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IZA DP No. 16556

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ISSN: 2365-9793

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ABSTRACT

The Impact of Offshoring and Import Competition on Firm-Level Carbon Emissions*

We use Danish firm-level data to examine the causal link between carbon emissions, offshoring, and import competition. Offshoring reduces firms' emission intensity but increases their production. Import competition reduces firms' production without affecting their emission intensity. For Denmark, these effects imply that observed offshoring trends reduced the overall manufacturing emission intensity while import competition did not. However, despite the emission reducing effects in local manufacturing, offshoring did not affect global emissions. Furthermore, import competition substantially increased global emissions. Therefore, based on offshoring and Chinese import competition, our results suggest that international trade may be bad for the global environment.

JEL Classification: F14, F18, Q54, Q56
Keywords: carbon emissions, offshoring, import competition

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* We thank Morten Bennedsen, Jevan Cherniwchan, Rikard Forslid, Alessia Lo Turco, Luca Macedoni, Joel Rodrigue, Bertel Schjerning, Joe Shapiro, Reed Walker and seminar and conference participants at SNEE Malmø 2021, OASIS 2022, Midwest International Trade Conference Purdue 2022, Berkeley 2022, DIEW Aarhus 2022, SETC Sardinia 2022, LSE Environment Week 2022 and EWMES Berlin 2022 for helpful comments.

1 Introduction

As carbon emissions associated with manufacturing fall in rich countries, they increase substantially in developing countries (Copeland, Shapiro, and Taylor 2022). At the same time, two dominant trends in globalization, import competition from China and the off-shoring of intermediate inputs, have a potentially substantial impact on the location of production (Autor, Dorn, and Hanson 2013; Johnson and Noguera 2012). However, causal evidence on the effect of international trade on local and global environmental outcomes is surprisingly limited (Najjar and Cherniwchan 2021). Therefore, in this paper we use Danish firm-level data to examine how increased international trade affects local and global carbon emissions in manufacturing.

To guide our empirical analysis, we first decompose the decline in the overall Danish manufacturing emission intensity into technique (within-firm) and composition (between-firm) components using firm-level data. The technique component reflects changes in firms' emission intensities over time, and the composition component represents the contribution from changes in output across firms.[1] We use detailed firm-level data with information about carbon emissions to perform the decomposition. We find that the technique and composition components contribute equally to the fall in the manufacturing emission intensity. Therefore, trade related mechanisms that explain within-firm and between-firm adjustments appear equally important to understand the effect of international trade on the environment.

Consequently, our first contribution is to jointly estimate the effects of Chinese import competition and offshoring on firm-level emissions to investigate how they have contributed to the cleanup of Danish manufacturing. We focus on firm level sales and emission intensities to be consistent with the decomposition framework. Chinese import competition is expected to lead to reallocation across firms and industries, so it should drive the composition component. Offshoring is a firm-specific choice, which we expect mainly to affect the technique component, as polluting production processes are moved to places with comparative advantage in producing those inputs. However, offshoring may also increase productivity of firms (Grossman and Rossi-Hansberg 2008) leading to higher

[1] Similar decompositions have mainly been carried out at the industry or product-level (e.g. Antweiler, Copeland, and Taylor 2001; Levinson 2009; Shapiro and Walker 2018). In such decompositions, the technique (within-industry) component is typically found to clearly dominate.

output and emissions, which will feed into the composition component.

We face endogeneity issues as imports from China may depend on the performance of local firms, and as firms may select into offshoring. To solve this identification challenge we rely on the existing trade literature and use two different instruments, that build on supply and demand shocks driven by changes to comparative advantages abroad. Chinese import penetration in an industry is instrumented with the share of Chinese final goods in imports in a group of other developed countries in that industry (e.g. Autor, Dorn, and Hanson 2013). Offshoring is instrumented by a shift-share instrument in which the "shares" are firm-level origin-product import shares and the "shifts" are origin-product export flows to other countries than Denmark following Hummels et al. (2014).

We find that Chinese import competition has a negative impact on firm-level sales. The effect is significantly larger for the most pollution intensive firms. However, Chinese import competition is found not to affect the firm-level emission intensity. Offshoring has a negative impact on the firm-level emission intensity, such that firms become cleaner when they increase their offshoring. On the other hand, we find that offshoring increases firm scale through higher sales and emissions. Thus, comparative advantage driven changes in Chinese import competition and offshoring have very distinct effects on firm-level carbon emissions, and the net effect on overall manufacturing emissions is unclear without further investigation.

Our second contribution is then to put the estimated firm-level responses to Chinese import competition and offshoring into the context of our decomposition of the overall decline in the manufacturing emission intensity. In particular, we generate the hypothetical decline in the manufacturing emission intensity in the absence of import competition and offshoring and compare it to the observed decline in the manufacturing emission intensity.

We find that offshoring has contributed to the overall decline in the manufacturing emission intensity through its effect on firm-level emission intensities and the technique component. In isolation this effect accounts for roughly four fifths of the decline.[2] There is also a contribution to the decline in the manufacturing emission intensity from the productivity effect of offshoring. Firms that grow due to offshoring tend to be relatively clean such that dirty firms are left with lower market shares, which in total leads to a lower

[2] Cherniwchan and Taylor (2022) outlines the "third empirical challenge" in international trade and the environment, which is to obtain estimates of the trade-induced technique effect. Our finding provides strong evidence that trade helps explain the technique effect.

overall manufacturing emission intensity. By contrast, even if Chinese import competition causes exposed domestic firms to shrink, there is no net contribution to the overall manufacturing emission intensity. This is because the least pollution intensive Danish manufacturing industries have experienced the largest inflows of final goods from China (e.g. textiles and electronics), which tends to reallocate economic activity towards dirtier production. In other words, exposed clean firms shrink, while dirtier firms gain market shares. Thus offshoring and Chinese import competition have very different implications for the domestic manufacturing emission intensity.

Our third contribution is to assess the implications of offshoring and Chinese import competition for global emissions. Climate change is a global challenge caused by the global carbon emission level, and so it is important to assess the extent to which reductions in local emissions are offset by increased emissions elsewhere. We quantify the impacts of offshoring and Chinese import competition by calculating carbon leakage rates that incorporate the causal relationships previously estimated. To calculate the increase in emissions abroad associated with changes in final good imports and offshoring in Danish firms, we use product-by-country CO_2 intensities from around fifty countries. The leakage rate calculations show that emissions embodied in imports of intermediate inputs are similar in magnitude to the domestic emission reduction caused by the import flows. By contrast, emissions embodied in final good imports from China are much larger than the domestic emission reduction.[3] Thus, overall, offshoring leaves global carbon emissions largely unchanged, while import competition from China strongly increases global carbon emissions.

As highlighted by Copeland, Shapiro, and Taylor (2022) there has been relatively little work that attempts to identify the causal effect of increased trade due to comparative advantage in affecting environmental outcomes, and only very few papers consider a global pollutant such as CO_2 as the outcome.[4] The work closest related to ours are Dussaux,

[3]Bombardini and Li (2020) provide evidence for comparative advantage playing a role in deteriorating environmental outcomes in China (as measured by child mortality) in response to their recent export expansion.

[4]A small set of papers examine the implications of trade liberalization for firm-level pollution. Martin (2011) finds that trade reform in India increased firm-level fuel efficiency, and Cherniwchan (2017) documents that NAFTA reduced emissions of local pollutants from manufacturing firms in the U.S. Gutiérrez and Teshima (2018) finds that increased import competition triggered by tariff reductions in Mexico caused firms to increase their energy efficiency. Choi et al. (2023) shows that a reduction in US trade policy uncertainty against China reduced emissions of a local pollutant (particulate matter) from U.S. firms.

Vona, and Dechezleprêtre (2023) and Akerman, Forslid, and Prane (2021), who estimate the effect of firm-level offshoring on CO_2 emissions in French and Swedish firms. They also find that offshoring reduces the firm-level emission intensity. Compared to the findings of the literature, we consider both offshoring and Chinese import competition and find very distinct effects, we quantify our estimation results and show the contribution of offshoring and Chinese import competition to the overall manufacturing emission intensity in our decomposition framework, and we examine the consequences for global pollution. In particular, we show how the rise of China has a strong positive impact on global carbon emissions, while offshoring leaves global emissions unchanged.

The rest of the paper is structured as follows. Section 2 describes the firm level data for carbon emissions and international trade transactions. Section 3 performs a decomposition of the change in the Danish manufacturing emission intensity. Section 4 outlines the empirical methodology including our identification strategy. Section 5 presents estimation results, counterfactual decompositions and leakage rate calculations. Section 6 concludes.

2 Data and Descriptive Statistics

We rely on firm-level data for 1995-2016 from administrative registers in Statistics Denmark. Firms are identified by a unique identifier in the FirmStat register that holds information about basic variables such as industry affiliation (NACE classification), sales, value added and employment. The firm identifier enables us to merge on two main sources of additional data: firm-level carbon emissions and detailed records of trade flows.

Our measure of firm-level emissions is based on the Industrial Energy Use Survey conducted by Statistics Denmark. The survey covers manufacturing firms with 20 or more employees, and the firms included capture around 90 percent of total energy use in manufacturing. The survey has a high response rate of 98-99 percent and asks firms about their use of an exhaustive list of energy goods including oil, coal and electricity, all measured in giga joules (GJ). The survey is typically conducted biannually, with the first year being 1995 and the last 2016.[5] We convert energy in giga joules to emissions of CO_2 in tonnes using energy good-specific 'emission coefficients'. This approach follows

[5]The complete list of years we use is 1995, 1996, 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2012, 2014 and 2016.

from basic physics whereby the amount of carbon dioxide emitted from burning e.g. a ton of coal is approximately fixed (e.g. Metcalf 2019).[6] See appendix A.2 for a more detailed description of how we construct the firm-level emissions data. In addition to firm-level Danish emissions, we also use country-product-year specific emission intensities from Exiobase to calculate emissions embodied in import flows (see the results section for more details).

We use the Foreign Trade Statistics Register to measure offshoring and Chinese import competition. Considering HS6 products, we observe imports at the firm-product-origin-year unit of observation. Based on this data, we measure narrow offshoring from all source countries following Hummels et al. (2014) and Hummels, Munch, and Xiang (2018). We include all source countries in our offshoring measure as Danish firms rely on suppliers from a wide range (mainly European) source countries, while, e.g., China accounts for less than three percent of imported intermediate inputs, see Appendix Table A4.[7]

Narrow offshoring is intended to capture intermediate inputs that the firm could produce in-house but has decided to import from abroad. This measure therefore excludes from the firm's total imports of inputs imported (HS4) products that the firm never produced or sold, domestically or abroad, during the sample window. Offshoring for firm i in year t is then the total value of the remaining imported inputs, that is

$$\mathrm{OFF}_{it} = \sum_{c,k \in \Omega_i} m_{ckit}, \tag{1}$$

where m_{ckit} is the value of firm i's import of input k from origin country c at time t, and Ω_i is firm i's set of inputs that it could potentially produce inhouse. This set is defined from both firm-level production (the PRODCOM register) and exports (Foreign Trade Statistics) data at the HS4 product level.

The Data Appendix shows that offshoring of a particular firm is concentrated in just a few origin-products and that the number of firms for the median offshored origin-product is 1. This means that a supply shock to a particular origin-product affects Danish firms idiosyncratically.

Following e.g. Bernard, Jensen, and Schott (2006), who considers competition from

[6]For example Dussaux, Vona, and Dechezleprêtre (2023), Akerman, Forslid, and Prane (2021), Marin and Vona (2021) and Wagner et al. (2020) use a similar approach to measure firm-level carbon emissions for firms in several European countries.

[7]In Section section 5.1 we examine the impact of offshoring to a particular set of countries.

imports more broadly (i.e., not only from China), we define import competition from China at the level of four-digit NACE industries:

$$\text{ImpPen}_{jt}^{CN \to DK} \equiv \frac{\text{FinalGoods}_{jt}^{CN \to DK}}{\text{Imports}_{jt}^{World \to DK} + \text{Sales}_{jt}^{DK}}, \tag{2}$$

where t indexes time and j industries. $\text{FinalGoods}_{jt}^{CN \to DK}$ denotes the imports from China to Denmark in non-manufacturing industries of products belonging to manufacturing industry j, and captures that when products are purchased by non-manufacturing firms such as wholesalers and retailers it is for immediate reselling as final goods, and not for use as inputs. The denominator measures the total domestic market size of these same products by summing domestic sales (total sales minus exports) and imports from the entire world. In total, $\text{ImpPen}_{jt}^{CN \to DK}$ measures China's share of the Danish market for each industry j and year t.

In our preferred specification we focus on import competition from China, because Denmark has seen a substantial increase of imports of final products from China, such imports tend to have a substantial effect on production (Autor, Dorn, and Hanson 2013), and, Denmark is too small to affect China's comparative advantage which allows us to construct a plausibly valid instrumental variable.[8] We draw on bilateral trade flow data from BACI to construct our instruments (see next section).

To construct our manufacturing firm sample, we require all firm-years to have positive emissions, more than twenty employees, more than 300.000 DKK offshoring (following Hummels et al. (2014)), positive sales, positive world export supply (WES) instrument and defined Chinese export supply (CES) instrument.[9] The resulting number of firm-years is 11,591 across 2019 unique firms and they cover most of the total carbon emissions (73 percent) and economic activity (roughly two thirds of sales and value added) in the manufacturing sector (see table A1 in appendix A.1).

Table 1 reports key summary statistics for the sample documenting e.g. that there is considerable within-firm time variation in key variables such as the emission intensity and offshoring. The table also shows that the average firm emits 5,148 tons of CO_2.

We now examine the extent of heterogeneity in carbon emission intensities across firms within industries in a single year (2016). Figure 1 shows large differences in median emis-

[8]We examine the role of import competition from other source countries in Section section 5.1.
[9]Both instruments will be defined precisely below.

Table 1: Summary statistics

			Absolute		Natural log		
	Obs.	Firms	Average	Median	Average	Standard dev.	Dev. from firm mean
CO2	11,591	2019	5147.62	243.88	5.78	1.85	0.41
CO2 intensity	11,591	2019	0.01	0.00	-6.08	1.46	0.45
Offshoring	11,591	2019	86,480.10	17,396.76	9.77	1.72	0.49
ImpPen$^{CN \rightarrow DK}$	11,591	2019	0.04	0.01	-	-	-
Sales	11,591	2019	453,503.38	120,310.09	11.86	1.20	0.23
Value-added	11,591	2019	134,245.58	40,326.68	10.78	1.15	0.25
Employment	11,591	2019	186.65	72.09	4.45	1.03	0.19

Notes: Monetary variables are measured in thousand DKK, emissions are measured in tons and employment is measured in yearly full-time equivalents. "Dev. from firm mean" denotes the average log-points deviation for any value from its across-year firm mean. Monetary variables are deflated to year 2015 using the consumer price index.

sion intensities across two-digit NACE industries with Non-Metallic Minerals standing out as the clearly most emission intensive industry. It is also evident that there is vast heterogeneity across firms within most industries, emphasizing the need to account for this dimension of variation. The average ratio between the 90th and 10th percentile is 382. This means that in the average industry the firm at the 90th percentile of CO2 intensity emits 382 times more than the firm at the 10th percentile whenever they produce the same amount of output.[10] Lyubich, Shapiro, and Walker (2018) and Wagner et al. (2020) document similar heterogeneity in firm-level emissions across firms within industries in the U.S. and several European countries.

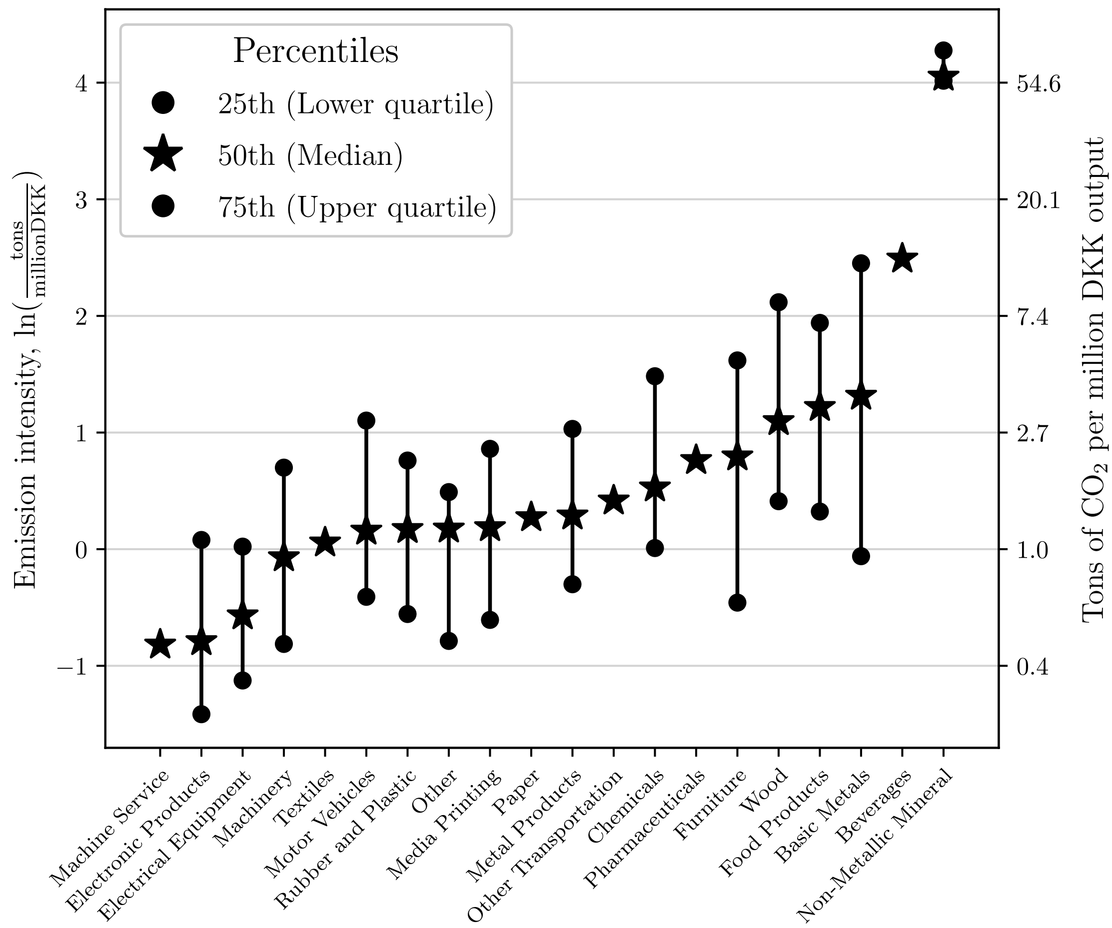
Finally, we take a first look at simple correlation patterns between our main variables of interest in the raw firm data. We first verify that sales correlate negatively with Chinese import competition, see Figure 2. This has been documented by the literature previously and is consistent with the view that Chinese import exposure acts like a negative demand shock. Second and unsurprisingly, firm-level carbon emissions are strongly correlated with firm scale as measured by total sales (the correlation coefficient is 0.27)[11]. That is, based on these data patterns firm-level carbon emissions should correlate negatively with Chinese import competition.

Offshoring is about relocation of production processes abroad, which should reduce domestic emissions for a given level of output, i.e., the firm-level emission intensity should

[10] The heterogeneity persists when one changes the industry classification to even the 6-digit level; the average 90/10 percentile ratio is 248.

[11] An OLS regression with log (CO_2) on left hand side, and log (Sales), firm and year fixed effects on the right hand side yields a highly significant correlation coefficient of 0.45.

Figure 1: Heterogeneity in emission intensities across and within industries



Notes: Firm-level emission intensities are calculated as $\log(\frac{CO_2}{\text{Output}})$ with CO_2 emissions measured in tons and output measured in million DKK. Some industries have been removed due to too few observations.

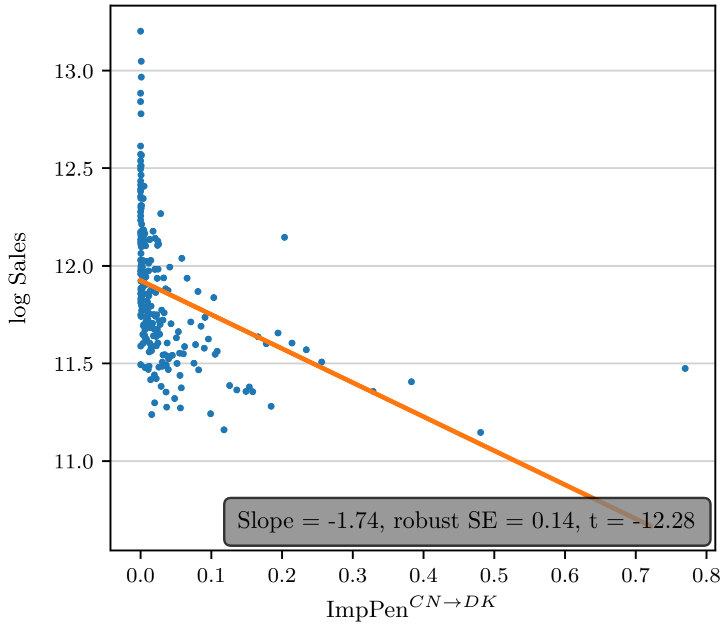
fall. Figure 3 indeed shows that the firm-level emission intensity correlates negatively with firm-level offshoring.

Clearly, these patterns rely on both cross firm variation and within firm time variation, and they do not account for the fact that offshoring and Chinese import competition may be endogenous to firm-level emissions. We will deal with these challenges in the empirical analysis below.

3 Decomposition of the Decline in Carbon Intensity

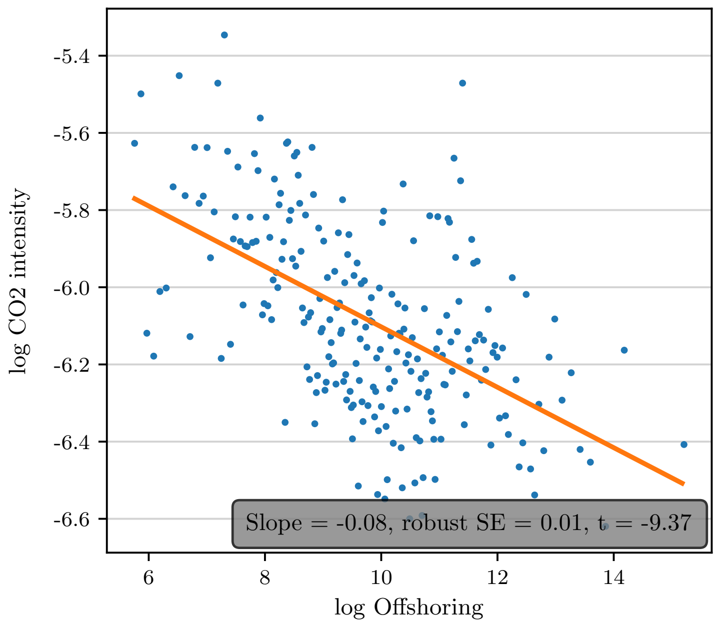
This section first decomposes the change in the overall Danish manufacturing emission intensity into a technique component, a composition component, a cross component and a net entry component. Then we discuss how each component may be influenced by import competition and offshoring to guide our subsequent empirical analysis. Finally, we explain

Figure 2: Scatterplot of ImpPen$^{CN \rightarrow DK}$ against log sales



Notes: The scatter plot shows binned values. Each bin contains at least 50 firm-years. The regression line is based on all underlying observations (N = 11591). The legend contains information about the slope parameter of the regression line.

Figure 3: Scatterplot of log offshoring against log CO2 intensity



Notes: The scatter plot shows binned values. Each bin contains at least 50 firm-years. The regression line is based on all underlying observations (N = 11591). The legend contains information about the slope parameter of the regression line.

how the empirical framework may be used to understand counterfactual scenarios such as what the change in the overall emission intensity would be in a world without rising import competition and offshoring.

Existing research typically perform decompositions of the overall emission intensity at the industry level (e.g., Antweiler, Copeland, and Taylor 2001; Bunel 2017; Levinson 2009; Shapiro and Walker 2018). They find that the technique effect accounts for most of the decline in emission intensities. That is, for fixed initial relative sizes of industries, declining emission intensities within industries explain most of the decline in the overall emission intensity. In contrast, the composition effect only explain a minor portion of the decline in the overall emission intensity. That is, for fixed initial industry-level emission intensities, reallocation of economic activity across industries does not play a large role.

Since we are interested in the role of firm-level adjustments, we decompose the change in the manufacturing emission intensity at the level of firms.[12] We will then reinterpret the technique effect as the contribution from changes in firm-level emission intensities and the composition effect as the contribution from changes in the relative size of firms.

Our data shows that aggregate manufacturing emissions have fallen and that output has increased over the sample window. These changes amount to a decline of approximately 50 percent in the overall manufacturing emission intensity from 1996 to 2016. We decompose the corresponding decline (also of 50 percent) in the change in the market share weighted sum of firm-level emission intensities, following much of the firm-level productivity decomposition literature, see e.g. Melitz and Polanec (2015).

We use the Foster, Haltiwanger, and Krizan (2001) decomposition method because it has the technique and composition components measured at the firm level (our primary focus) and it allows for entry and exit of firms and a cross term.[13] The decomposition is performed between some start year ($t = 1$) and some end year ($t = 2$). Denote by Φ_t the aggregate emission intensity in some time period, defined as the market-share weighted

[12] A small set of papers (e.g. Holladay and LaPlue III 2021; Najjar and Cherniwchan 2021) also perform decompositions at the firm level. They refer to a process effect (changes in industry emission intensity due to within-firm changes in emission intensity), a reallocation effect (changes in industry emission intensity owing to shifts in economic activity across continuing firms) and a selection effect (changes in industry emission intensity created by firm entry and exit) calculated by decomposing industry emission intensities and not the aggregate emission intensity. We sidestep the intermediate industry level analysis since our ultimate aim is to connect our firm-level regression results in the next section with the decomposition of the decline in the overall manufacturing emission intensity.

[13] Other decompositions such as Melitz and Polanec (2015) do not separate the cross term from the composition component. We prefer the more straightforward interpretation of the composition component as defined by Foster, Haltiwanger, and Krizan (2001).

sum of emission intensities across all firms:

$$\Phi_t = \sum_i s_{it}\phi_{it}, \qquad \sum_i s_{it} = 1, \tag{3}$$

where i indexes firms, s denotes market shares and ϕ is firm-level emission intensities. Then the decomposition decomposes the change in the aggregate emission intensity relative to the initial aggregate emission intensity, Φ_1, as

$$\begin{aligned}\frac{\Delta\Phi}{\Phi_1} = &\underbrace{\frac{\sum_{i\in S} s_{i1}\left(\phi_{i2}-\phi_{i1}\right)}{\Phi_1}}_{\text{Technique}} + \underbrace{\frac{\sum_{i\in S}(s_{i2}-s_{i1})(\phi_{i1}-\Phi_1)}{\Phi_1}}_{\text{Composition}} + \underbrace{\frac{\sum_{i\in S}(s_{i2}-s_{i1})(\phi_{i2}-\phi_{i1})}{\Phi_1}}_{\text{Cross/interaction}} \\ &+ \underbrace{\frac{\sum_{i\in E} s_{i2}(\phi_{i2}-\Phi_1)}{\Phi_1}}_{\text{Entry}} \underbrace{-\frac{\sum_{i\in X} s_{i1}(\phi_{i1}-\Phi_1)}{\Phi_1}}_{\text{Exit}},\end{aligned} \tag{4}$$

where the set S refers to firms who exist in both year $t = 1$ and $t = 2$, the set E refers to entrants (year $t = 2$ only) and the set X refers to exiting firms (year $t = 1$ only). The technique effect measures the contribution from changing firm-level emission intensities for a given initial market share, the composition effect measures the contribution from changing firm-level market shares for given initial emission intensities. The cross term measures an interaction between changes to emission intensities and changes to market shares, and the entry and exit components measure the contributions from entering and exiting firms during the time period.

The first row of Table 2 shows the contribution from these five components. It is evident that the technique and composition components are important; together they account for more than three quarters of the total decline in the emission intensity, with a decline of 0.19 percent accounted for by the technique effect and a decline of 0.20 percent by the composition effect. That is, the technique effect is also sizable when measured at the firm-level, but the composition effect is of the same magnitude.

Table 2: Decomposition of the change in the aggregate emission intensity

	Observations	Total	Technique	Composition	Cross	Net entry
Unbalanced panel	1829	-0.50	-0.19	-0.20	0.01	-0.13
Balanced panel	726	-0.55	-0.28	-0.29	0.02	0

Notes: The table shows decompositions of the relative change in the aggregate emission intensity as defined in equation (4). Both rows show decompositions over the enire period from 1996 to 2016. The second row performs the decomposition on a balanced panel where the net entry effect is zero by construction because entering and exiting firms have been removed.

The cross term contributes with a decline in the overall emission intensities of just one percent. This means that mechanisms that simultaneously affect emission intensities within firms and market shares across firms are less important than the direct technique and composition effects. Table 2 also shows that net entry of firms contributes to the decline in emission intensities by roughly one quarter of the overall decline in the manufacturing emission intensity. However, we will focus on the technique and composition components in the following empirical analysis as they are largest and together account for most of the decline in emission intensities.[14] The last row of Table 2 reproduces the decomposition for the balanced panel of firms who survive from 1996 to 2016, i.e., the entry and exit effects are zero. We will use this decomposition as the benchmark for the counterfactual decomposition calculations in section 5.2 below.

As noted above, previous research showed that the technique effect tends to dominate when measured at the level of industries.[15] Interpreted through the lens of traditional comparative advantage trade theories such as the Hecksher-Ohlin model, this seems to rule out trade as a potential explanation for declining emission intensities, since they predict a reallocation of economic activity across industries. However, our results show that the composition component measured at the firm level is of the same size as the technique effect. This suggests that globalization effects that change the relative size of firms may potentially play a role for the decline in manufacturing emissions.

According to newer heterogeneous firm trade theories, globalization may induce reallocations across firms within industries. If globalization reallocates economic activity towards more efficient firms (e.g. induced by increased competition from abroad (Melitz 2003)), then that will tend to reduce emissions as more productive firms are less emission intensive (Copeland, Shapiro, and Taylor 2022). Offshoring may cause firms to become more productive and larger (Grossman and Rossi-Hansberg 2008), which could also lead to reallocation and relative size differences across firms within industries.

Globalization may also potentially reduce emission intensities within firms. Offshoring

[14] It is difficult to consider the entry and exit components for two reasons. First, the biannual nature of the Industrial Energy Use Survey makes it hard to consider entry of small firms. Second, our identification strategy requires a balanced sample, where all firms import before the shock as our instruments (defined in Section 4.2) work at the intensive margin of trade and would not be able to predict entry and exit of firms.

[15] In this case, the technique effect includes shifts in market shares between firms in the same industry. In other words, if globalization affects the relative size of firms in an industry, this is not counted as a composition effect but as technique as long as the decomposition is performed at the industry level.

may, ceteris paribus, directly reduce domestic emissions per dollar of output as production processes are moved abroad, and increased import competition may induce firms to invest in R&D activities (Bloom, Draca, and Van Reenen 2015), that may lead to lower firm-level emission intensities through a productivity effect.[16]

To examine the scope for globalization to affect emission intensities through both reallocation of economic activity across firms and within firms over time, we will perform two main empirical exercises. First, we will examine how globalization (Chinese import competition or offshoring) causes firm-level (log) sales to change, as this directly feeds into explaining the composition component. Second, we will examine how globalization causes firm-level (log) emission intensities to change, which directly relates to the technique component. These regressions will then allow us to assess through counterfactual calculations how much of the decline in the overall manufacturing emission intensity (and of the technique and composition components) that can be attributed to globalization. The next section outlines in detail how we implement these regressions.

4 Empirical Approach

This section outlines our approach to estimate the impact of our two globalization variables on firm-level (log) emission intensities, which addresses the technique effect, and on firm-level (log) sales, which relates to the composition effect. We specify our estimating equations and, relying on existing literature, we define our instrumental variables for offshoring and Chinese import competition.

4.1 Regression equations

To be consistent with the decomposition from the previous section, we measure the firm-level emission intensity as carbon emissions by the firm per unit of output.[17] The globalization variables of interest are (log) offshoring and Chinese import competition as defined in (1) and (2). We relate emission intensities to offshoring and Chinese import competition

[16]See Cherniwchan, Copeland, and Taylor (2017a) for a review of the theoretical literature and model specification that directly links trade and pollution.

[17]This is also in line with studying the impact of import competition on firm-level output as specified below. Alternatively, one could also measure emissions as a share of firm-level value added, and we will report results for emission intensities defined this way in Section 5.1.

by estimating the following regression equation:

$$\log\left(\frac{\text{Emissions}_{it}}{\text{Sales}_{it}}\right) = \beta \log \text{OFF}_{it} + \lambda \text{ImpPen}_{jt}^{CN \rightarrow DK} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{5}$$

where i indexes firms, j indexes industries and t indexes year, α_i is a firm fixed effect, γ_t is a year fixed effect and ε_{it} is an error term. We will first estimate (5) including only one of the two endogenous variables at a time and then jointly by including both globalization variables simultaneously. While the latter approach is theoretically more appealing, it is not the conventional approach in the literature (see e.g. Mion and Zhu (2013)) as jointly estimating effects of multiple endogenous regressors is challenging. After having defined the instruments for our globalization variables below in section 4.2, we discuss this further.

The elasticity of the emission intensity with respect to the offshoring, β, is a parameter of interest. If firms offshore intermediate inputs and keep output unchanged, then, all else equal, we expect $\beta < 0$. However, this is not a forgone conclusion if, for example, the emission intensity is measured in terms of value added and firms offshore the least emission intensive inputs. In that case, offshoring may actually increase emissions per dollar of value added created in the firm.

Import competition reduces emission intensities if innovation activities increase in response to competition (Bloom, Draca, and Van Reenen 2015), and, innovation leads to productivity improvements such that production requires lower amounts of inputs and in particular lower amounts of energy per unit of output. This is also not a foregone conclusion. Instead of innovating to improve competitiveness, firms may, e.g., lower costs by neglecting expensive abatement activities.

The composition components in the decomposition of the manufacturing emission intensity depend on changing market shares, i.e., a reallocation of sales across firms within the industry. To examine if offshoring and import competition affect firm-level sales we estimate

$$\log(\text{Sales}_{it}) = \theta \log \text{OFF}_{it} + \delta \text{ImpPen}_{jt}^{CN \rightarrow DK} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{6}$$

where the parameters of interest are θ and δ, i.e., either the elasticity of firm-level sales with respect to offshoring or the semi-elasticity of firm-level sales with respect to Chinese import competition. Again, we will estimate (6) including only one of the two endogenous variables at a time and then jointly. Note that in our specification these elasticities also represent the effects of import competition and offshoring on log market shares. The reason is that the denominator of market shares (market size) is identical across all firms in a year and is log separable from sales in the log market share. As a consequence, it is fully absorbed by the year fixed effect γ_t.

If offshoring causes firms to become more productive and larger (Grossman and Rossi-Hansberg 2008) then we should expect sales to rise, i.e., the offshoring elasticity is positive. If exposure to Chinese import competition is akin to a negative demand shock, we expect firm-level sales to fall and the import competition semi-elasticity to be negative.

4.2 Identification

We now outline how we deal with possible endogeneity of offshoring and Chinese import competition in equations (5) and (6). Offshoring may be endogenous to firm performance affecting both sales and emission intensity if e.g. unobserved productivity shocks induce firms to offshore and sell more and to become cleaner (productivity correlates with energy efficiency, Copeland, Shapiro, and Taylor (2022)). Chinese import competition may also be endogenous to firm performance if e.g. Chinese firms tend to increase more in industries with poorly performing domestic firms.

To generate exogenous variation in offshoring, we employ a 2SLS procedure applying a shift-share Bartik instrument similar to the World Export Supply (WES) instrument developed in Hummels et al. (2014). Formally, the instrument is calculated as

$$WES_{it} = \sum_{p}^{\mathcal{P}} \sum_{c}^{\mathcal{C}} \left(s_{ipc,t_0} \times X_{cpt} \right), \qquad \sum_{p}^{\mathcal{P}} \sum_{c}^{\mathcal{C}} s_{ipc,t_0} = 1, \tag{7}$$

where s_{ipc,t_0} (the "shares") denote product p from country c's share of firm i's total imports in the pre-sample years t_0. X_{cpt} (the "shift") is exports from country c of product p to the rest of the world at time t. To avoid confounding factors, we exclude both Denmark and China when defining WES. Products are measured at the HS6 level. The pre-sample years are firm-specific and defined as the two immediate years before the firm first reports emissions and hence enters the sample. For the instrument to be defined and positive, at least one of the origin-products (source country and HS6 product code combination) imported in Denmark must simultaneously be exported to a different country (excluding China).

The instrument exploits that Danish importers source different products from different countries. For example, a Danish cement producer importing cement bricks from Germany will likely offshore more, i.e. import more cement bricks, if producers of cement bricks in Germany can produce at lower costs. At the same time, if German producers of cement bricks produce with lower costs it will show up in the global trade data as increased exports of cement bricks from Germany to the rest of the world. This is the "shift" part of the instrument. Whether a firm is exposed indirectly to productivity shocks of German cement brick producers depends on whether the firm is already tied to those producers. Therefore, a measure of this exposure is whether the firm initially imports cement bricks from Germany. This is the idea behind the "share" part of the instrument.

The necessary and sufficient conditions for consistency of the 2SLS estimator rely on the theory of Borusyak, Hull, and Jaravel (2021). The central condition is that the shocks - in our setting export flows of a particular product from a particular origin to the world excluding Denmark and China - are as-good-as-randomly assigned from the perspective of the Danish firm. Appendix A shows that any given firm's imports are concentrated on just a few products, the importing behavior is relatively stable in terms of origin-products imported and that different firms import very different origin-products. The two latter insights help ensure relevance and validity of the shift-share instrument respectively.

We also deal with possible endogeneity of Chinese import competition following the existing literature (e.g. Autor, Dorn, and Hanson (2013)) by defining an instrumental variable that captures China's improving comparative advantage as reflected in growing export supply to the rest of the world. The instrument measures imports from China relative to imports from the entire world, for a group of developed countries that are not geographically close to Denmark, e.g. we do not include Germany or Sweden.[18] Formally, we define it as

$$CES_{jt}^{CN \to OC} = \frac{\text{Imports}_{jt}^{CN \to OC}}{\text{Imports}_{jt}^{World \to OC}} \tag{8}$$

where CN and OC refer to China and a group of other countries. The instrument is measured at the same industry level as the Chinese import competition measure, $\text{ImpPen}_{jt}^{CN \to DK}$. The identifying assumption is that the import share of China in the

[18]The group of countries, "OC", consists of United States, Canada, Japan, France, Italy, Spain, Australia, New Zealand.

group of foreign countries only affects Danish firms through its effect on the Chinese import competition measure. When Chinese exporters become more productive, exports to this group of countries increases relative to other countries' exports to these countries. At the same time, more productive exporters in China should lead to a larger market share for Chinese firms in Denmark.

As explained above in section 4.1, we will run regressions where either the endogenous variables enter individually or jointly. Since our globalization variables are related (they both measure imports, but at firm- and industry-level respectively) and their instruments both rely on bilateral world trade flows, one may worry that the exclusion restriction in separate IV regressions is violated if our instruments affect firm performance through the left-out globalization variable. As explained above, we take steps to alleviate such concerns by excluding China as a source and destination country in the offshoring instrument. We also report estimates where, instead of instrumenting both variables, the "other" globalization variable is simply included as a control.

5 Results

In this section we first present the main results from estimating equation (5) and (6). We then show the results from a number of extensions and robustness exercises. This is followed by a subsection that returns to the decomposition of Section 3 and asks how much of the decline in the overall domestic emission intensity that can be attributed to offshoring and Chinese import competition. Finally, we calculate emissions embodied in offshoring and Chinese import flows to assess consequences for global emissions and the extent of carbon leakage associated with international trade.

We first report results from regressions with only one of the globalization variables included at a time, in table 3. The first column shows the IV regression results with offshoring included on the right hand side.[19] Offshoring has the expected negative sign on the firm-level emission intensity, and the estimated elasticity means that a one percent increase in offshoring leads to a 0.57 % drop in the emission intensity, all else equal. This result is statistically significant and economically important at the firm level. Firms change their offshoring at varying degrees over the sample window, and one way to quantify the implication of the parameter estimate is to relate it to observed five year changes

[19] Appendix Table A5 shows the corresponding OLS results.

in the data. The 10th percentile firm has a five-year log change in offshoring of -0.74. This fall in offshoring corresponds to a 42 % higher emissions intensity. By contrast, the 90th percentile firm has a log change of 1.35 which corresponds to a 77 % lower emissions intensity.

Table 3: Firm-level Effects of Offshoring and Chinese Import Competition

	log CO_2 Int.		log Sales	
	(1)	(2)	(3)	(4)
log Offshoring	-0.574**		0.687***	
	(0.25)		(0.17)	
ImpPen$^{CN \rightarrow DK}$		0.581		-3.501***
		(1.12)		(0.99)
F-stat (log Off.)	13.36		13.36	
log WES	0.14***		0.14***	
F-stat (ImpPen)		51.06		51.06
CES$^{CN \rightarrow OC}$		0.23***		0.23***
Observations	11591	11591	11591	11591

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1) and (3) standard errors are heteroscedasticity robust, in columns (2) and (4) they are clustered at the 4-digit NACE industry by year level. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (3) shows that exogenous increases in offshoring causes firm sales to rise with a highly significant and economically meaningful elasticity of 0.69. Thus offshoring may induce firms to become more productive and sales to rise as a result.[20] Again, the heterogeneity in offshoring changes across firms means that sales respond very differently: the 10th percentile firm see sales falling by 51 % as a result of offshoring over a five year period, while sales of the 90th percentile firm rises by 93 %. These sales changes feed directly into the composition component of our decomposition.

We examine the impact of Chinese import competition on firm-level sales in column (4), and we find the expected negative effect. The estimated semi-elasticity means that when Chinese import competition increases by one percentage point, sales fall by 3.5 %, all else equal. We can illustrate the economic importance by considering the distribution of changes over the sample window in Chinese import competition across firms. Over five-year periods the 10th percentile firm has a modest drop of 0.3 percentage points, which

[20] Offshoring has opposite effects on the emission intensity and sales, but Appendix Table A7 shows that the combined effect of offshoring on firm-level carbon emissions is positive but insignificant.

corresponds to a 0.01 % rise in sales. The 90th percentile firm sees a substantial increase of 4.7 percentage points, which corresponds to a 16.5 % fall in sales. Again, these sales changes connect to the composition component in the emission intensity decomposition as they determine firm-level changes in market shares and ultimately, via firm-level emission intensities, the emission reduction that can be attributed to reallocation across firms triggered by Chinese import competition.

Finally column (2) shows that Chinese import competition does not have a statistically significant impact on firm-level emission intensities. That is, Chinese import competition only affects the overall manufacturing emission intensity through the reallocation of economic activity across firms.

We now turn to the results with two endogenous regressors included simultaneously. Consider first the firm-level emission intensity as the outcome of interest. Column (1) of Table 4 first reproduces the estimate from Table 3 for comparison. Columns (2) and (3) show that the offshoring coefficient increases slightly in magnitude when Chinese import competition or its instrument are added as "controls". Column (4) shows the joint estimation results, and again the offshoring coefficient is only slightly larger in magnitude (but now only marginally significant), and the impact of import competition is statistically insignificant as in the separate regression in Table 3. Turning to firm-level sales as outcome variable, we find largely the same pattern as adding offshoring "controls" in columns (6) and (7) and estimating the joint specification in column (8) only moderately changes the estimated impact of Chinese import competition (stated in column (5) for comparison). Compared to Table 3, offshoring's effect on sales is reduced moderately and becomes insignificant in column (8).[21]

Overall, we take these findings as evidence that the parameter estimates are relatively robust to estimating them jointly or separately. In the quantification exercises below, we apply the preferred estimates from the joint regressions, columns (4) and (8) in Table 4, and report corresponding calculations using the estimates from Table 3 in the appendix.

To summarize our main regression results, we find that, one, offshoring has counteracting effects on firm-level emissions. Firms become cleaner per unit of output, but they also become more productive and increase their sales. However, the aggregate effect

[21] Standard errors in column (8) are clustered at the industry level due to the inclusion of Chinese import competition as a regressor. The effect of offshoring on firm-level sales is significant when using only heteroscedasticity robust standard errors.

Table 4: Two endogenous regressors

	log CO_2 Int.				log Sales			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log Offshoring	-0.574**	-0.588**	-0.604**	-0.754*		0.222***		0.343
	(0.25)	(0.27)	(0.27)	(0.45)		(0.01)		(0.22)
$\text{ImpPen}^{CN \to DK}$		-0.106		-1.371	-3.501***	-2.927***	-3.377***	-2.613**
		(0.26)		(1.89)	(0.99)	(0.81)	(1.01)	(1.09)
$\text{CES}^{CN \to OC}$			-0.228					
			(0.29)					
log WES							0.034	
							(0.03)	
F-stat (log Off.)	13.36	11.57	12.06	12.06				10.64
log WES	0.14***	0.13***	0.13***	0.131***				0.13***
$\text{CES}^{CN \to OC}$			-.49***	-.49***				-.49***
F-stat (ImpPen)				241.58	51.06	50.45	47.04	47.04
log WES				-.01***			-.01***	-.01***
$\text{CES}^{CN \to OC}$				0.22***	0.23***	0.23***	0.22***	0.22***
Observations	11591	11591	11591	11591	11591	11591	11591	11591

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1)-(4) standard errors are heteroscedasticity robust, in columns (5)-(8) they are clustered at the 4-digit NACE industry by year level. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of offshoring on the overall manufacturing emission intensity is unclear without further investigation. Two, we find that import competition mainly affects emissions through reallocation of economic activity across firms. Again, the net effect on the overall domestic manufacturing emission intensity is unclear as it depends on initial firm-level emission intensities. Three, we examine offshoring and Chinese import competition in a coherent framework and show that these two driving forces behind the growth in international trade have clear (but quite distinct) implications for firm-level carbon emissions. Given the distinct effects of offshoring and import competition on emission intensities and sales, it is not clear based on the regression results alone how imports affect local emissions. In Section 5.2 we take advantage of our decomposition to answer this question.

5.1 Extensions and Robustness

In this section we provide results from a number of extensions of the results above. All extensions are implemented in the regressions where we only include a single globalization variable at a time.[22] We explore mechanisms behind the results, we examine effect heterogeneity, we investigate alternative definitions of our offshoring and import competition variables, and we show the implications of using value added instead of sales in the firm-level emission intensity variable.

In the first extension we explore some mechanisms behind how firms adjust to increasing globalization. Offshoring reduces the firm-level emission intensity and one question is if this is accomplished by changing the firm-level mix of energy inputs. For example, if offshoring moves out heavily energy consuming production processes that require the use of relatively dirty energy inputs such as coal or fuel, then the share of cleaner energy inputs such as electricity may rise.

One way to address this question is to decompose the effects on the firm-level emission intensity (CO_2 per unit of sales) in Table 3 into an emission factor (CO_2 per GJ) and an energy efficiency component (sales per GJ). The emission factor captures energy input substitution as measured by the emission of carbon per unit of energy input, GJ, and the energy efficiency component measures sales generated per unit of energy input. Table 5 first replicates the effects on the emission intensity from Table 3 in columns (1) and (2) and then shows the effect on the emission factor (columns (3) and (4)) and on the energy efficiency component (columns (5) and (6)). The effect of, e.g., offshoring on the emission intensity adds up to the effect on the emission factor minus the effect on energy efficiency. It is evident that offshoring reduces the emission factor such that firms rely more heavily on cleaner energy sources and that this channel explains roughly two-thirds of the effect on the emission intensity. The remaining third can be attributed to improved energy efficiency.

We can also more directly examine the extent to which globalization affects the use of a relatively clean energy input, electricity. Column (1) of Table 6 shows that offshoring has a positive impact on the use of energy from electricity but no impact on the use of non-electricity energy inputs (column 3). As a consequence the electricity share in energy inputs rises (column 5) although this effect is not significant. Chinese import competition does not have an impact on the composition of energy inputs. Instead we find a negative impact on both electricity and non-electricity inputs consistent with the

[22] The extension concerning heterogeneous effects requires splitting each of the instruments according to a dummy. Doing so when estimating all parameters jointly would require including four instruments and four endogenous variables at a time, which we do not have sufficient statistical power to do.

Table 5: Energy Input Substitution and Energy Efficiency

	log CO_2/Sales		log CO_2/GJ		log Sales/GJ	
	(1)	(2)	(3)	(4)	(5)	(6)
log Offshoring	-0.574**		-0.393**		0.181	
	(0.25)		(0.17)		(0.18)	
ImpPen$^{CN \rightarrow DK}$		0.581		0.554		-0.027
		(1.12)		(0.62)		(0.90)
F-stat	13.36	51.06	13.36	51.06	13.36	51.06
Observations	11591	11591	11591	11591	11591	11591

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1), (3) and (5) standard errors are heteroscedasticity robust, in columns (2), (4) and (6) they are clustered at the 4-digit NACE industry by year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

finding that Chinese import competition is akin to a negative demand shock for exposed firms that scales down firm-level activity.

Table 6: Electricity switching

	log Electricity		log Non Electricity		log Electricity share	
	(1)	(2)	(3)	(4)	(5)	(6)
log Offshoring	0.684***		0.142		0.188	
	(0.22)		(0.23)		(0.13)	
ImpPen$^{CN \rightarrow DK}$		-3.900***		-3.247***		-0.112
		(0.87)		(1.10)		(0.47)
F-stat	13.01	51.84	13.36	51.06	13.01	51.84
Observations	11514	11514	11591	11591	11514	11514

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1), (3) and (5) standard errors are heteroscedasticity robust, in columns (2), (4) and (6) they are clustered at the 4-digit NACE industry by year level. log Electricity is the log of giga joule from electricity. Electricity share and non-electricity is the share of total energy from electricity and other types of energy respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We next examine if our globalization variables affect firms differently depending on whether they are clean or dirty. To do so, we split firms into two groups and label firms dirty if their initial emission intensities are high (top half for offshoring and fourth quartile for import competition). We then interact the globalization variables with this "dirty" dummy. Column (1) of Table 7 shows that when offshoring increases by 1 %, the emission intensity drops by 0.46 % for the clean firms, while the intensity for the dirty firms falls by 0.76 %. Thus changes in offshoring affect dirty firms' emission intensity more than clean firms'. By contrast, offshoring has a similar impact on log sales across firm types (column 3). We also find that emission intensities and sales fall by more in dirty firms when they are hit by Chinese import competition shocks (columns 2 and 4). This may suggest that dirty local firms are more directly exposed to Chinese import competition potentially because they produce more homogeneous products.

Table 7: Effect Heterogeneity

	log CO_2 Int.		log Sales	
	(1)	(2)	(3)	(4)
log Offshoring	-0.458**		0.662***	
	(0.22)		(0.15)	
log Off. × Top half of CO_2 Int.	-0.306**		0.066	
	(0.13)		(0.09)	
$\text{ImpPen}^{CN \to DK}$		1.387		-2.776***
		(1.14)		(0.99)
$\text{ImpPen}^{CN \to DK}$ × 4. Quartile of CO2 Int.		-5.358***		-4.813***
		(1.78)		(1.05)
F-stat (log Off.)	8.72		17.45	
F-stat (Off. × Top half of CO_2 Int.)	81.19		128.73	
F-stat (ImpPen)		26.13		52.13
F-stat (ImpPen × 4. Quartile of CO2 Int.)		35.16		69.24
Observations	11591	11591	11591	11591

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1) and (3) standard errors are heteroscedasticity robust, in columns (2) and (4) they are clustered at the 4-digit NACE industry by year level. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We now turn to the question about how we define our globalization variables. We have so far examined import competition from China and offshoring to all countries. However, import competition from other low income countries or offshoring to a particular set of countries may affect performance of domestic firms in distinct ways. For example, Dauth, Findeisen, and Südekum (2014) find that import competition from emerging Eastern European countries plays a dominant role in explaining labor market outcomes in Germany. In Table 8 we estimate the impact of offshoring to and import competition from Eastern Europe (defined by the new Eastern European EU member countries). We find that offshoring to Eastern European countries still has a positive impact on sales but the negative effect on emission intensities is no longer significant (columns 1 and 3). It is also evident that import competition from Eastern Europe does not have a significant impact on emission intensities or sales (columns 2 and 4), which justifies our focus on China.

We next examine the importance of using value added instead of sales as a measure of firm-level activity and adding firm-level controls to our empirical specification.

Table 8: Eastern European Countries

	log CO_2 Int.		log Sales	
	(1)	(2)	(3)	(4)
log Offshoring (EEUC)	-0.329		0.310**	
	(0.21)		(0.15)	
$\text{ImpPen}^{EEUC \rightarrow DK}$		0.741		0.158
		(1.29)		(0.65)
F-stat (log Off.)	4.67		4.67	
log WES (EEUC)		32.32		32.32
F-stat (ImpPen)	4932	11591	4932	11591

Notes: All columns show 2SLS regressions and include year and firm fixed effects. 'EEUC' refers to the new Eastern European EU member countries. In columns (1) and (3) standard errors are heteroscedasticity robust, in columns (2) and (4) they are clustered at the 4-digit NACE industry by year level. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the central first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 reports results where we use value added as the denominator in the firm-level emission intensity and we use log value added as the dependent variable rather than log sales. Qualitatively we obtain similar results and the estimated elasticities change only marginally. This suggests that the within-firm time variation in sales and value added driven by offshoring and import competition is similar.

Table 9: Value Added

	log CO_2 Int. (VA)		log Value Added	
	(1)	(2)	(3)	(4)
log Offshoring	-0.569**		0.663***	
	(0.28)		(0.19)	
$\text{ImpPen}^{CN \rightarrow DK}$		0.956		-3.863***
		(1.13)		(1.01)
F-stat (log Off.)	12.30		12.30	
log WES		50.69		50.69
F-stat (ImpPen)	11543	11543	11543	11543

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1) and (3) standard errors are heteroscedasticity robust, in columns (2) and (4) they are clustered at the 4-digit NACE industry by year level. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the central first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, Appendix Table A6 shows the implications of adding firm-level employment and capital as control variables. Offshoring still has a negative impact on the emission intensity and a positive impact on sales, but the magnitude is smaller when conditioning on employment and capital. Unsurprisingly, the impact of Chinese import competition on sales is muted when employment and capital is kept fixed.

5.2 Counterfactual Decomposition and Domestic Emissions

In this section, we go back to our initial question and use the estimated globalization elasticities of Table 4 to perform counterfactual decompositions of the change in the overall manufacturing emission intensity. That is, we use our estimated effects of offshoring and Chinese import competition to calculate counterfactual declines in the overall emission intensity in the hypothetical situations where offshoring or Chinese import competition are held fixed at their initial 1996 level.[23] Clearly this is only a partial equilibrium exercise but it serves the purpose to illustrate the magnitude of the effects.

For comparison Table 10 first reproduces the basic decomposition from Table 2 based on the balanced sample of firms (labeled "Actual"). The next row shows that the overall decline in the emission intensity would have been only 11 percent if offshoring's impact on firm level emission intensities had been switched off, i.e., if offshoring had not changed since 1996 and if this would only affect firm-level emission intensities, i.e., the technique effect. In other words, offshoring accounts for more than three quarters of the overall decline in the manufacturing emission intensity and all of the technique effect through its effect on firm-level emission intensities.[24] It is also evident from Table 10 that this effect works through the technique component as expected.

The third row shows the implications of accounting for offshoring's impact on firm-level sales. Offshoring increases sales and thus reshuffles market shares across firms depending on their firm-specific offshoring exposure and, in turn, this impacts the composition component depending on initial firm-level emission intensities. The overall decline in the emission intensity would have been 45 percent (81 percent of its actual decline) if offshoring had been at its initial level throughout. That is, firms that grow due to offshoring tend to be relatively clean such that dirty firms are left with lower market shares, which

[23] Details about how we calculate the counterfactual decompositions are provided in Appendix B.1.

[24] Appendix Table A10 shows that the results are robust to using either the estimated coefficients from Table 3 or Table 7 instead of the main results in Table 4. In Appendix Table A11 the decomposition is performed on three shorter periods of roughly seven years each. The decompositions are in line with decompositions over the full 20 year period.

Table 10: Counterfactual decompositions of the change in the aggregate emission intensity

Scenario	Total	Technique	Composition	Cross
Actual	-0.55	-0.28	-0.29	0.02
Counterfactual emission intensity with offshoring at initial level	-0.11	0.16	-0.29	0.02
Counterfactual sales with offshoring at initial level	-0.45	-0.28	-0.16	-0.01
Counterfactual sales with Chinese import penetration at initial level	-0.55	-0.28	-0.30	0.03

Notes: The table shows decompositions of the relative change in the aggregate emission intensity as defined in equation (4). The decompositions rely on a balanced sample of firms operating in 1996 and 2016, so the net entry effect is zero by construction. The counterfactual scenarios rely on the methodology explained in appendix B.1. Counterfactual values are calculated with parameter estimates from the regressions with two endogenous regressors (columns 4 and 8, table 4).

in total leads to a lower overall manufacturing emission intensity.[25] As expected, the composition component is responsible for a large part of the effect, but the cross term also adds a small contribution.

Chinese import competition affects emissions of firms through its impact on sales. The composition component in the decomposition could then potentially contribute to changes in the overall manufacturing emission intensity through changes in Chinese import competition. The composition component changes in response to Chinese import competition only if firms are differentially exposed to import competition (thus implying a reshuffling of market shares) and if they differ in their initial emission intensities (see the definition of the composition component in equation 4). That is, Chinese import competition reduces the overall emission intensity through the composition component if firms in the dirtiest industries are hit harder by increased competition and vice versa.

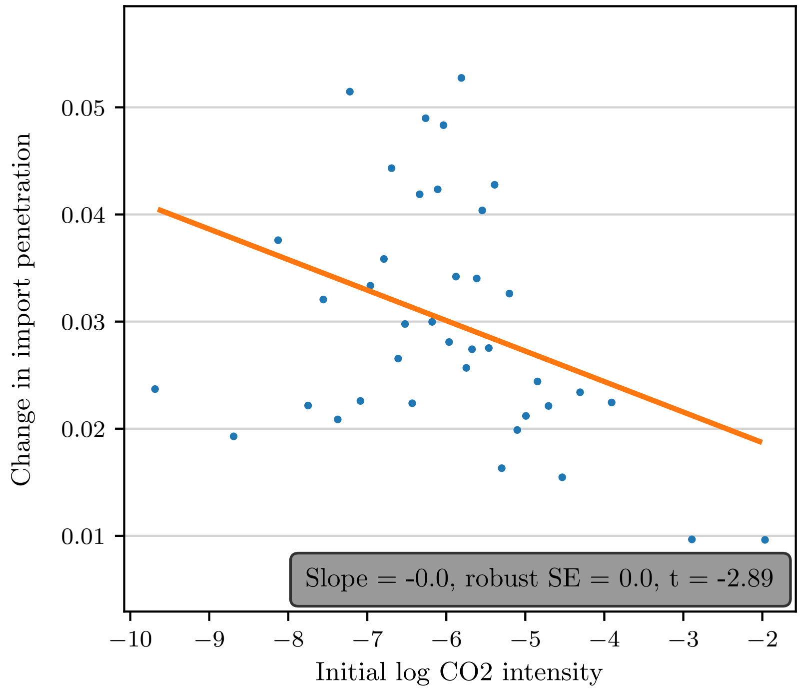
Firms are indeed exposed differentially to Chinese import competition. Firms in the cleanest industries such as textiles and electrical equipment (see Figure 1) experienced the largest increases in Chinese import competition, while relatively dirty industries, e.g., pharmaceuticals and non-metallic minerals, have seen smaller increases in exposure to Chinese import competition. Figure 4 suggests that there is a negative relationship between initial emission intensities and the change in Chinese import competition.[26] However, if Chinese import competition is held unchanged at its initial level, the overall manufactur-

[25] Firms that see their market shares fall in response to offshoring have on average an emission intensity of 0.043, while firms that gain market shares have on average an emission intensity of 0.008.

[26] Firms that see their market shares fall in response to Chinese import competition have on average an emission intensity of 0.008, while firms that gain market shares have on average an emission intensity of 0.057.

ing emission intensity is largely unchanged according to the last row of Table 10.[27] Thus the relationship between exposure and initial emission intensities is not strong enough to substantially change the overall manufacturing emission intensity.

Figure 4: Scatterplot of changes in import penetration against initial log CO2 intensities



Notes: The figure plots the long difference of import penetration for each firm against the firm's own initial CO2 intensity. The scatterplot is binned with at least 50 observations in each bin. The regression line is based on all underlying observations (N = 1965). The legend contains information about the slope parameter of the regression line.

5.3 Carbon Leakage and Global Emissions

We now ask if international trade triggered by changing comparative advantages are good or bad for the environment and calculate carbon leakage rates for offshoring and Chinese import competition. The carbon leakage rate measures the number of tonnes of carbon created abroad for each tonne removed domestically:

$$L = -\frac{\Delta E_t^{ROW}}{\Delta E_t^{DK}}. \tag{9}$$

As outlined in Appendix B.2, we can calculate the leakage rate for offshoring by differentiating the estimation equations (5) and (6) and use these in the definition of the

[27]This result is robust to allowing for the effect heterogeneity of Chinese import compeition found in Table 7, see Appendix Table A10.

leakage rate (9) to obtain

$$L_{it}^{O} = -\frac{1}{\hat{\beta}+\hat{\theta}}\frac{E_{it}^{O}}{E_{it}}, \tag{10}$$

where E_i^O is emissions embodied in the imported intermediate inputs, E_i^Y is local emissions by the Danish firm, $\hat{\beta}$ is the estimated elasticity from column (4) in Table 4 and $\hat{\theta}$ is the estimated elasticity from column (8) in Table 4. The leakage rate is high if firms have a high rate of emissions embodied in offshoring relative to emissions from local production. The leakage rate also reflects the causal relationship estimated earlier, and the leakage rate is higher the closer the estimated offshoring elasticity is to zero. That is, if offshoring only has a moderate effect on the firm-level emission intensity, more carbon will be emitted abroad per unit of emission reduction at home.

Likewise, the leakage rate for Chinese import competition for industry j is

$$L_j = -\frac{1}{\hat{\delta}}\frac{e_j^{CN}Y_j^{DK}}{\sum_{i\in j}E_i}, \tag{11}$$

where the numerator is a product of industry specific Chinese emission rates, e_j^{CN}, and the output by the Danish industry, Y_j^{DK}, i.e., it is a measure for emissions from local production had it been produced with Chinese production technology. The denominator is actual emissions by domestic firms in the industry and δ is the estimated semi-elasticity from column (8) in Table 4.

Following e.g. Shapiro (2021) and Copeland, Shapiro, and Taylor (2022) we obtain a measure for emissions generated abroad embodied in import flows using emission intensities by broad product categories and origin countries from Exiobase. Exiobase is an environmentally extended multi-regional input-output database from which emission coefficients capturing both direct emissions and indirect emissions from supply chains are derived. To be consistent we not only calculate emissions embodied in imports using Exiobase emission coefficients, but we also use them to obtain a measure for local emissions in the denominators of the leakage rates in equations (10) and (11).[28] We provide more details about Exiobase and how we implement it in our context in Appendix A.

We find that the average offshoring leakage rate is 1.03 (0.95 when weighted by absolute emissions), see Table 11. That is, when offshoring reduces emissions in the average

[28] We use the available average emission coefficients by country and product in Exiobase. A possible source of measurement error is that exporters potentially may be cleaner than nonexporters (Rodrigue, Sheng, and Tan 2022). In this case, our leakage rates will show upper bounds for actual leakage rates.

firm by 1 tonne in Denmark, emissions increase by roughly the same amount abroad. In other words, emissions embodied in imports of intermediate inputs are in the same order of magnitude as the domestic emission reduction caused by the import flows such that offshoring does not contribute to changing global emissions. Partly this result reflects that firms offshore production processes to suppliers (predominantly located in European countries, see Table A4), who are similarly emission intensive in producing the intermediate input in question.[29]

Table 11: Carbon Leakage Rates

	Average	Average (weighted)	25th percentile	Median	75th percentile
Offshoring	1.03	0.95	0.23	0.57	1.23
Chinese import penetration	6.42	3.75	1.73	3.30	7.11

Notes: The table calculates leakage rates based on the regression parameter estimates from table 4, domestic emissions and imported emissions calculated using Exiobase emission coefficients. For offshoring, the unit of observation is a firm-year, i.e. the underlying calculation has one leakage rate for each firm year. For Chinese import competition, the unit of observation is an industry-year, i.e. the underlying calculation has one leakage rate for each 4-digit NACE-year. The column denoted 'Average (weighted)' weights each leakage rate by absolute emissions (in the firm for offshoring and in the 4-digit NACE industry for Chinese import competition). Some firms only produce products that cannot be matched to Exiobase products. These are not included in the calculations. The top and bottom percentiles of leakage rates have been trimmed.

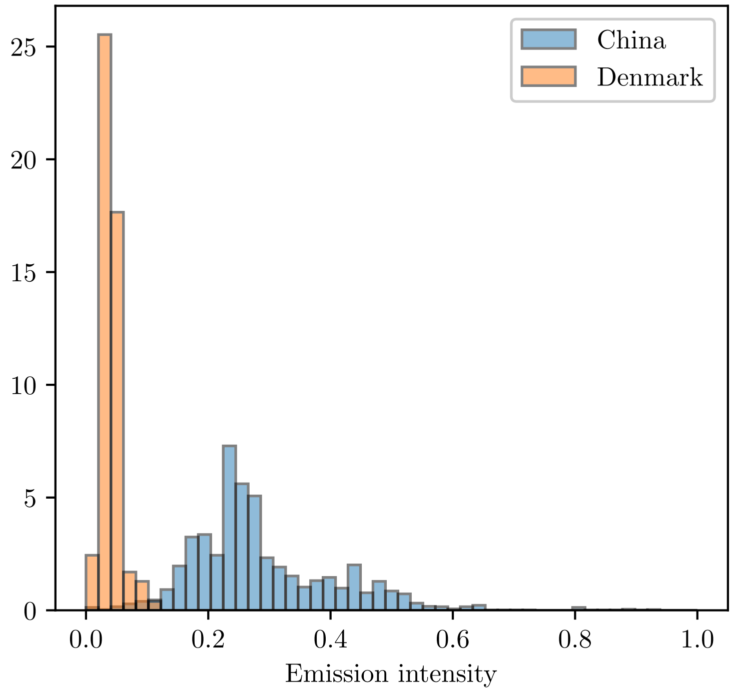
The average import competition leakage rate is much higher at 6.42, such that when Chinese import competition reduces emissions (through sales) in Denmark by 1 tonne, emissions in China increase by more than 6 tonnes. Although the average leakage rate drops to 3.75 when weighting each industry by their total emissions, even the industry at the 25th percentile has a leakage rate higher than 1.[30] That is, on average import competition from China massively increases global carbon emissions. This result is mainly driven by the fact that Exiobase emission intensities in China are much higher than the corresponding intensities in Denmark, see Figure 5.[31]

[29]Two issues about the robustness of this result should be noted. First, the dispersion in leakage rates across firms is substantial, which is evident from the percentiles reported in table 11. Second, when we use the parameter estimates from the equations where each regressor is included separately (Table 3), or the parameter estimates that allow for heterogeneous effects across firms (Table 7), the resulting average leakage rate deviates substantially from 1.03 (to values of -3.74 and 4.00 respectively, see Table A12 in Appendix B.2). The reason is that the sum of the two parameter estimates is close to zero and enter in the denominator of the leakage rate calculation in (10). The average leakage rate becomes negative when the sum of these two parameters is above zero, because offshoring's total effect on domestic emissions is positive in this scenario.

[30]Appendix Table A9 reports leakage rates for Chinese import competition by two-digit NACE industries. Large domestic industries such as Furniture and Pharmaceuticals have leakage rates around 2, while Wearing Apparel and Leather have leakage rates of 10 or more.

[31]Appendix Table A12 shows that the leakage rates for Chinese import competition in Table 11 are robust to using either the estimated coefficients from Table 3 or Table 7 instead of the main estimation results in Table 4.

Figure 5: Histogram of emission intensities in Denmark and China



Notes: The figure compares emission intensities between China and Denmark at the Exiobase product level. The emission intensity of a given Exiobase product is the across-year average. The included HS6 products are those that enter at least one firm's import penetration measure. Some HS6 products are not represented in Exiobase and are excluded. The histogram is normalized so it integrates to one.

These results show that globalization may be good or bad for the environment depending on the type of trade in question. Offshoring is likely driven by efficiency and costs saving considerations by domestic firms and involves relocation of production processes to foreign suppliers who can produce the inputs more efficiently. Still, our results indicate that offshoring leaves global carbon emissions unchanged on average. Note that the leakage rates for offshoring might be underestimated since transport emissions are unaccounted for. Cristea et al. (2013) find that emissions from transport amount to as much as one third of total emissions from producing and transporting the goods, but they also show that transport emissions tend to be lower for goods traded between proximate countries on the same land mass, which is the case for most of Danish offshoring (see Appendix A). Such goods tend to be transported by relatively energy efficient transport modes (e.g., rail and truck). In addition, there may be general equilibrium effects involving higher domestic emissions than what is accounted for by the leakage rates. For example, offshoring may free up labor and capital in the manufacturing sector and these production factors may be employed in other sectors leading to higher emissions.

On the other hand, Chinese import competition has a negligible impact on the overall domestic manufacturing emission intensity, but it increases global emissions substantially because final goods imported from China are produced with much higher emission intensity than the domestic production they replace. On top of this come emissions from transport and general equilibrium effects that are not accounted for in the leakage calculations.

6 Conclusion

As noted by Copeland, Shapiro, and Taylor (2022) relatively little work has provided evidence for the causal impact of globalization on environmental outcomes, and this paper contributes to filling this gap. We use Danish firm-level data for carbon emissions and globalization exposure as measured by offshoring and Chinese import competition. To set the stage, we first decompose the decline in the manufacturing emission intensity into technique, composition and cross components. We then estimate the causal impacts of offshoring and Chinese import competition on firm-level emission intensities and sales. We use the estimation results to quantify the contribution of offshoring and Chinese import competition to the overall manufacturing emission intensity. Finally, we also use the estimation results to calculate carbon leakage rates to assess the consequences for global emissions.

To summarize our basic regression results, we find that, one, offshoring has counteracting effects on firm-level emissions. Firms become cleaner per unit of output, but they also become more productive, larger and emit more as a result. We are the first to highlight these counteracting effects, and the net effect of offshoring on the manufacturing emission intensity is unclear without further investigation. Two, we are the first to jointly examine how Chinese import competition affects the overall domestic manufacturing emission intensity through changes in technique and composition components. We find that import competition mainly affects emissions through reallocation of economic activity across firms. Again, the net effect on the overall domestic manufacturing emission intensity is unclear without further scrutiny as it depends on initial firm-level emission intensities and firm-level exposure to import competition. Three, we examine offshoring and Chinese import competition in a coherent framework and show that these two driving forces behind the growth in international trade have clear (but quite distinct) implications for firm-level carbon emission intensities and sales. This is potentially important for how the overall emission intensity changes in response to international trade.

We then compute how firm-level emission intensities and sales would have evolved had they not been affected by offshoring and Chinese import penetration and relate it to our decomposition exercise. We show that offshoring has contributed to the overall decline in the manufacturing emission intensity through both the technique and composition components. On the other hand, Chinese import competition does not affect the overall manufacturing emission intensity because firm-level exposure to import competition is only weakly correlated with initial emission intensities. Thus offshoring and Chinese import competition have very different implications for the domestic manufacturing emission intensity.

Finally we show that offshoring and Chinese import competition also have very different implications for global carbon emissions. We calculate embodied carbon emissions in offshoring and import flows and use them to derive carbon leakage rates based on our regression results. We find that emissions embodied in imports of intermediate inputs are about the same in magnitude compared to the domestic emission reduction caused by the import flows. In other words, offshoring is emission neutral and leaves the global environment unaffected. By contrast, emissions embodied in final good imports from China are much larger in magnitude than the domestic emission reduction. Thus, overall, import competition from China strongly increases global carbon emissions. This implies that global environmental policy negotiation is particularly important in the context of international trade in final products.

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Appendices

A Data Appendix

A.1 Coverage of Regression Sample

For the regression sample, we require all firm-years to have positive emissions, more than 300.000 DKK offshoring, positive sales, positive world export supply (WES) instrument and defined Chinese export supply (CES) instrument. The resulting number of firm-years is 11,591 across 2019 unique firms. Table A1 shows that the sample covers most of total carbon emissions (72.6 percent) and economic activity (roughly two thirds of sales and value added).

Table A1: Share of Economic Activity in Sample

Annual Emissions	% of Value-added	% of Employment	% of Sales	% of Imports	% of CO2
7,525,363.64	63.38	59.28	66.56	77.16	72.55

Notes: This table considers firms in manufacturing and compares firm characteristics for the firms in the regression sample with the entire population of manufacturing firms. The table only includes firms with 20 or more employees (except for aggregate emissions, see below). The table reports how large a share of e.g. employment sample firms account for. The total emissions reported here are the aggregate manufacturing emissions including biomass as reported by Statistics Denmark. Each cell reports an across-year average.

A.2 Firm-Level Carbon Emissions

To calculate firm-level carbon emissions, we measure for each firm in the regression sample the energy use of various fuels from the Industrial Energy Use Survey, multiply each fuel by its physically determined emission coefficient, and sum over fuels. We also add 'process emissions', i.e. emissions related to the production process rather than the burning of fuels.

The fuel-specific emission coefficients rely on data from Statistics Denmark. Each emission coefficient measures CO2 emissions per giga joule of energy generated from burning the fuel. Coefficients are constant across sectors and time because physically, the calorific value of the fuel as well as the emissions per unit of mass is constant.[32] Metcalf (2019) puts it this way: "The amount of CO2 associated with burning a ton of coal, a gallon of gasoline, or a therm of natural gas is, for all intents and purposes, constant. Changes in

[32] One exception in our data is the fuel 'general waste', since its components shift over time. Still, the time variation for this fuel is very limited.

industrial processes may affect the amount of fossil fuel burned but not the emissions per unit of fuel input."

The process emissions are measured at an aggregated sector level (a Danish sector definition slightly more granular than the 2-digit NACE industries). We distribute these process emissions onto firms in the relevant industry in proportion to the individual firm's share of the total sales in that industry in that year. Appendix Table A8 shows that our main results are robust to leaving out process emissions from the firm level carbon emission measure.

Table A2 shows the average share that the emissions from individual fuels and process emissions constitute of the average firm's emissions. For example, it shows that natural gas is the most important energy input, and that process emissions amount to 10 percent of the average firm's emissions.

Table A2: Average emission share of inputs and process emissions

Type	Average share
Natural gas	0.45
Gas diesel	0.18
Gasoline	0.13
Process emissions	0.10
Liquified petroleum gas	0.04
Fuel oil	0.04
Remainder	0.05

Notes: The table shows the average emission share of various energy inputs and process emission across all firm-years in the sample. The type called 'Remainder' refers to all remaining energy inputs: Biodegradable waste, wood pellets, additional gas types such as biogas and refinery gas, general waste, coal, petroleum, coke and additional oil types.

A.3 Firm-Level Importing Statistics

Table A3 presents summary statistics of the importing and offshoring behavior of the firms in the regression sample. The table takes all firm-year-origin-product import flows, where origin refers to the source country and product refers to an HS6 code, and calculates various summary statistics.

Panel A calculates the total number of HS6 products as well as the total and across-year average of origin-product combinations. This shows that the 2019 firms observed

Table A3: Summary statistics regarding importing behavior

	All import flows	Offshoring flows only
Panel A: Totals		
Total unique products (HS6-codes)	5530	5107
Avg. yearly unique origin-products	22,865	19,674
Total unique origin-products	72,998	63,136
Panel B: Origin-product-level		
Number of firms importing an origin-product, median product	1.00	1.00
Number of firms importing an origin-product, average product	2.59	2.23
Panel C: Firm-level number of products		
Number of origin-products, median firm	34.39	22.06
Number of origin-products, average firm	58.42	43.32
Panel D: Share of total value of flows		
2 most imported origin-products, median firm	0.54	0.61
5 most imported origin-products, median firm	0.80	0.86
Pre-sample origin-products, aggregate	0.54	0.56
Panel E: Share of imports		
Offshoring, aggregate	0.92	-
Offshoring, median firm	0.95	-

Notes: This table presents calculations from firm-year-origin-product import flows. An origin-product is a combination of an origin country and an HS6 product code. All panels except Panel A (rows 1 and 3) calculate the stated statistic for each year separately and then reports the across-year average. The columns indicate the set of import flows (all or only those categorized as offshoring) used to calculate the statistic.

Panel B calculates for each origin-product, how many firms that import it, and presents the median and average products.

Panel C calculates the number of unique origin-products that a firm has in a given year, and then reports the median and average firm respectively.

Panel D, the first two rows, take each firm-year and calculates the share that the 2/5 most imported origin-products have out of that firm-year's total imports and offshoring respectively, and reports those statistics for the median firm. The third row of panel D reports the fraction of total values that the flows of pre-sample origin-products account for. The pre-sample origin-products are firm-specific and correspond to the origin-products that a firm has imported in the two years prior to the first year that the firm enters the regression sample. These pre-sample origin-products correspond to those used for the shares in our Bartik shift-share instrument for our IV-regressions.

Panel E calculates the fraction of total imports (either at the aggregate or inside each firm-year) that offshoring flows constitute.

during the sample window import 22,865 unique origin-products in an average year. When considering offshoring flows only, this number drops to 19,674 and is still large relative to the number of firms. That the number of origin-products is large relative to the number of firms is also reflected in panel B: The average origin-product is imported by only 2.59 firms or 2.23 firms when considering offshoring flows. For the median product, the number is 1 for both imports and offshoring. That is, the importing behavior of Danish firms is highly dispersed across different source countries and products. This is useful for our identification strategy as it provides variation across firms, i.e., a supply shock to a particular origin-product only affects few Danish firms directly.

Panel C shows the number of origin-products in all firms for the median and average firm. The median firm imports 34 origin-products for all imports but only 22 origin-products for offshoring flows. This limits the extent of overlap between the origin-products that firms import. Panel D calculates how large a share of import or offshoring flows that the 2 or 5 most imported products cover for each firm individually. For example, for the median firm, the 5 most important origin-products cover 86 percent of total offshoring. Essentially, the imports of a particular firm are concentrated in just a few origin-products.

A second important calculation from panel D is its third row. It identifies the origin-products that a firm imported during its pre-sample years, i.e. the two years preceding the first year that a given firm has emission data. Then, it reports how large a share of the total import/offshoring value that these origin-products cover for the flows in the regression sample. Importantly for our identification strategy, the share is large for offshoring (0.56), reflecting a relatively stable importing behavior of firms. This stability is an important reason why the instrument is a strong predictor of offshoring.

Finally, panel E reports that offshoring flows cover 92 percent of the aggregate import flows and 95 percent of the firm level imports for the median firm. This reflects that firms' imports are in fact mainly in product categories that they themselves produce, although there is substantial variation across firms, e.g. the 25th percentile is 82 percent.

In summary, Table 1 and Table A3 document significant within-firm variation in offshoring and also that the few products that make up offshoring are highly specific to individual firms.

Finally, Table A4 shows the source country distribution for offshoring in the sample. The top ten source countries account for more than 70 percent of intermediate input import flows, and it is evident that proximate countries dominate with Germany as a particularly important source country for Danish firms. It is also seen that China accounts for a modest 3 percent of total offshoring flows.

Table A4: Top 10 offshoring origin countries

Origin country	Share of Offshoring
Germany	21.36
Norway	12.38
Sweden	9.34
United kingdom	5.89
Netherlands	5.22
USA	3.94
Belgium	3.29
France	3.22
Italy	3.10
China	2.95

Notes: The table shows the percentage of total offshoring that is accounted for by specific origin countries. The reported share is the across year average among all sample years.

A.4 Exiobase

Calculating carbon leakage rates for offshoring and Chinese import competition requires internationally comparable emission intensities. To measure such emission intensities, we use the environmentally extended multi-regional input-output (EE MRIO) tables of the Exiobase 3 database (Stadler et al. 2018). Exiobase uses national accounts, trade statistics, national input-output tables and emission accounts from The International Energy Agency as its sources, among others. International consistency was prioritized in the construction of the database. This is important for our analysis, since a leakage rate is inherently a cross-country metric.

Exiobase contains 44 countries, including all EU countries and 16 additional major economies including China, plus an additional 5 "rest of world" regions. The database covers roughly 90 percent of global GDP. It contains 200 product categories across all sectors of the economy and measures variables such as output, emissions and the corresponding emission intensities for all years from 1995 to 2016. The emission intensities measure CO_2 emissions from fossil fuel combustion as well as non-combustion emissions from cement and lime production per million euros of output for each country-product-year combination. We convert these into emissions per DKK from emission per million Euros by using yearly averages of the exchange rate from EUR to DKK (extrapolating 1999, the initial year of the Euro, backwards to 1995) and deflating to 2015 as with other monetary variables. The structure of Exiobase allows us to use emission intensities which reflect indirect emissions embedded in the input-output linkages of the world economy. We map each of these emission intensities to each HS6-country-year in the foreign trade statistics and PRODCOM. When the mapping is not unique, we calculate a weighted average across Exiobase emission intensities using output in the particular product-country-years as weights. For a comparison of Exiobase to other EE MRIOs, see e.g. the online appendix of Shapiro (2021).

B Counterfactual Decomposition and Carbon Leakage

B.1 Counterfactual Decompositions

We wish to perform the decomposition of equation (4) in a way that allows us to assess how the overall manufacturing emission intensity would have evolved had offshoring or import competition stayed constant at their initial levels. To do so, we calculate counterfactual data series. For offshoring, we replace actual values of firm-level emission intensities by those predicted by the regression results of Table 4:

$$\tilde{\phi}_{it} = \phi_{it,\text{data}} - \hat{\beta}\left(\log \text{OFF}_{it} - \log \text{OFF}_{i1996}\right), \tag{12}$$

where $\tilde{\phi}_{it}$ denotes the counterfactual emission intensity and $\phi_{it,\text{data}}$ denotes the actual emission intensity. When predicting counterfactual sales for offshoring, we perform the corresponding calculation using the parameter estimate $\hat{\theta}$. Similarly for import competition, we replace actual values of log sales by their predicted value when Chinese import competition is kept fixed:

$$\widetilde{\log \text{Sales}}_{it} = \log \text{Sales}_{it,\text{data}} - \hat{\delta}\left(\text{ImpPen}_{jt}^{CN \rightarrow DK} - \text{ImpPen}_{j1996}^{CN \rightarrow DK}\right). \tag{13}$$

After calculating counterfactual log sales, we can calculate the counterfactual market shares $\widetilde{s}_{it}$ used in the decomposition simply by taking the exponential and dividing by the sum of (counterfactual) sales.

B.2 Carbon Leakage

Our estimation results show that offshoring reduces firm-level emission intensities but increases sales, and the counterfactual decomposition exercise showed that a substantial portion of the decline in the overall manufacturing emission intensity can be attributed to offshoring. Likewise, Chinese import competition reduces firm-level sales and emissions. Both of these phenomena, however, are associated with increasing emissions abroad. This section outlines how we quantify this relationship by calculating carbon leakage rates.

For any specific firm i we are interested in the change in global emissions coming from the reduction in Danish emissions (triggered by offshoring or Chinese import competition) and the associated increase in emissions in the rest of the world:

$$\Delta E_t^{\text{Global}} = \Delta E_t^{DK} + \Delta E_t^{ROW}. \tag{14}$$

We express this as a carbon leakage rate that measures the change in emissions in the rest of the world per unit of domestic emission reduction $\left(-\frac{\Delta E_t^{ROW}}{\Delta E_t^{DK}}\right)$. To calculate the terms underlying this fraction, we rely on Exiobase emission coefficients (see appendix A.4).

B.2.1 Foreign emissions

Emissions in the rest of the world associated with imports by Danish firms or industries are measured as the change in the value of imports at the country-product-time level multiplied by the corresponding emission coefficient:

$$\Delta E_{it}^{ROW} = \sum_c \sum_p \Delta I_{cpit} e_{cpt}, \tag{15}$$

where e_{cpt} refers to the emission intensity of product p from Exiobase. Since the products in Exiobase are more aggregated than the product level in imports (HS6), we aggregate import flows from HS6 into Exiobase-products before doing the calculation.

B.2.2 Offshoring

This subsection derives the leakage rate for offshoring, $L_i^O = -\Delta E_i^O / \Delta E_i$, where ΔE_i^O is the change in emissions embodied in firm i's offshoring corresponding to ΔE_i^{ROW} above, and ΔE_i is the change in emissions from domestic firm i corresponding to ΔE_i^{DK} above (we suppress subscript t). To be consistent we not only calculate emissions embodied in imports using Exiobase emission coefficients, but we also use them to obtain a measure for local emissions in the denominators, i.e., the domestic emissions, of the leakage rate.

To calculate the leakage rate for offshoring we first consider the numerator, i.e., the change in foreign emissions induced by offshoring. The emissions embodied in offshoring are defined as $E_i^O = e_i^O OFF_i$, where e_i^O is the emission intensity in firm i's offshoring, which is measurable from Exiobase as outlined above. The total differential, keeping the foreign emission intensity fixed, is $\Delta E_i^O = e_i^O \Delta OFF_i = \frac{E_i^O}{OFF_i} \Delta OFF_i$.

The denominator of the leakage rate is derived from totally differentiating domestic emissions of firm i, $E_i = e_i^Y Y_i$, where e_i^Y is the emission intensity in firm i's output, Y_i. We then have $\Delta E_i = e_i^Y \Delta Y_i + Y_i \Delta e_i^Y$, where the first term comes from the productivity effect of offshoring and the second term from offshoring's impact on the firm-level emission intensity. We can then use the estimated output and emission intensity elasticities of offshoring to get

$$\Delta E_i = e_i^Y Y_i \underbrace{\frac{\Delta OFF_i \hat{\theta}}{OFF_i}}_{\frac{\Delta Y_i}{Y_i}} + Y_i e_i^Y \underbrace{\frac{\Delta OFF_i}{OFF_i}\hat{\beta}}_{\frac{\Delta e_i^Y}{e_i^Y}} = E_i \frac{\Delta OFF_i}{OFF_i}(\hat{\beta} + \hat{\theta}). \tag{16}$$

We can now plug into the leakage rate and, writing year subscripts explicitly, obtain

$$L_{it}^O = -\frac{\Delta E_{it}^O}{\Delta E_{it}} = -\frac{1}{\hat{\beta} + \hat{\theta}} \frac{E_{it}^O}{E_{it}}. \tag{17}$$

That is, the leakage rate is a function of the estimated elasticities and domestic and imported emissions for the firm-years in the sample.

B.2.3 Chinese import competition

This subsection outlines how we calculate the leakage rate between emissions generated in China and the associated emissions generated in Denmark caused by Chinese import competition. Since this is an industry measure, we define a leakage rate for each industry j. The Chinese import competition leakage rate for industry j may then be defined as

$$L_j = -\frac{\Delta E_j^{CN}}{\sum_{i \in j} \Delta E_i}, \tag{18}$$

where the numerator is the change in emissions embodied in industry j's imports of final goods from China, and the denominator is the change in emissions from all domestic firms belonging to industry j.

The starting point is again the estimated coefficient from equation (6), which is a semi-elasticity

$$\hat{\delta} = \frac{\Delta \log Y_i}{\Delta \text{ImpPen}_j} = \frac{\Delta Y_i / Y_i}{\Delta \text{ImpPen}_j}. \tag{19}$$

Under the assumption that the emission intensity of firm i (e_i^Y) stays constant, the numerator may be written in terms of emissions, $\Delta E_i / E_i$, such that we have $\Delta E_i =$

$\hat{\delta}E_i\Delta\text{ImpPen}_j$. This may be rewritten further assuming that the denominator in the import penetration measure ImpPen_j, i.e., the domestic market size of industry j, Y_j^{DK}, stays fixed, such that $\Delta E_i = \hat{\delta}E_i\Delta\text{Imports}_j^{CN}/Y_j^{DK}$, which feeds into the denominator of the leakage rate.

For the numerator, assuming again that the emission intensity of the average import flow stays constant, the change in emissions embodied in imports from China is $\Delta E_j^{CN} = e_j^{CN}\Delta Imports_j^{CN}$. We can then rewrite the leakage rate, stating year subscripts explicitly, as

$$L_{jt} = -\frac{\Delta E_{jt}^{CN}}{\sum_{i\in j}\Delta E_{it}} \tag{20}$$

$$= -\frac{e_{jt}^{CN}\Delta Imports_{jt}^{CN}}{\sum_{i\in j}\hat{\delta}\frac{\Delta Imports_{jt}^{CN}}{Y_{jt}^{DK}}E_{it}} \tag{21}$$

$$= -\frac{1}{\hat{\delta}}\frac{e_{jt}^{CN}Y_{jt}^{DK}}{\sum_{i\in j}E_{it}}. \tag{22}$$

That is, the leakage rate measures emissions from local production had it been produced with Chinese production technology divided by the actual emissions by domestic firms in the industry and the estimated semi-elasticity.

C Additional Tables

Table A5: Firm-level Effects of Offshoring and Chinese Import Competition - OLS

	log CO_2 Int.		log Sales	
	(1)	(2)	(3)	(4)
log Offshoring	-0.135***		0.227***	
	(0.01)		(0.01)	
$\text{ImpPen}^{CN \to DK}$		0.244		-0.339***
		(0.18)		(0.12)
Observations	11591	11591	11591	11591

Notes: All columns show OLS regressions and include year and firm fixed effects. In columns (2) and (4) standard errors are clustered at the 4-digit NACE industry-year level, otherwise they are heteroscedasticity robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Firm-level Effects of Offshoring and Chinese Import Competition with controls

	log CO_2 Int.		log Sales	
	(1)	(2)	(3)	(4)
log Offshoring	-0.704*		0.481**	
	(0.38)		(0.19)	
$\text{ImpPen}^{CN \to DK}$		-0.178		-0.677
		(1.10)		(0.55)
log Employment	0.349	-0.191***	0.432***	0.797***
	(0.29)	(0.03)	(0.15)	(0.02)
log Capital	0.016	-0.025	0.033*	0.058***
	(0.03)	(0.02)	(0.02)	(0.01)
F-stat (log Off.)	7.90		7.90	
log WES	0.09***		0.09***	
F-stat (ImpPen)		48.21		48.21
$\text{CES}^{CN \to OC}$		0.22***		0.22***
Observations	11522	11522	11522	11522

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1) and (3) standard errors are heteroscedasticity robust, in columns (2) and (4) they are clustered at the 4-digit NACE industry by year level. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the central first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: CO_2 Emissions - Firm-level Effects of Offshoring and Chinese Import Competition

	log CO2 Emissions		
	(1)	(2)	(3)
	IV	IV	IV
log Offshoring	0.113		-0.411
	(0.21)		(0.42)
$\text{ImpPen}^{CN \rightarrow DK}$		-2.920***	-3.984**
		(1.05)	(1.84)
F-stat (log Off.)	13.36		12.06
log WES	0.14***		0.13***
$\text{CES}^{CN \rightarrow OC}$			-.49***
F-stat (ImpPen)		51.06	241.58
log WES			-.01***
$\text{CES}^{CN \rightarrow OC}$		0.23***	0.22***
Observations	11591	11591	11591

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In column (2) standard errors are clustered at the 4-digit NACE industry by year level, otherwise they are heteroscedasticity robust. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the central first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: CO_2 without process emissions

	log CO_2 Int.		log Sales		log CO_2	
	(1)	(2)	(3)	(4)	(5)	(6)
log Offshoring	-0.543**		0.687***		0.144	
	(0.26)		(0.17)		(0.23)	
$\text{ImpPen}^{CN \rightarrow DK}$		0.210		-3.501***		-3.290***
		(1.20)		(0.99)		(1.15)
F-stat (log Off.)	13.36		13.36		13.36	
log WES	0.14***		0.14***		0.14***	
F-stat (ImpPen)		51.06		51.06		51.06
$\text{CES}^{CN \rightarrow OC}$		0.23***		0.23***		0.23***
Observations	11591	11591	11591	11591	11591	11591

Notes: All columns show 2SLS regressions and include year and firm fixed effects. In columns (1) and (3) standard errors are heteroscedasticity robust, in columns (2) and (4) they are clustered at the 4-digit NACE industry by year level. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments and the central first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: 2-digit industry level leakage rates

2-digit NACE industry	Avg.	Weighted avg. (CO2)	Weighted avg. (sales)	Weighted avg. (FG imports)
Coke and Refined Petrolium	0.28	0.27	0.32	0.29
Food Products	1.61	1.10	0.69	0.72
Furniture	2.03	1.67	1.65	1.47
Pharmaceuticals	2.40	1.72	1.36	1.64
Motor Vehicles	2.48	1.91	2.05	1.83
Beverages	3.15	4.58	3.86	2.64
Paper	3.86	3.75	3.78	4.08
Machinery	4.68	2.61	2.12	3.82
Electronic Products	4.86	2.68	2.54	7.49
Tobacco	4.87	3.06	2.96	4.30
Other	5.47	3.60	1.99	5.36
Metal Products	6.61	5.23	5.08	5.89
Electrical Equipment	7.52	4.16	3.66	6.15
Textiles	7.82	4.34	4.50	6.31
Basic Metals	8.62	7.50	5.65	7.36
Non-Metallic Mineral	10.58	6.08	6.13	10.62
Rubber and Plastic	10.97	3.06	2.53	3.95
Wood	11.85	6.90	6.93	17.23
Chemicals	13.78	2.83	3.15	7.13
Wearing Apparel	15.75	8.66	9.71	17.28
Leather	17.98	5.79	5.51	28.82
Other Transportation	30.15	11.75	10.72	182.16
Media Printing	44.81	40.85	35.93	35.74

Notes: The table calculates leakage rates based on the regression parameter estimate for Chinese import penetration. The leakage rates are calculated using emission coefficients from Exiobase. After calculating leakage rates at the 4-digit NACE by year level, the numbers are aggregated to the 2-digit NACE level by taking averages. 'FG import' refers to final goods imports. 2-digit NACE-years with zero import penetration are excluded.

Table A10: Counterfactual decompositions with alternative parameter estimates

Scenario	Total	Technique	Composition	Cross
Panel A: Actual Decomposition				
Actual	-0.55	-0.28	-0.29	0.02
Panel B: Single endogenous regressor				
Counterfactual emission intensity with offshoring at initial level	-0.28	0.00	-0.29	0.01
Counterfactual sales with offshoring at initial level	-0.42	-0.28	-0.13	-0.01
Counterfactual sales with Chinese import penetration at initial level	-0.56	-0.28	-0.31	0.03
Panel C: Heterogeneity				
Counterfactual emission intensity with offshoring at initial level	-0.36	-0.08	-0.29	0.01
Counterfactual sales with offshoring at initial level	-0.42	-0.28	-0.12	-0.01
Counterfactual sales with Chinese import penetration at initial level	-0.55	-0.28	-0.31	0.03

Notes: The table shows decompositions of the relative change in the aggregate emission intensity as defined in equation (4). Panel A replicates the actual decomposition of the balanced panel reported in table 2. Panel B performs decompositions where values are calculated with parameter estimates from the regressions with one endogenous regressors (table 3). In Panel C the decompositions are performed with counterfactual emission intensities and sales calculated by using the parameter estimates that incorporate heterogeneous effects (table 7). All decompositions rely on a balanced sample of firms operating in 1996 and 2016, so the net entry effect is zero by construction and not shown. The counterfactual scenarios rely on the method outlined in appendix B.1.

Table A11: Counterfactual decompositions over seven year periods

Scenario	Total	Within	Between	Cross
Panel A: 1996 - 2003				
Actual	-0.23	-0.07	-0.12	-0.04
Counterfactual emission intensity with offshoring at initial level	0.07	0.20	-0.12	-0.01
Counterfactual sales with offshoring at initial level	-0.09	-0.07	0.04	-0.07
Counterfactual sales with Chinese import penetration at initial level	-0.25	-0.07	-0.14	-0.04
Panel B: 2003 - 2009				
Actual	-0.32	-0.19	-0.13	-0.00
Counterfactual emission intensity with offshoring at initial level	-0.14	-0.09	-0.13	0.08
Counterfactual sales with offshoring at initial level	-0.22	-0.19	-0.04	0.00
Counterfactual sales with Chinese import penetration at initial level	-0.33	-0.19	-0.14	-0.00
Panel C: 2009 - 2016				
Actual	-0.27	-0.06	-0.14	-0.07
Counterfactual emission intensity with offshoring at initial level	0.55	0.72	-0.14	-0.04
Counterfactual sales with offshoring at initial level	-0.27	-0.06	-0.15	-0.05
Counterfactual sales with Chinese import penetration at initial level	-0.26	-0.06	-0.13	-0.07

Notes: The table shows decompositions of the relative change in the aggregate emission intensity as defined in equation (4). Each panel uses a balanced sample of firms that operate in the indicated period, so the net entry effect is zero by construction. The counterfactual scenarios rely on the methodology explained in appendix B.1. Counterfactual values are calculated with parameter estimates from the regressions with two endogenous regressors (columns 4 and 8, table 4).

Table A12: Carbon Leakage Rates with alternative parameter estimates

	Average	Average (weighted)	25th percentile	Median	75th percentile
Panel A: Single endogenous regressors					
Offshoring	-3.74	-3.45	-4.47	-2.06	-0.83
Chinese import penetration	6.42	3.75	1.73	3.30	7.11
Panel B: Heterogeneity					
Offshoring	4.00	8.14	-1.18	0.09	5.87
Chinese import penetration	5.73	2.32	1.53	3.15	6.20

Notes: The table calculates leakage rates based on the regression parameter estimates, domestic emissions and imported emissions calculated using Exiobase emission coefficients. In Panel A, the parameter estimates used are those from the regressions with one endogenous regressor (columns 1, 3 and 4 of table 3). In Panel B, the parameter estimates used are those from the regressions with heterogeneous effects (table 7). For offshoring, the unit of observation is a firm-year, i.e. the underlying calculation has one leakage rate for each firm year. For Chinese import competition, the unit of observation is an industry-year, i.e. the underlying calculation has one leakage rate for each 4-digit NACE-year. The column denoted 'Average (weighted)' weights each leakage rate by absolute emissions (in the firm for offshoring and in the 4-digit NACE industry for Chinese import competition). Some firms only produce products that cannot be matched to Exiobase products. These are not included in the calculations. The top and bottom percentiles of leakage rates have been trimmed.