particular, column 4 of Table 4 estimates the effect of importing intermediates that are not produced within the same 3-digit industry as that of the importing firm. Because this type of imports is less likely to substitute for in-house production, the estimated effect is arguably less likely to be explained by offshoring. We see that the estimate in column 4 is almost identical to the baseline estimate reported in column 3.

Table 4. The effect of importing on CO2 intensity – Excluding trade flows

	IV					
	OECD imports		Non-offshoring		Narrow offshoring	
	Baseline		Baseline		Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)
log imports	-0.646***		-0.628***		-0.931***	
	(0.229)		(0.225)		(0.341)	
log imports (OECD)		-0.911**				
		(0.376)				
log non-offshoring				-0.643***		
				(0.243)		
log offshoring						-0.495*
						(0.283)
N	7,886	7,886	7,740	7,740	6,516	6,516
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
F-statistic	15.7	6.9	13.8	10.2	12.0	3.7

Notes: The samples are unbalanced and cover the years 2004-2016. Columns (1), (3) and (5) report the baseline 2SLS estimates for the maximum sample of firm-year observations available when we exclude imports from non-OECD countries, imports produced by the same 3-digit NACE industry as that of the importing firm, and imports not produced by the same 2-digit NACE industry as that of the importing firm, respectively. Columns (2), (4) and (6) report the 2SLS estimates when we exclude imports from non-OECD countries, imports produced by the same 3-digit NACE industry as that of the importing firm, and imports not produced by the same 2-digit NACE industry as that of the importing firm, respectively. The dependent variable in all columns is the log carbon intensity, i.e. the log of CO2 over value added. All regressions include year and firm fixed effects. The reported F-statistic is the first-stage Kleibergen-Paap F-statistic. Robust standard errors are in parentheses. *** 1%, ** 5% and * 10%.

The estimated effect of within-industry import flows, referred to as narrow offshoring, is reported in column 6. Confining the analysis to this type of imports substantially weakens the first-stage. It also results in a smaller and less significant point estimate. However, the estimated effect is not significantly different from the baseline estimate in column 5.

We interpret the results in Table 4 as suggesting that import flows that are commonly thought to be associated with offshoring are not what seems to be driving the effect of imports on emission intensity. At the same time, this does not rule out that firms adjust their production as a response to an increase in imports. It may very well be the case that the firms primarily offshore tasks that are not within their area of specialization and thus performed inefficiently with a high emission intensity. If so, our non-offshoring variable could still pick up the effect of outsourcing. Indeed, one of the channels through which importing is thought to be beneficial to firms is that it allows them to focus on their core competencies (Schwörer, 2013). We explore this possibility in a mediation analysis presented in Section 5.

4.4 Robustness checks and heterogeneous effects

As discussed in Section 3.2, our estimates might confound the effect of importing with common trends in demand and productivity among Swedish importers and foreign suppliers. Since this is most likely to be the case for firms belonging to the same industry, our result in Table 4, showing that the estimated effect is insensitive to excluding within-industry imports, is reassuring. To further explore this issue, we add industry-specific and regional time-trends to our model which control for time-variant shocks to emission intensity at the 2-digit industry- and county-level, respectively. The results reported in Table 5 show that neither the significance level nor the point estimate are meaningfully affected by this.

We also investigate the possibility of pre-trends at the firm-level by controlling for lagged emission intensity as well as lagged measures of productivity, exports and value added. In Table D.5 in Appendix D, we find that this does not have a significant impact on our baseline estimate. An alternative way to check for pre-trends is to change the pre-sample year for which we use the firms' import shares as shock exposure weights in the instrument. These import shares are allowed to be endogenous but they are not allowed to be correlated with future foreign export supply shocks. For example, if firms with declining emission intensity are better at predicting shocks to the export supply of their source partners and adjust their import patterns accordingly, then our instrument would be endogenous. Changing to an earlier pre-sample year reduces the likelihood of this threat but it should also weaken the first-stage relationship between the instrument and importing. In column 4 of Table D.5 we report the estimated effect when we base the exposure weights on year 2000 instead of 2003. As expected, the first-stage F-statistic goes down as a result but the point estimate does not change significantly. Taken together, these results support our assumption that the foreign export supply shocks are not correlated with pre-existing trends in the firms' emission intensity.

Another concern discussed in Section 3.2 is that changes in the import demand of Swedish firms may affect the world export supply of the inputs they source by affecting the prices of these inputs in foreign markets. In column 2 of Table D.5 we account for this by excluding all inputs for which more than 10 percent of the world export supply is exported to Sweden. That is, we construct the instrument such that it only depends on trade flows that are unlikely to be influenced to any large extent by changes in Swedish import demand. We see that this results in a somewhat larger negative estimate, but that it is not significantly different from the estimate obtained using our original instrument, suggesting that our baseline result is not confounded by import demand shocks.

Table 5. The effect of importing on CO2 intensity – Robustness analysis

	IV			
	Baseline	Industry trends	Regional trends	Industry + regional trends
	(1)	(2)	(3)	(4)
log imports	-0.553***	-0.587***	-0.567***	-0.549***
	(0.208)	(0.218)	(0.203)	(0.193)
N	7,930	7,930	7,930	7,930
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Industry trends		✓		✓
Regional trends			✓	✓
F-statistic	15.3	13.6	15.1	16.0

Note: The sample is balanced and covers the years 2004-2016. All columns refer to the two-stage IV regression in equation (1) where we instrument log imports by the instrument defined in equation in (2). The dependent variable in all regressions is the log carbon intensity, i.e. the log of CO2 over value added. All regressions include year and firm fixed effects. Column (1) reports our baseline regression. Columns (2), (3) and (4) include trends for 2-digit NACE industry, region (county), and both industry and region, respectively. The reported F-statistic is the first-stage Kleibergen-Paap F-statistic. Standard errors are in parentheses. *** 1%, ** 5% and * 10%.

Finally, we investigate whether the effect of importing is heterogeneous across industries. A potential worry is that our baseline estimate is driven by firms in relatively clean industries and therefore has low environmental significance. To address this, we create indicators for each of the five industries with the highest emission intensity listed in Table D.3. We then interact each indicator with the log of imports and the log world export supply, where the latter interactions instrument for the former. Adding these interactions to the regression model separately allows us to estimate how the average effect in these industries differ from the average effect across all firms. The results are reported in Table D.6. Columns 1-5 show that the negative effect is significantly larger among firms in the industries producing basic metal products (NACE C24) and chemical products (C20). For firms in the other three industries, producing paper products (C17), non-metallic mineral products (C23), and wood products (C16), the effect is indistinguishable from the average effect of importing. Grouping all five industries together, we find in column 6 that the negative effect is generally larger among firms in these dirty industries. Although the difference is quite small (-0.03), this shows that importing improves the environmental performance of firms in industries that emit the most CO2 per value added.

5 Mediation analysis of mechanisms

There are many channels through which importing potentially affects the emission intensity of firms. However, theory emphasizes two in particular. Importing may increase the productivity of firms by giving them access to inputs that are better suited to their needs, or by allowing them to specialize in the tasks in which they have a comparative advantage. Moreover, a rise in total factor productivity (TFP) makes firms use less inputs, including emission-generating energy, per unit of value added. Importing may also induce firms to change the set of products they produce, and in a country with high taxes on emissions, there is an incentive to replace in-house production of emission-intensive products with imports.

In this section we employ a mediation analysis, which builds on the work by Heckman et al. (2013), Heckman and Pinto (2015) and Fagereng et al. (2021), to quantify the importance of these two mechanisms. We are interested in how much of the average causal effect that can be explained by induced changes in productivity, and how much that can be explained by a shift in the products firms produce. To analyze this, one would ideally have both experimental or quasi-experimental variation in firm-level imports *and* experimental or quasi-experimental variation in the mediators. Because our shift-share design only captures exogenous variation in imports, we will make some additional assumptions, as outlined below, under which identification of the effect of the mediators is possible.

5.1 Mediators

The first mediator we are interested in, productivity, is notoriously hard to measure. This is because estimation of firms' production functions – from which firm-specific TFP can be residually determined – tend to suffer from bias unless one account for the correlation between factor levels and productivity shocks. Estimation procedures that alleviate this concern have been developed by e.g. Olley and Pakes (1996) and Levinsohn and Petrin (2003). Our detailed firm-level data on production factors, factor costs and intermediate inputs, allow us to take advantage of this work and to estimate the firms' TFP using the method proposed by Levinsohn and Petrin (2003). Under certain conditions, this procedure yields consistent estimates of the production function parameters by leveraging intermediate inputs to control for the correlation between factor levels and productivity shocks. The details of this approach and our implementation of it are described in Appendix A.

Our second mediator concerns whether firms change the set of products they produce in a way that affects their emission intensity. In order to quantify this mediator we want to create a measure of how emission-intensive a firm's production is based on what products it produces. For example, we want to measure how much more emission-intensive a steel producer is compared to a furniture producer based on their choice of product and not on other differences between the firms such as differences in productivity. However, we observe production technology and energy usage at the firm level and not at the product level, and can therefore not directly infer the emission intensity of specific products. To estimate this, we run a regression of the emission intensity of firms on a set of product-specific variables that represent the share of a firm's total sales that is accounted for by a specific product. We do this at the four-digit HS-level to preserve some detail but to still avoid making an individual firm too important in determining a particular coefficient.[12] The coefficient on each of these variables is our measure of the carbon intensity of each product category. Finally, to measure the emission intensity of a firm's set of products, we calculate a weighted average of the estimated coefficients, where the weights are the relative shares of the firm's total sales that is accounted for by each product.

5.2 *Empirical model of mediation*

Applying a simplified version of the framework developed by Heckman and Pinto (2015), we derive a mediation model that decomposes the average causal effect of importing into an explained component and an unexplained component. The model, which is formally derived in Appendix C, is given by,

$$\log E_{it} = \beta_0 + \beta_M \log M_{it} + \sum_j \beta_j \log G^j_{it} + \vartheta_i + \eta_t + \varepsilon_{it}, \tag{4}$$

where E_{it} is the carbon intensity of firm i in year t; M_{it} is the level of imports; G^j_{it} is the level of the observed mediator j; ϑ_i and η_t are firm and year fixed effects, respectively; and ε_{it} is a zero-mean error term which contains shocks to unobserved mediators of the effect of importing on emission intensity. β_M measures the unexplained effect that operates either directly or through mediators that we do not observe, and β_j measures the effect of mediator j on the emission intensity.

We approximate the structural relationship between each observed mediator j and imports by the following log-linear models,

$$\log G^1_{it} = \gamma_{10} + \gamma_{1M} \log M_{it} + \vartheta_{1i} + \eta_{1t} + \varepsilon_{1it} \tag{5}$$

[12] Specifically, we estimate the following regression with OLS: $\log E_{it} = \alpha_0 + \sum_p \alpha_p s_{itp} + \eta_t + \varepsilon_{it}$, where the α_p's are the coefficients of interests; E_{it} is carbon intensity of firm i in year t; s_{itp} is the share of firm i's total sales of product p in year t; η_t is a year fixed effect; and ε_{it} is the error term.

$$\vdots$$

$$\log G^k_{it} = \gamma_{k0} + \gamma_{kM} \log M_{it} + \vartheta_{ki} + \eta_{kt} + \varepsilon_{kit}, \tag{6}$$

where γ_{jM} denotes the causal effect of importing on the jth mediator and ε_{jit} is a mean-zero error term, for all $j = 1,...,k$. Substituting equations (5)-(6) into equation (4), we can express the average causal effect of an increase in imports from M_{it} to M'_{it} by,

$$\mathbb{E}[\log E'_{it} - \log E_{it}] = \underbrace{\beta_M[\log M'_{it} - \log M_{it}]}_{\text{Unexplained effect}} + \underbrace{\sum_j \beta_j \gamma_{jM}[\log M'_{it} - \log M_{it}]}_{\text{Explained effect}}. \tag{7}$$

It follows that the share of the average causal effect that the unexplained effect represents, P_U, and the share that each observed mediator represents, P_j, can be expressed as:

$$P_U = \frac{\beta_M}{\beta_M + \sum_i \beta_i \gamma_{iM}} \tag{8}$$

$$P_j = \frac{\beta_j \gamma_{jM}}{\beta_M + \sum_i \beta_i \gamma_{iM}}, \tag{9}$$

where β_M is the unexplained component; $\beta_j \gamma_{jM}$ is the explained component that works through the observed mediator j; and $\beta_M + \sum_i \beta_i \gamma_{iM}$ is the total average causal effect.

The parameters that we seek to identify are β_M, β_j and γ_{jM}. Our shift-share instrument in equation (2) allows us to estimate equations (5)-(6) with 2SLS to obtain consistent estimates of the causal effect of importing on the observed mediators of interest. The parameters γ_{jM} are therefore well-identified within our empirical framework. To obtain consistent estimates of β_M and β_j we estimate equation (4) with 2SLS where we again use our shift-share instrument to capture exogenous variation in imports. However, for this regression to identify the parameters of interest, we also need to assume that the observed mediators are uncorrelated with unobserved mediators. If this assumption is violated, some of the effect that should be attributed to the unexplained component, β_M, may instead be attributed to one of the observed mediators, β_j. A second assumption underlying our mediation model is that the effect of each observed mediator, β_j, is unaffected by imports. That is, we assume that the individual effects of the observed mediators on emission intensity do not vary with the import levels of firms.[13]

[13]This structural-invariance assumption is formally described in Appendix C in our derivation of the mediation model.

5.3 Mediation analysis results

We begin by analyzing how imports impacts our observed mediators. In Table 6, columns 1 and 2, we report the effect of imports on the two potential mediators. These correspond to equations (5) to (6). We note that imports affect the product portfolio of firms in a way so that they produce less emission-intensive goods. Imports also increase the productivity of firms. An increase in imports by 10 percent causes a reduction in the carbon intensity of the product mix by 0.9 percent, and an increase in productivity by 2 percent. Both of the mediators we incorporate therefore appear to be affected by imports. However, only the effect on productivity is statistically significant.

We also estimate how each component affects the emission intensity of firms by estimating equation (4) and report the results in column 3 of Table 6. While the estimated direct effect of imports is still large at -0.58, it is lower than our baseline estimate of -0.69 as reported in column 3. This suggests that the mediators matter from a quantitative point of view. The coefficients on the mediators are statistically significant and quantitatively large. As expected, readjusting the product portfolio towards more emission intensive products tend to increase the emission intensity of a firm. Likewise, a higher TFP decreases the emission intensity of firms.

Finally, we are interested in understanding the relative importance of the two mediators we analyze and the impact of unobserved mediators. In column 5 we calculate the share of the average causal effect that the direct or unexplained effect accounts for, P_U, and find that this share is 85 percent. This effect captures the effect of all unobserved or ignored mediators as well as measurement error in our observed mediators. The observed mediators on the other hand account for 15 percent of the average causal effect. Within the set of observed mediators (column 6), we find that the productivity channel accounts for about two thirds of the effect that is channeled through the observed mediators, and one third is accounted for by changes in the set of products produced.

Our mediation analysis provides well-identified causal evidence on the effect of importing on productivity. It also provides suggestive evidence on the importance of the two mediators for the effect of importing on emission intensity. Consistent with the results in Section 4.3, changes in the products firms produce cannot explain more than a small share of this effect. This further suggests that offshoring of dirty production is not the main explanation for why firms become cleaner by importing intermediate goods. The productivity effect appears to be more important and might even be underestimated due to measurement error. The result that two thirds of the explained reduction in emission intensity is due to productivity growth suggests that international trade generates quantitatively important efficiency gains that may reduce aggregate emissions. In the following section, we analyze this mechanism more closely in a theoretical model.

6 Theoretical framework for the productivity channel

We propose a simple theoretical framework in order to understand how importing affects levels of productivity among firms. Such a model will also facilitate an analysis of what effect that importing might have on aggregate welfare and aggregate emissions. We introduce our mechanism into a small open economy trade model with heterogeneous firms and Dixit-Stiglitz demand such as in Melitz (2003). All manufacturing firms in our model import intermediates and, for simplicity, we ignore exporting. The price of intermediates is set in the world market, and they are therefore given for firms in the small economy. We assume that firms produce a consumption good as well as emissions, which are a public bad, and we will follow Copeland and Taylor (2003) and assume that firms can engage in costly abatement and thereby reduce their levels of emissions.

The economy we analyze consists of a manufacturing sector M, and a non-manufacturing numéraire sector A. There is a single primary factor of production. This may be a composite factor but, for the sake of simplicity, we refer to it as labor, L. The M sector is characterized by increasing returns and monopolistic competition and producers in this sector use imported intermediate inputs. The production by firms in the M sector generates emissions of a pollutant, E. These emissions are a pure public bad. The government levies a tax on pollution, and the tax revenues are used to pay for an outside public good. The A sector produces a homogeneous good, and it operates under constant returns to scale and perfect competition. This sector does not produce any pollution.

6.1 Demand

Consumers have CES-preferences over the differentiated varieties within the M sector, and they have the utility function

$$U = C_M^{\varepsilon} C_A^{1-\varepsilon} - g(E) \tag{10}$$

where $\varepsilon \in (0,1)$, and C_A and C_M denote the consumption of the homogeneous good and the differentiated good, respectively. The function $g(E)$ measures the disutility associated with emissions, and it is assumed that $g'(E) > 0$. The constant returns to scale A good is chosen as the numéraire, and the price of the A good, p_A, is thus equal to unity. By choice of units, the labor requirement in the A sector is one, which gives

$$p_A = w = 1 \tag{11}$$

Table 6. The effect of importing on CO2 intensity – Mediation analysis.

	Equations (5) to (6)		Baseline	Equation (4)		
Dependent variable:	log carbon intensity of product mix	log productivity	log carbon intensity		Share of total	Share of observed
	(1)	(2)	(3)	(4)	(5)	(6)
log imports	-0.093	0.239**	-0.686**	-0.582**	*85%*	
	(0.096)	(0.108)	(0.288)	(0.284)		
log carbon intensity of product mix				0.335***	*5%*	*31%*
				(0.045)		
log productivity				-0.305***	*11%*	*69%*
				(0.110)		
N	6,967	6,967	6,967	6,967		
Year FE	✓	✓	✓	✓		
Firm FE	✓	✓	✓	✓		

Note: The sample is balanced and covers the years 2004-2016. Columns (1) to (4) refer to the two-stage IV regression in equation (1) where we instrument log imports by the instrument defined in equation in (2). The dependent variable is the log carbon intensity of a firm's product mix in column (1), log productivity in column (2), log carbon intensity, i.e. the log of CO2 over value added, in columns (3) and (4). All regressions include year and firm fixed effects. Columns (1) to (2) report estimates for equations (5) to (6). Column (3) reports our baseline regression. Column (4) reports the estimates for equation (5). Standard errors are in parentheses. *** 1%, ** 5% and * 10%.

and wages are thus equal to one across sectors. Consumer preferences over goods from the M sector are represented by C_M, which is an aggregate over a continuum of varieties indexed by i:

$$C_M = \left(\int\limits_{i \in I} c(i)^{(\sigma-1)/\sigma} di \right)^{\sigma/(\sigma-1)} \tag{12}$$

where $c(i)$ represents the consumption of each variety with the elasticity of substitution between any pair of differentiated goods being $\sigma > 1$. The measure of the set I represents the mass of varieties consumed. Each consumer spends a share ε of his income on goods from industry M, and the demand for each single variety is given by

$$x_i = \frac{p_i^{-\sigma}}{P^{1-\sigma}} \varepsilon L \tag{13}$$

where p_i is the price of variety i, L is income, and P is the price index of M goods. P is given by

$$P = \left(\int\limits_{i \in I} p_i^{1-\sigma} di \right)^{\frac{1}{1-\sigma}}. \tag{14}$$

6.2 *Production*

The M sector is characterized by monopolistic competition and there is a large pool of prospective entrants. To enter, a firm i bears the fixed costs of entry f_E measured in labor units. After having sunk f_E, the entrant draws a labor-per-unit-output coefficient a_i from a cumulative distribution $F(a)$.

Since a_i is the unit labor requirement of firm i, $1/a_i$ depicts the labor productivity of the firm. The variable cost in production is a Cobb-Douglas aggregate of labor, with a share $1-\mu$, and imported intermediate inputs, with a share μ. Intermediate inputs in turn are aggregated using a CES-index with a corresponding price index G:

$$G \equiv \left(\int\limits_{i \in \Omega} \phi p_i^{*\,1-\sigma} di \right)^{\frac{1}{1-\sigma}} \tag{15}$$

where Ω denotes the set of imported intermediate inputs. $\phi \equiv \tau^{1-\sigma} \in (0,1]$ is a measure of the freeness of trade where $\tau > 1$ is an iceberg trade cost. For each unit of a good that is imported, τ units must be shipped from abroad. p_i^* is the exogenous world market price of intermediate input i. It is seen from (15) that

$$\frac{\partial G}{\partial \phi} < 0 \tag{16}$$

which means that trade liberalization will lower the price index of imported intermediates.

The industrial activity in sector M entails pollution in terms of environmental emissions. A firm has an incentive to reduce emissions since these emissions are subject to taxation. In the modeling of emissions, we assume that each firm i produces two outputs: an industrial good (x_i) and emissions (e_i). Following Copeland and Taylor (2003), we assume that in order to reduce the emissions, a firm can divert a fraction θ_i of the production factors away from the production of x_i to be used in abatement. Thus, θ_i is a variable abatement cost that is chosen by each firm in order to maximize the profits. The joint production of industrial goods and emissions is given by

$$x_i = (1-\theta_i)\, S^{\mu} \left(\frac{l_i}{a_i}\right)^{1-\mu} \tag{17}$$

$$e_i = \varphi(\theta_i) S^{\mu} \left(\frac{l_i}{a_i}\right)^{1-\mu} \tag{18}$$

where $0 \leq \theta_i < 1$, and S is a CES-aggregate of imported intermediate inputs,

$$S = \left(\int\limits_{i \in \Omega} x_i^{*(\sigma-1)/\sigma} di \right)^{\sigma/(\sigma-1)}, \tag{19}$$

and x_i^* is the quantity of intermediate i. Emissions depend on the activity level as well as the firm's abatement efforts. The abatement function

$$\varphi(\theta_i) = (1-\theta_i)^{1/\alpha} \tag{20}$$

where $0 < \alpha < 1$ determines the level of emissions for a given activity level. $\frac{1}{\alpha}$ may be interpreted as the abatement efficiency.

It is seen from (17) that output decreases linearly as primary production factors are moved from production to abatement (as θ increases). However, emissions are, from (18) and (20), a decreasing and convex function of θ. Firms chose a profit maximizing trade-off between production and abatement (the level of θ) depending on parameters of the production function and on the emission tax.

We proceed by using (20) to substitute for φ in (18), which can then be solved for $(1-\theta_i)$, and, in turn, be used to substitute for $(1-\theta_i)$ in (17). This gives an integrated expression for the joint production of goods and emission, which exploits the fact that although pollution is an output, it can equivalently also be treated as an input:[14]

$$x_i = e_i^{\alpha}\left(S^{\mu}\left(\frac{l_i}{a_i}\right)^{1-\mu}\right)^{1-\alpha}. \tag{21}$$

Hence, with such an interpretation, production implies the use of labor and intermediates as well as emissions. The parameter α denotes how intensive the industry M is in the use of labor and intermediates versus the use of emissions. A "dirty" industry will thus be characterized by a high α.

Note that while firms are heterogeneous with respect to labor productivity and abatement, they are identical with respect to the structure of their basic production technology. Firms minimize their costs subject to the production function (21), taking wages ($w = 1$) and emission taxes ($t > 0$) as given. Disregarding the sunk entry cost, we can derive firms' total cost function using (21).

$$C_i = \kappa t^{\alpha}\left(G^{\mu} a_i^{1-\mu}\right)^{1-\alpha} x_i \tag{22}$$

with $\kappa \equiv \alpha^{-\alpha}(1-\alpha)^{\alpha-1}$ and $t > 1$ being the emission tax. The cost function reflects that emissions are not free.

Our analysis focuses on steady-state equilibria and intertemporal discounting is ignored. The present value of firms is kept finite by assuming that firms face a constant Poisson hazard rate δ of "death" independently of productivity. An entering firm with productivity a_i will produce and earn a profit $\pi(a_i) \geq 0$ in every period until it is hit by a bad shock and is forced to exit.

6.3 Pricing and profit

Having drawn their productivity, firms calculate their optimal pricing rule. Implicitly, they then also decide on the emission intensity and the share of the input factor that they divert away from production and towards abatement, i.e. the variable abatement efforts.

Each producer operates under increasing returns to scale at the plant level and in line with Dixit and Stiglitz (1977) we assume there to be large group monopolistic competition between the producers in the M sector. The perceived elasticity of demand thus equals the elasticity of substitution between any pair of differentiated goods and is equal to σ. Each

[14]See Copeland and Taylor (2003) for a discussion of this feature of the model.

firm sets a price equal to a markup over the marginal costs, which yields a pricing rule

$$p_i = \frac{\sigma}{\sigma - 1}\kappa t^{\alpha}\left(G^{\mu}a_i^{1-\mu}\right)^{1-\alpha} \tag{23}$$

for each producer. Using (22) and (23), we can formulate the expression for firms' profits:

$$\pi_i = \left(\left(G^{\mu}a_i^{1-\mu}\right)^{1-\alpha}t^{\alpha}\right)^{1-\sigma}B \tag{24}$$

where $B \equiv \frac{\kappa^{1-\sigma}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}\mu L}{P^{1-\sigma}}$ is an index of the market potential. The model is closed by the free-entry condition

$$f_E = \int_0^{a_0}\pi(a)dF(a), \tag{25}$$

where 0 and a_0 represent the bounds of the marginal cost.

6.4 *Emission levels and abatement*

Using (17) and (18) and Shepard's lemma on the cost function allows us to calculate the variable abatement cost as a share of the production factors that are dedicated to abatement activities:

$$\theta_i = 1 - (\alpha\kappa)^{\frac{\alpha}{1-\alpha}}t^{-\alpha}\left(G^{\mu}a_i^{1-\mu}\right)^{\alpha}. \tag{26}$$

This expression leads to the following proposition:

Proposition 1. *Abatement costs measured in terms of the share of production factors diverted away from the production of good x, increases in firm productivity, the tax rate on emissions, and trade freeness.*

Proof. The statement follows directly from (26), and that $\frac{\partial G}{\partial \phi} < 0$ from (16). □

Turning to the emission intensity of firms, we again use Shepard's lemma on the cost function in (22) to get

$$\frac{e_i}{x_i} = \alpha\kappa t^{\alpha-1}\left(G_i^{\mu}a_i^{1-\mu}\right)^{1-\alpha}. \tag{27}$$

This expression immediately leads to the following conclusions.

Proposition 2. *More productive firms have a lower emission intensity.*

Proof. The statement follows directly from equation (27). □

Proposition 3. *Trade liberalization (a higher ϕ) lowers the emission intensity of importers.*

Proof. The statement follows from (27) , and from the fact that $\partial G / \partial \phi < 0$ from (16). $\square$

Hence, higher productivity leads to an increased output but also to more resources being directed towards abatement. A tax expectedly encourages increased abatement. Finally, we observe that lower trade costs decreases G, which has a very similar effect to higher productivity (a decrease in a). All of these increases in the abatement make production cleaner and reduce the emission intensity.

The intuition for these results is that a firm with a lower marginal cost will forego less operating profit when reducing its output by one unit, because of constant markup pricing. This implies that the optimal production abatement trade-off implies more abatement (a higher θ) for such a firm.

6.5 Aggregate emissions and welfare

We finally want to analyze the impact of a reduction in import tariffs on aggregate levels of welfare and emissions.

We follow Helpman et al. (2004) in assuming the probability distribution, $F(a)$, to be a Pareto distribution,[15] i.e.

$$F(a) = \left(\frac{a}{a_0}\right)^k, \tag{28}$$

where k is the shape parameter of the distribution, and we normalize the scale parameter to unity, $a_0 \equiv 1$.

Using (25), (14), (24) and the definition of B gives the number (mass) of firms in the economy:

$$n = \frac{\varepsilon L}{\sigma f_E} \tag{29}$$

We integrate over firms with different productivities to calculate the aggregate emissions:

$$E = n \int_0^1 e\, dF(a). \tag{30}$$

[15] This assumption is consistent with the empirical findings by e.g. Axtell (2001).

Using the distribution of size and emission intensity across firms in (13), (23), (27) and (29) in (30), we get

$$E = \frac{\sigma-1}{\sigma}\frac{\alpha\varepsilon L}{t}. \tag{31}$$

Aggregate emissions decrease in the tax rate on emissions because firms engage in more abatement. Moreover, a high abatement efficiency (a low α) yields less emissions. However, aggregate emissions are unaffected by international trade and the cost of obtaining foreign inputs. This result is generated by the iceberg trade costs and the constant mark-ups. The revenues of each firm will be constant since cheaper intermediates have an equiproportional effect on the price of all firms, and aggregate expenditures on manufacturers are fixed.

The welfare impact of trade liberalization is to increase welfare through the price index. Indirect utility is given by

$$V = P^{-\varepsilon} - g(E). \tag{32}$$

Using the expression for prices and the number of firms in (14) and (29), respectively, and noting that $G = \tau\left(\int\limits_{i\in\Omega} p_i^{*1-\sigma} di\right)^{\frac{1}{1-\sigma}}$, indirect utility may be rewritten as

$$V = \Theta\tau^{-\varepsilon\mu(1-\alpha)}t^{-\varepsilon\alpha} - g(E), \tag{33}$$

where $\Theta \equiv \left(\kappa\frac{\sigma}{\sigma-1}\left(\frac{\lambda\varepsilon L}{\sigma f_E}\right)^{\frac{1}{1-\sigma}}\left(\int\limits_{i\in\Omega} p_i^{*1-\sigma} di\right)^{\frac{\mu(1-\alpha)}{1-\sigma}}\right)^{-\varepsilon} > 0$. We see from (33) that lower frictional barriers, τ, increase welfare since E, from (31), is independent of τ. The mechanism causing the improvement in welfare is thus that trade liberalization reduces the price index for consumers rather than a reduction in emissions.

However, we can conclude from this expression that it is possible to combine trade liberalization and a higher emission tax in a way that leads to both higher welfare and lower emissions. One such policy that would prioritize reductions in emissions instead of an increase in consumption would be to increase the taxes sufficiently to keep the term $\Theta\tau^{-\varepsilon\mu(1-\alpha)}t^{-\varepsilon\alpha}$ constant. This policy would result in the utility from consumption remaining constant since P is held constant. However, there would instead be utility gains from the reduction in emissions. The policy does ensure that utility increases since $g'(E) > 0$. We can thus calculate how much trade liberalization can reduce emissions when we keep the utility from consumption constant. Total differentiation of $\Theta\tau^{-\varepsilon\mu(1-\alpha)}t^{-\varepsilon\alpha}$, with the restriction that the term should be constant, gives the percentage increase in taxes that holds the price index constant as the trade costs decrease by one percent:

$$\varepsilon_{t,\tau} \equiv -\frac{dt}{d\tau}\frac{\tau}{t} = \frac{\mu\,(1-\alpha)}{\alpha}. \tag{34}$$

The expression increases in the share of intermediates in production μ. This reflects that, due to trade liberalization, cheaper intermediates have a stronger effect on marginal costs and prices the more important intermediates are for firms. The expression also increases in the abatement efficiency $\frac{1}{\alpha}$, since this makes costs less sensitive to the increase in the environmental tax rate. Finally, the expression also denotes an elasticity of aggregate emissions to trade liberalization under the policy that keeps utility from consumption constant, since emissions, from (31), are inversely proportional to the emission tax:

$$\varepsilon_{E,\tau} \quad = \quad -\varepsilon_{t,\tau}.$$

Thus, if a policy maker adjusts the emission taxes such that the welfare from consumption remains constant, $\varepsilon_{E,\tau}$ shows the elasticity of aggregate emissions to trade costs. This elasticity is higher the more important intermediates are in production and the easier it is for firms to engage in abatement.

6.6 *Computing the emission elasticity of trade liberalization*

We can use the estimates from our empirical results to compute the elasticity of aggregate emissions with respect to trade costs. This estimate will thus both be based on causal empirical inference of the firm-level effects and on a theoretical structure and therefore take general equilibrium effects into account.

To estimate $\varepsilon_{E,\tau}$ we need estimates for both abatement efficiency, $1/\alpha$ and the share of intermediates in the economy, μ. We will derive an estimate for the average abatement efficiency in the Swedish economy, $\frac{1}{\alpha}$, by analyzing our empirical results through the lens of our model. In the baseline specification in our empirical section, see for example equation (1), we analyze the impact on the emission intensity of firms. In our theoretical model, the expression for emission intensity is (27), which in logarithmic form becomes:

$$\log\frac{e_i}{x_i} = c + \mu\,(1-\alpha)\log G_i + (1-\alpha)\,(1-\mu)\log a_i \tag{35}$$

where $c \equiv \log(\alpha\kappa t^{\alpha-1})$. The parameter μ is the intermediate share in production. In the model we assume that all inputs are imported so the most relevant measure for μ is the

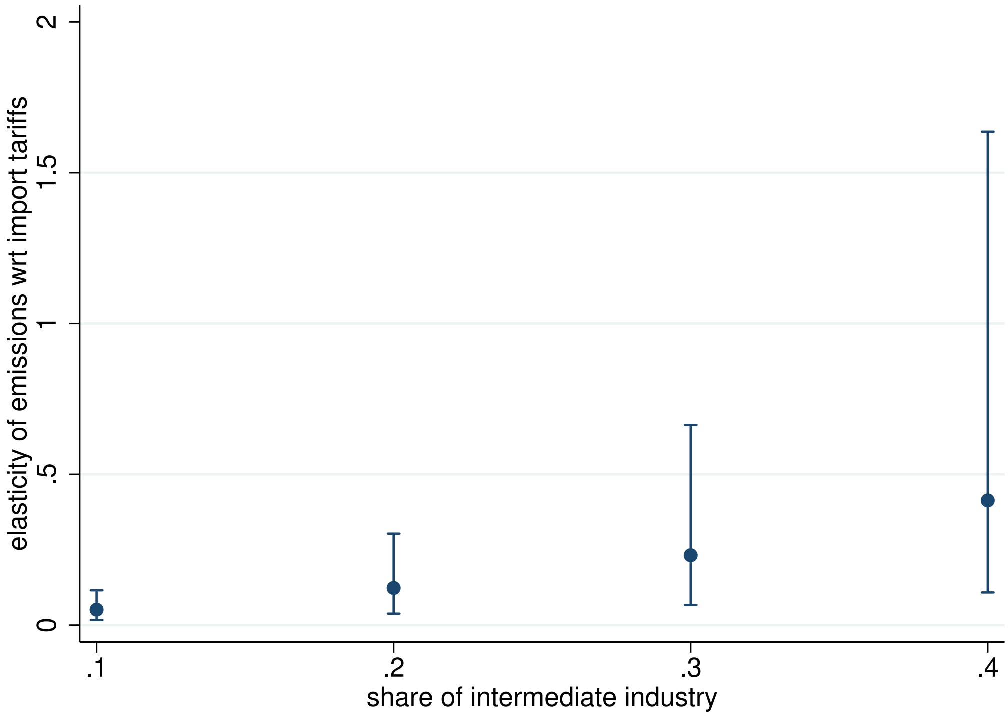


Figure 3. The elasticity of aggregate emissions with respect to import tariffs.
Notes: The figure shows computed values for the elasticity of aggregate emissions to the cost of importing, $\varepsilon_{t,\tau}$, for a range of values for the share of intermediate inputs in production. The expression for $\varepsilon_{t,\tau}$ is given by (34) and the values for α are calculated by setting $(1-\alpha)(1-\mu)$ equal to the coefficient on log productivity in column 3 in Table 6. The point estimates are indicated by dots while the lines display 90% confidence intervals based on the standard errors in the regression.

share of foreign intermediate inputs in production. According to the World Input-Output Database (WIOD), this number was 25.1% in the Swedish manufacturing sector in 2014. In order to back out α we use this number together with the estimated coefficient for productivity in Column 2 of Table 6, noting that a is an inverse measure of productivity. This gives $\alpha = 0.59$ and that the elasticity of aggregate emissions with respect to the cost of importing is 0.17.[16]

A higher intermediate share implies from Figure 3 that trade liberalization has a stronger effect on firms' marginal cost and therefore, that the rise in emission taxes that keeps the price index constant is higher. Trade liberalization therefore leads to a stronger decrease in emissions when μ is high. Using the WIOD number for μ and the implied elasticity of 0.17 means that a trade liberalization of 10 percent on imports would in this case imply that a 1.7 percent decrease in emissions would be feasible while maintaining the utility from consumption constant.

[16] We here use that according to equation (35), our coefficient on productivity in Column 4 of Table 6 is equal to $-(1-\alpha)(1-\mu)$. The coefficient on productivity is -0.305 and μ is 0.251 from the WIOD database which implies that $\alpha = 0.59$. We then use these values to compute $\varepsilon_{t,\tau} = \frac{\mu(1-\alpha)}{\alpha} = 0.17$.

7 Conclusion

Our paper explores the role of importing in determining the carbon emissions of firms. Estimating this effect at the firm level is challenging. For example, more productive firms are both likely to offshore more and have lower emission intensities since they use inputs more efficiently. Therefore, we exploit shocks to importing that originate outside Sweden. Specifically, we interact firm-level sourcing patterns by country and product in the years prior to our sample with how the aggregate supply of products by source country has changed, and use this to predict the levels of importing which are only due to events abroad and not at the firm level. In this way we break the correlation at the firm level between unobservable determinants of emission intensity and importing. A positive supply shock among the Canadian producers of steel bolts will, for example, increase the predicted level of importing for firms that imported steel bolts from Canada prior to the sample more than for other firms.

We find a statistically significant effect of importing on the emission intensity of Swedish firms. Importing reduces the emission intensities. We challenge our data by including industry-specific and region-specific time trends, but we find that this does not alter our results. We go further by arranging all firms according to the year in which their firm-specific largest increase in predicted importing takes place, and we find that the largest drop in emission intensity on average occurs in exactly this year.

Why does importing reduce carbon emissions? The most important mechanism, that we identify, is that access to foreign inputs improves the total factor productivity of firms. This could, for example, be due to the fact that importing allows firms to access a wider set of potential intermediate inputs and therefore find inputs that better match their specific needs. We develop a theoretical model that incorporates this effect of importing into a heterogenous firm model in which production generates emissions. The model allows us to analyze the general equilibrium effect of a reduction in the cost of importing on aggregate emissions. We first note that the improvement in productivity from importing reduces the marginal costs of firms and thus also prices. This increases the consumption of goods which may actually lead to there not being any reduction in emissions at all – all efficiency gains of importing are channeled into an increase in consumption rather than a reduction of emissions. However, a policy maker can use emission taxation as a way of avoiding this outcome. Using our empirical estimates, we find that if a policy maker introduces an emission tax that keeps utility from consumption constant, then the elasticity of aggregate emissions with respect to import tariffs is 0.17. This implies that a trade liberalization of 10 percent on imports could be coupled with a 1.7 percent decrease in emissions while maintaining the utility from consumption constant.

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Appendix A (for online publication): Productivity estimates

We implement the two-stage estimation routine developed in Levinsohn and Petrin (2003) and Petrin et al. (2004) to estimate firm-level productivity. In particular, we let the value-added production function for firm i in year t be approximated by

$$v_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \tag{36}$$

where v_{it} is the log of value-added, l_{it} is the log of labor costs, and k_{it} is the log of capital. l_{it} is assumed to be a freely variable input whereas k_{it} is a state variable. The error term is additively separable and consists of one productivity component ω_{it}, a state variable that influences firms' decisions, and one i.i.d. component η_{it} which is uncorrelated with the regressors.

The objective is to consistently estimate the parameters β_k and β_l. This is achieved by using an intermediate input ι as a proxy to control for the correlation between ω_{it} and the regressors. The critical assumption is that the demand for this input is a function of the two state variables capital and productivity

$$\iota_{it} = \iota_t(\omega_{it}, k_{it}) \tag{37}$$

and that this function is monotonically increasing in ω_{it}. This allows the unobserved productivity component to be expressed as a function of the intermediate input and capital

$$\omega_{it} = \omega_t(\iota_{it}, k_{it}) \tag{38}$$

It is also assumed that ω_{it} follows a first-order Markov process

$$\omega_{it} = \mathbb{E}[\omega_{it} | \omega_{it-1}] + \xi_{it} \tag{39}$$

and that the innovations to productivity ξ_{it} do not influence the current capital stock k_{it}.

We use the log of raw materials as our intermediate input ι_{it}. Equation (38) makes it possible to express the production function as

$$v_{it} = \beta_l l_{it} + \phi_t(\iota_{it}, k_{it}) + \eta_{it} \tag{40}$$

where

$$\phi_t(\iota_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + \omega_t(\iota_{it}, k_{it}) \tag{41}$$

The simultaneity problem can now be solved by approximating $\phi_t(\iota_{it}, k_{it})$ with a flexible polynomial in k_{it} and ι_{it}.[17] However, estimating (40) with OLS only gives a consistent estimate of β_l. To obtain a consistent estimate of β_k as well requires a second stage of the estimation routine. In particular, what is needed is a consistent estimate of $\mathbb{E}[\omega_{it}|\omega_{it-1}]$ in equation (39). Levinsohn and Petrin (2003) show that this can be achieved by using the estimates $\hat{\beta}_l$ and $\hat{\phi}_{it}$ obtained from the first stage of the routine. With this at hand, $\hat{\beta}_k$ is then given by

$$\hat{\beta}_k = \arg\min_{\beta^*} \sum_t \sum_i \left(v_{it} - \hat{\beta}_l l_{it} - \beta_k^* k_{it} - \widehat{\mathbb{E}[\omega_{it}|\omega_{it-1}]}\right)^2 \tag{42}$$

Lastly, firm-level productivity is computed using the plug-in estimator

$$\hat{\omega}_{it} = \exp(v_t - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}) \tag{43}$$

There are a few things worth noting about this estimator in general and our implementation of it in particular. First, an implicit assumption underlying the input demand function $\iota_{it} = \iota_t(\omega_{it}, k_{it})$ is that input prices are common across firms. To allow more flexibility, we estimate β_l and β_k for each industry separately at the NACE two-digit level. Thus, factor prices are allowed to vary across industries in our application.

Second, there are several possible candidates of intermediate inputs to be used as proxies in this routine. Levinsohn and Petrin (2003) propose a "non-zeros" criterion to guide this decision where inputs with a small fraction of zero observations in the data are preferred to inputs with a large fraction. We note that only about 6 percent of the firm-level observations on raw materials in our sample are zero values.

Third, our measure of l_{it} differs from that used by Levinsohn and Petrin (2003). Instead of measuring labor input by the number of workers employed and distinguishing between skilled and unskilled labor in the production function, we use the total wage bill. As suggested by Fox and Smeets (2011), the wage bill may be viewed as a quality-adjusted measure of labor input that accounts for productivity differences across workers.

[17] We use a third-order polynomial following Petrin et al. (2004).

Appendix B (for online publication): Shift-share instrument

We build on the framework developed by Borusyak et al. (forthcoming) to motivate our shift-share design. The causal relationship of interest is given by

$$e_{it} = \beta m_{it} + x_{it}'\delta + \varepsilon_{it} \tag{44}$$

where e_{it} denotes the emission intensity of firm i in year t; β denotes the structural parameter of interest; m_{it} denotes the log of imports, x_{it} denotes a vector of control variables including a constant and firm and year fixed-effects; and ε_{it} denotes the residual which is defined as being orthogonal with x_{it}.

Our shift-share instrument is given by

$$z_{it} = \sum_c \sum_p s_{icp} X_{cpt} \tag{45}$$

where s_{icp} is firm i's import share of input p from country c in a pre-sample year; and X_{cpt} is the world export supply of input p from country c in year t. Importantly, we consider the foreign supply shocks, X_{cpt}, in this instrument to be random variables which implies that we cannot assume independent and identically distributed observations at the firm-year level.

The key identifying assumption is the following full-data moment condition

$$\mathbb{E}\left[\sum_i \sum_t z_{it}\varepsilon_{it}\right] = 0 \tag{46}$$

which states that z_{it} is orthogonal with ε_{it} in expectation over $\{z_{it}, \varepsilon_{it}\}$ for all $(i,t) \in N_i \times N_t$, where N_i is the set of all firms and N_t is the set of all years. Together with an instrument-relevance condition, β is identified.

Proof. Let

$$e_{it} = x_{it}'\alpha + e_{it}^{\perp} \tag{47}$$

$$m_{it} = x'\gamma + m_{it}^{\perp} \tag{48}$$

By the Frisch-Waugh-Lovell theorem we then have

$$e_{it}^{\perp} = \beta m_{it}^{\perp} + \varepsilon_{it} \tag{49}$$

It follows by assumption that

$$\mathbb{E}\left[\sum_i \sum_t z_{it}\varepsilon_{it}\right] = \mathbb{E}\left[\sum_i \sum_t z_{it}e_{it}^{\perp}\right] - \beta\mathbb{E}\left[\sum_i \sum_t z_{it}m_{it}^{\perp}\right] = 0 \tag{50}$$

Re-arranging gives

$$\beta = \frac{\mathbb{E}\left[\sum_i \sum_t z_{it}e_{it}^{\perp}\right]}{\mathbb{E}\left[\sum_i \sum_t z_{it}m_{it}^{\perp}\right]} \tag{51}$$

where $\mathbb{E}\left[\sum_i \sum_t z_{it}m_{it}^{\perp}\right] \neq 0$ is the instrument-relevance condition. $\square$

We can re-formulate the full-data moment condition in equation (46) by substituting for z_{it} using equation (45)

$$\mathbb{E}\left[\sum_c \sum_p \sum_t X_{cpt}\varepsilon_{cpt}s_{cp}\right] = 0 \tag{52}$$

where $\varepsilon_{cpt} = \frac{\sum_i s_{icp}\varepsilon_{it}}{\sum_i s_{icp}}$ is an exposure weighted average of the residuals and $s_{cp} = \frac{1}{|N_i|}\sum_i s_{icp}$ is the average pre-sample exposure to supply shock (c,p). A sufficient condition for equation (52) to be satisfied is that the shocks are as-good-as-randomly assigned conditional on $\varepsilon = \left\{\varepsilon_{cpt}\right\}_{cpt}$ and $s = \left\{s_{cp}\right\}_{cp}$

$$\mathbb{E}\left[X_{cpt}|\varepsilon, s\right] = \mu \tag{53}$$

for all (c,p,t).

Proof. By the Law of Iterated Expectations and equation (53) we have

$$\begin{aligned}
\mathbb{E}\left[\sum_c \sum_p \sum_t X_{cpt}\varepsilon_{cpt}s_{cp}\right] &= \mathbb{E}\left[\mathbb{E}\left[\sum_c \sum_p \sum_t X_{cpt}\varepsilon_{cpt}s_{cp}\middle|\varepsilon, s\right]\right] \\
&= \mathbb{E}\left[\sum_c \sum_p \sum_t \varepsilon_{cpt}s_{cp}\mathbb{E}[X_{cpt}|\varepsilon, s]\right] \\
&= \mu\mathbb{E}\left[\sum_c \sum_p \sum_t \varepsilon_{cpt}s_{cp}\right]
\end{aligned} \tag{54}$$

By the definitions of ε_{cpt} and s_{cp}, the last term can be re-written as

$$\begin{aligned}\mathbb{E}\left[\sum_c\sum_p\sum_t \varepsilon_{cpt}s_{cp}\right] &= \frac{1}{|N_i|}\mathbb{E}\left[\sum_c\sum_p\sum_t\sum_i s_{icp}\varepsilon_{it}\right] \\ &= \frac{1}{|N_i|}\mathbb{E}\left[\sum_i\sum_t \varepsilon_{it}\sum_c\sum_p s_{icp}\right] \\ &= \frac{1}{|N_i|}\sum_i\sum_t \mathbb{E}[\varepsilon_{it}]\end{aligned} \tag{55}$$

where the last equality follows from $\sum_c\sum_p s_{icp} = 1$ for all i. Since $\mathbb{E}[\varepsilon_{it}] = 0$ for all (i,t) by construction, we conclude that equation (53) is a sufficient condition for equation (52) to be satisfied. $\square$

Equation (53) is however an unnecessary strong condition to impose in our setting. With fixed exposure shares $\{s_{icp}\}_{cp}$ that sum to one for all firms i, the firm and year fixed effects purge both the time-invariant component of the shocks, X_{cpt}, as well as their common year-specific component (Borusyak et al., Forthcoming). To identify β it is therefore sufficient to instead impose

$$\mathbb{E}[X_{cpt}|\varepsilon,q,s] = q'_{cpt}\mu \tag{56}$$

for all (c,p,t), where q_{cpt} is a shock-specific vector including a constant, shock-level fixed effects and time fixed effects, and $q = \{q_{cpt}\}_{cpt}$ is the set containing these vectors. This implies that only shock-specific changes in the foreign export supply over time is required to be as-good-as-randomly assigned to identify a causal effect.

For consistency, we also assume that the following two conditions hold

$$\mathbb{E}\left[\sum_c\sum_p s_{cp}^2\right] \to 0 \quad \text{as } |N_i| \to \infty \tag{57}$$

$$\text{Cov}[\tilde{X}_{cpt},\tilde{X}_{c'p't'}|\varepsilon,q,s] = 0 \quad \text{for all } (c,p) \neq (c',p') \tag{58}$$

where $\tilde{X}_{cpt} = X_{cpt} - q'_{cpt}\mu$ denotes demeaned export supply shocks. Equation (57) holds if the number of shocks X_{cpt} grows with the sample (in the i-dimension) and the average pre-sample exposure weights s_{cp} are sufficiently dispersed. Equation (58) states that time-varying changes in the foreign supply shocks (c,p) are mutually uncorrelated but that serial correlation within each (c,p) is allowed.

Given equations (56), (57), (58), a first-stage and a set of regularity assumptions, the shift-share estimator is consistent. For a proof, see Borusyak et al. (forthcoming).

Appendix C (for online publication): Linear mediation model

The mediation model in Section 5 is derived using the framework developed by Heckman and Pinto (2015) and is closely related to the model used by Fagereng et al. (2021). In its most general form, our linear mediation model, which approximates the structural relationship between the mediators of importing and the emission intensity of firms, is given by,

$$e_m = \kappa_m + \sum_{j \in \mathscr{J}_O} \beta_m^j g_m^j + \sum_{j \in \mathscr{J}_U} \beta_m^j g_m^j + x'\delta_m + \tilde{\varepsilon}_m \tag{59}$$

where e_m is the potential log emission intensity of a firm with log import level $M = m$; κ_m is an import-specific intercept; $\mathscr{J}_O$ and $\mathscr{J}_U$ are the sets of observed and unobserved mediators, respectively; g_m^j is the log of mediator j; β_m^j is the effect of mediator j when the import level is m; x is a vector of pre-determined variables which in our setting contains firm and year fixed effects; δ_m contains the effects of the pre-determined variables which may depend on the import level m; and $\tilde{\varepsilon}_m$ is a mean-zero error term that is orthogonal to the set of mediators $\left\{g_m^j\right\}_j$ and the vector of controls x, by assumption.

We can reformulate this model by moving the unobserved mediators into an intercept and an error term as follows,

$$e_m = \zeta_m + \sum_{j \in \mathscr{J}_O} \beta_m^j g_m^j + x'\delta_m + \varepsilon_m \tag{60}$$

where $\zeta_m = \kappa_m + \sum_{j \in \mathscr{J}_U} \beta_m^j \mathbb{E}[g_m^j]$ is the new intercept and $\varepsilon_m = \tilde{\varepsilon} + \sum_{j \in \mathscr{J}_U} \beta_m^j (g_m^j - \mathbb{E}[g_m^j])$ is the new mean-zero error term. The error term, ε_m, is not independent of the observed mediators if these are correlated with the unobserved mediators.

In the next step we follow Fagereng et al. (2021) and assume that the parameters in equation (60) depend either linearly on imports, or not at all, such that,

$$\begin{aligned}
\zeta_m &= \zeta_0 + \zeta m \\
\beta_m^j &= \beta^j \qquad \text{for all } j \in \mathscr{J}_O \\
\delta_m &= \delta.
\end{aligned} \tag{61}$$

The last two assumptions are so-called structural invariance assumptions. These entails that importing is assumed to only affect emission intensity by affecting the values of the observed mediators, not by changing the mapping between the observed mediators and emission intensity. Substituting equation (61) into equation (60) gives the mediation model in Section 5:

$$e_m = \zeta_0 + \zeta m + \sum_{j \in \mathscr{J}_O} \beta^j g_m^j + x'\delta + \varepsilon_m \tag{62}$$

where we model the relationship between each observed mediator and the log of imports as,

$$g_m^j = \gamma_0^j + \gamma^j m + x'\delta^j + \varepsilon^j \qquad \text{for all } j \in \mathscr{J}_O, \tag{63}$$

with ε^j being a mean-zero error term. For further details on the linear mediation model and its formal properties, see Heckman et al. (2013) and Heckman and Pinto (2015).

Appendix D (for online publication): Additional tables

Descriptive statistics

Table D.1. Descriptive statistics.

Production	2004	2010	2016	Overall
Revenues (log)	19.01	19.19	19.26	19.18
	(1.50)	(1.51)	(1.52)	(1.50)
Value added (log)	17.90	18.03	18.13	18.02
	(1.46)	(1.45)	(1.49)	(1.45)
Total factor productivity (log)	9.22	9.15	9.18	9.17
	(1.23)	(1.21)	(1.23)	(1.23)
Intermediates (log)	15.52	15.41	15.50	15.53
	(3.35)	(3.95)	(3.94)	(3.75)
Capital (log)	17.25	17.29	17.26	17.28
	(1.87)	(1.93)	(2.03)	(1.93)
Intermediate cost share	0.07	0.08	0.09	0.08
	(0.15)	(0.16)	(0.19)	(0.17)
Employees				
Number of employees (log)	4.62	4.62	4.63	4.64
	(1.31)	(1.26)	(1.28)	(1.28)
Total wage bill (log)	17.18	17.32	17.44	17.33
	(1.36)	(1.32)	(1.34)	(1.34)
Trade				
Imports (log)	16.62	16.90	16.84	16.88
	(2.32)	(2.30)	(2.57)	(2.30)
Exports (log)	17.30	17.60	17.60	17.56
	(2.72)	(2.51)	(2.62)	(2.60)
Emissions				
CO2 (log kilo)	12.96	12.90	12.57	12.81
	(2.56)	(2.53)	(2.65)	(2.57)
CO2 intensity (log kilo per value added SEK)	-4.94	-5.21	-5.68	-5.29
	(1.97)	(2.06)	(2.24)	(2.11)

Notes: The sample is balanced and covers the years 2004-2016. The total number of observations is 7,930. Total factor productivity is calculated by using the method outlined in Levinsohn and Petrin (2003). All nominal variables are in 2004 prices.

Table D.2. Share of imports from top 5 industries and countries

	Base sample	Full sample
Industries		
Machinery and equipment n.e.c. (NACE C28)	0.18	0.14 (1)
Motor vehicles, trailers and semi-trailers (NACE C29)	0.17	0.12 (3)
Chemicals and chemical products (NACE C20)	0.14	0.12 (2)
Basic metals (NACE C24)	0.12	0.10 (4)
Food products (NACE C10)	0.06	0.06 (7)
Countries		
Germany	0.21	0.18 (1)
France	0.09	0.06 (4)
United Kingdom	0.08	0.07 (3)
Belgium	0.08	0.05 (8)
Norway	0.06	0.07 (2)

Notes: The base sample is balanced and comprises 610 manufacturing firms and covers the years 2004-2016. The base sample consists of 7,930 firm-year observations. The full sample is unbalanced and comprises all manufacturing firms (NACE C10-C33) that import (however, some small importers may be excluded, see Section 2) and covers the years 2004-2016. The full sample consists of 109,564 firm-year observations. The upper panel reports the share of the total import flow over 2004-2016 in the base sample and the full sample, respectively, that is imported from the top five 2-digit NACE industries, where the top five industry ranking is based on the imports among firms in the base-sample. Within parenthesis, the corresponding ranking of the industry in the full sample is reported. The lower panel reports the share of the total import flow over 2004-2016 in the base sample and the full sample, respectively, that is imported from the top five countries, where the top five country ranking is based on the imports among firms in the base sample. Within parenthesis, the corresponding ranking of the country in the full sample is reported. All import flows are measured in SEK.

Table D.3. Top five industries in output, import intensity and emission intensity

	Base sample	Full sample
Output share		
Manufacture of motor vehicles, trailers and semi-trailers (NACE C29)	0.21	0.14 (1)
Manufacture of paper and paper products (NACE C17)	0.11	0.07 (5)
Manufacture of basic metals (NACE C24)	0.11	0.08 (4)
Manufacture of food products (NACE C10)	0.11	0.09 (3)
Manufacture of machinery and equipment n.e.c. (NACE C28)	0.09	0.10 (2)
Import intensity		
Manufacture of wearing apparel (NACE C14)	0.83	0.45 (2)
Manufacture of motor vehicles, trailers and semi-trailers (NACE C29)	0.38	0.31 (4)
Manufacture of electrical equipment (NACE C27)	0.33	0.22 (8)
Manufacture of chemicals and chemical products (NACE C20)	0.31	0.30 (5)
Manufacture of rubber and plastic products (NACE C22)	0.29	0.26 (6)
Carbon intensity		
Manufacture of paper and paper products (NACE C17)	0.59	
Manufacture of basic metals (NACE C24)	0.31	
Manufacture of other non-metallic mineral products (NACE C23)	0.13	
Manufacture of wood and of products of wood and cork (NACE C16)	0.11	
Manufacture of chemicals and chemical products (NACE C20)	0.03	

Notes: The base sample is balanced and comprises 610 manufacturing firms and covers the years 2004-2016. The base sample consists of 7,930 firm-year observations. The full sample is unbalanced and comprises all manufacturing firms (NACE C10-C33) and covers the years 2004-2016. The full sample consists of 703,646 firm-year observations. The upper panel reports the output share of the top five industries (in terms of output share) among firms in the base sample and the full sample, respectively, where the top five ranking of industries is based on the base sample. The corresponding ranking of the industry in the full sample is reported within parenthesis. The middle panel reports the import intensity (measured as total value of imports over total value of output) of the top five industries (in terms of import intensity) among firms in the base sample and the full sample, respectively, where the top five ranking of industries is based on the base sample. The corresponding ranking of the industry in the full sample is reported within parenthesis. The lower panel reports the carbon intensity (measured as total CO_2 emissions over total value of value added) of the top five 2-digit NACE industries (in terms of emission intensity) among firms in the base sample. All nominal variables are measured in SEK.

Regression results

Table D.4. First-stage effects – Robustness analysis.

	First stage			
	Baseline	Industry trends	Regional trends	Industry + regional trends
Dep. var.: log imports	(1)	(2)	(3)	(4)
log world export supply	0.201***	0.191***	0.199***	0.206***
	(0.051)	(0.052)	(0.051)	(0.052)
N	7,930	7,930	7,930	7,930
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Industry trends		✓		✓
Regional trends			✓	✓
F-statistic	15.3	13.6	15.1	16.0

Notes: The sample is balanced and covers the years 2004-2016. All columns refer to the first-stage regression where we instrument log imports by the instrument defined in equation in (2). The dependent variable in all regressions is log imports. All regressions include year and firm fixed effects. Column (1) reports our baseline regression. Columns (2), (3) and (4) include trends for 2-digit NACE industry, region (county), and both industry and region, respectively. The reported F-statistic is the first-stage Kleibergen-Paap F-statistic. Robust standard errors are in parentheses. *** 1%, ** 5% and * 10%.

Table D.5. The effect of importing on CO2 intensity - Additional robustness checks

	IV					
	Baseline	SWE share of WES < 10 %	Baseline	Year 2000 pre-sample	Baseline	Lagged controls
	(1)	(2)	(3)	(4)	(5)	(6)
log imports	-0.879***	-1.050**	-0.716***	-0.895**	-0.714***	-0.466**
	(0.325)	(0.459)	(0.248)	(0.368)	(0.261)	(0.200)
lag log CO2 intensity						0.553***
						(0.026)
lag log value added						0.302***
						(0.080)
lag log exports						0.023
						(0.024)
lag log productivity						0.023
						(0.050)
N	7,761	7,761	7,302	7,302	7,108	7,108
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
F-statistic	11.4	6.7	15.4	7.3	14.2	14.0

Notes: The samples are unbalanced and covers the years 2004-2016 and are sub-samples of the base sample. In columns (1) and (2), the sample consists of all firm-years for which the shift-share instrument in equation (2) is non-zero when excluding country-input-years in the world export supply variable, X_{cpt}, for which the share of total world export supply that is exported to Sweden exceeds 10 percent (since the log of the instrument is not defined for zero values). In column (2) we have excluded these country-input-years from the world export supply variable, X_{cpt}, in the instrument. This entails that the pre-sample exposure shares in the instrument, s_{icp}, are incomplete for some firms, i.e. they do not sum to one. To account for this, which can introduce bias if not addressed, we follow Borusyak et al. (forthcoming) and control for the sum of exposure shares for each firm and year. We also interact the sum of exposure shares with the year fixed effects. In column (1) we use the baseline instrument defined in equation (2). In columns (3) and (4), the sample consists of all firm-years in the base sample with positive imports in year 2000 and for which at least one X_{cpt} with positive weight is positive (since otherwise the log of the instrument is not defined). In column (4) we have computed the exposure shares, s_{icp}, in the instrument in equation (2) based on 2000 imports while in column (3) we use the baseline instrument based on 2003 imports. In columns (5) and (6), the sample consists of all firm-years in the base sample with non-missing values on the lag log CO2 intensity (measured as the previous year's log of total CO2 emissions over value added), the lag log value added, the lag log export volume and the lag log productivity (measured using the method outlined in Levinsohn and Petrin (2003)). Since we only have data on total CO2 emissions from 2004, the sample in column (5) and (6) covers the years 2005-2016. In column (5) and (6) we use the baseline instrument defined in equation (2). The dependent variable in all regressions is the log CO2 intensity. All regressions include year and firm fixed effects. The reported F-statistic is the first-stage Kleibergen-Paap F-statistic. Robust standard errors are in parentheses. *** 1%, ** 5% and * 10%.

Table D.6. The effect of importing on CO2 intensity - Heterogeneous effects across industries

	IV					
	(1)	(2)	(3)	(4)	(5)	(6)
log imports	-0.557***	-0.558***	-0.553***	-0.552***	-0.559***	-0.566***
	(0.201)	(0.200)	(0.200)	(0.199)	(0.201)	(0.203)
log imports × NACE C17	-0.012					
(Paper products)	(0.009)					
log imports × NACE C24		-0.020*				
(Basic metal products)		(0.011)				
log imports × NACE C23			0.002			
(Non-metallic mineral products)			(0.010)			
log imports × NACE C16				-0.008		
(Wood products)				(0.015)		
log imports × NACE C20					-0.075***	
(Chemical products)					(0.026)	
log imports × NACE Top Five						-0.026***
						(0.007)
N	7,930	7,930	7,930	7,930	7,930	7,930
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
F-statistic	7.6	7.6	7.6	7.7	7.7	7.6

Notes: The sample is balanced and covers the years 2004-2016. In column (1)-(5) we add an interaction between log imports and a dummy variable indicating whether a firm belong to NACE C17, C24, C23, C16 or C20, respectively, to our baseline specification in equation (1). We instrument for log imports using log Z_{it} defined in equation (2). We instrument for the interaction variable using an interaction between log Z_{it} and each of the respective dummy variables. In column (6) we add an interaction between log imports and a dummy variable indicating whether a firm belong to NACE C17, C24, C23, C16 or C20. We instrument for log imports using log Z_{it} defined in equation (2). We instrument for the interaction variable using an interaction between log Z_{it} and the dummy variable. The dependent variable in all regressions is the log CO2 intensity (measured as CO2 emissions over value added). All regressions include year and firm fixed effects. The reported F-statistic is the first-stage Kleibergen-Paap F-statistic. Robust standard errors are in parentheses. *** 1%, ** 5% and * 10%.