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

Jonathan Leisner Jakob R. Munch August Twile Nielsen Georg Schaur

June 2022

PRELIMINARY AND INCOMPLETE

Abstract

We use Danish firm-level data to examine the link between firm-level carbon emissions and international trade in the form offshoring and exposure to import competition. We show that offshoring reduces the emission intensity in Danish firms, while Chinese import competition reduces emissions by lowering sales of exposed domestic firms. Thus, offshoring contributes to declining overall emissions through a technique effect, while import competition changes the composition of economic activity across firms and affects overall emissions that way. We then 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. We find that emissions embodied in imports of intermediate inputs are lower in magnitude than 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. Thus, overall, offshoring contributes to reducing global carbon emissions, while import competition from China substantially increases global carbon emissions. (*JEL* F14, F18, Q54, Q56)

*Contact information: Leisner: University of Copenhagen, jl@econ.ku.dk; Munch: University of Copenhagen, jakob.roland.munch@econ.ku.dk; Nielsen: University of Copenhagen, aetn@econ.ku.dk; Schaur: University of Tennessee, gschaur@utk.edu.

1 Introduction

In most rich countries emissions of CO_2 from manufacturing have fallen, while emissions in developing countries have increased substantially (Copeland, Shapiro, and Taylor 2021). For example, China's emissions doubled between 2001 and 2009, but in Denmark carbon emission intensity in the manufacturing sector dropped by 48 percent between 1996 and 2016. Simultaneously globalization has proceeded at pace with increased specialization and international division of labor as a result. A third of global carbon emissions is now embodied in international trade and dirty industries are those most involved in international trade (Shapiro 2021). Hence, it is natural to consider whether the cleanup of manufacturing in advanced countries is due to globalization and if emissions, in response, have increased elsewhere. Yet evidence on the causal link between international trade and environmental outcomes is limited (Cherniwchan and Najjar 2021). In this paper, we examine whether the reduction of carbon emissions in Danish manufacturing can be attributed to international trade in the form offshoring and exposure to import com- petition from China triggered by changes in comparative advantages abroad, and we also assess the implied change in global emissions by accounting for the embodied emissions in imports.

Fueled by declining transportation costs and trade liberalizations, international trade volumes have increased markedly over recent decades. We focus on two core mechanisms driving this trend that potentially also affect carbon emissions from manufacturing firms. First, China's accession into the WTO in 2001 have led to a surge in final good imports from China in most countries. It is by now well established that increased import competition from China have led to declining domestic manufacturing production and employment (Autor, Dorn, and Hanson 2013), but we lack evidence for the impact on local and global carbon emissions. Second, globalization has enabled firms to increasingly split up production processes by offshoring the production of intermediate inputs. This becomes attractive when relative costs of acquiring intermediate inputs from abroad decreases. If firms offshore the most polluting parts of production their emission intensities decrease. We measure offshoring as the imports of products that the firm could realistically have produced itself following Hummels et al. (2014).

Common to both mechanisms is that a reduction of relative production costs abroad shifts economic activity away from home. The mechanisms may contribute to a reduction of aggregate domestic emissions, but it is, however, a priori unclear how global emissions are affected, as foreign production is also polluting. In that sense globalization can be thought to cause carbon leakage. Carbon leakage occurs when changes in comparative advantage pushes emissions from one country to another. Usually this is considered in relation to stricter environmental regulation at home, which reduces the costs of foreign goods relative to domestic goods. Changes in comparative advantage abroad, e.g. the rise of China, may also cause carbon leakage, as it changes relative costs and shifts the location of economic activity in a similar way.

To guide our empirical analysis, we first decompose the decline in the overall Danish manufacturing emission intensity into technique and composition effects using firm-level data. The technique effect reflects changes in firms' emission intensities over time, and the composition effect represents the contribution from changes in output across firms. Similar decompositions have mainly been carried out at the industry or product-level (Levinson 2009; Shapiro and Walker 2018). In such decompositions, the technique effect is often found to dominate.

We use detailed firm-level data with information about carbon emissions to perform the decomposition. We find that changes in composition and technique contribute equally to the fall in the emission intensity. From 1999 to 2016, where the aggregate manufacturing emission intensity dropped by 48 percent, the technique effect contributed with 21 percent and the composition effect contributed with 22 percent. The remaining five percent are due to e.g. entry and exit of firms.

Our main contribution is to estimate the effects of Chinese import competition and offshoring on emissions to investigate how they have contributed to the cleanup of Danish manufacturing. Chinese import competition is expected to lead to reallocation across industries, so it should mainly drive the composition effect. Offshoring is a firm-specific choice, which we expect mainly affects the technique effect, as polluting production processes are moved to places with comparative advantage in producing those inputs.

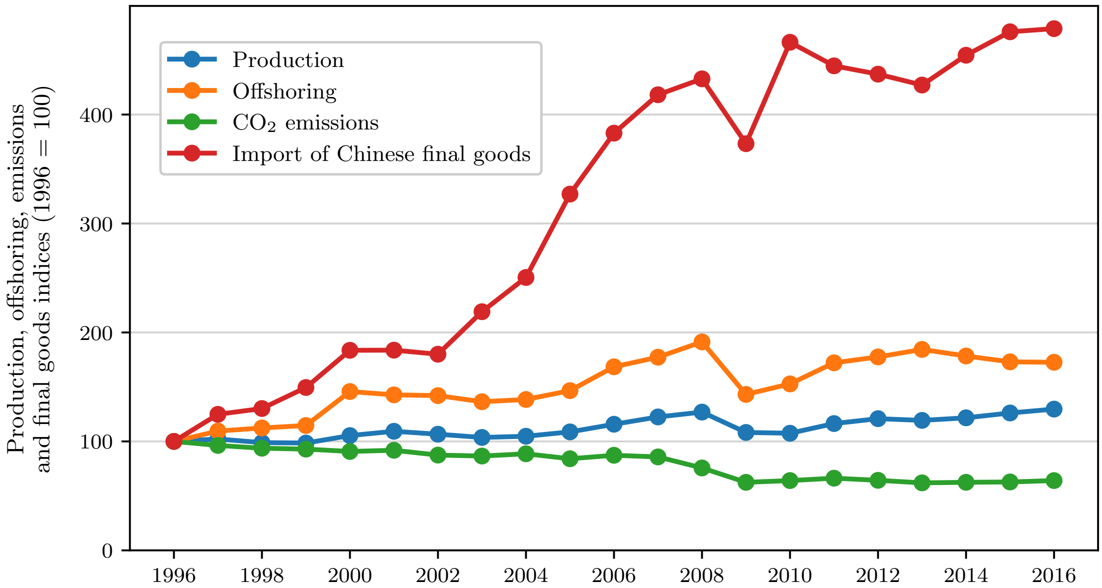
We face endogeneity issues as imports from China may depend on performance of local firms, and as firms may select into offshoring. To solve this identification challenge we rely on the existing literature and use two different instruments, that build on supply shocks in other countries driving comparative advantages. Chinese import penetration in a specific industry is instrumented with the share of Chinese final goods in that industry in a group of other developed countries (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 argue that the identifying assumptions, changes in foreign comparative advantages being exogenous to Danish firms, are fulfilled.

We find that the semi elasticity of sales with respect to Chinese import penetration is -5.5. The effect is significantly larger for the most pollution intensive quantile of firms. This indicates that import penetration causes polluting firms to shrink most and thereby the manufacturing industry to become cleaner. On the other hand, the least polluting Danish manufacturing industries have experienced the largest inflows of final goods from China, which tends to increase the overall emission intensity as economic activity are reallocated towards more polluting industries. We estimate the elasticity of emission intensity with respect to offshoring to be -0.52, indicating that firms do become cleaner when they increase offshoring. The effect is 60 percent larger for firms with above median emissions intensities compared to that of below median emission intensities. These estimates add to a sparse recent literature on the effects of firm-level imports on carbon emissions (Dussaux, Vona, and Dechezleprêtre 2020; Akerman, Forslid, and Prane 2021).

To gauge the importance of these estimates for aggregate emissions of Danish manufacturing, we compute how emission intensities and sales would have evolved if they were only affected by offshoring and Chinese import penetration. We then repeat our decomposition analysis and compare with the historical decomposition. To the best of our knowledge, we are the first to perform such firm-level regressions relating import competition to emissions, and to quantify the importance of these two globalization mechanisms for the technique and composition effects.

Climate change is a global challenge caused by the global carbon emission level, and so it is important to assess the extent to which the reductions in Danish emissions are offset by increased emissions elsewhere. We use product-by-country CO_2 intensities from around fifty countries (as in Shapiro (2021)) to calculate the increase in emissions abroad associated with changes in final good imports and offshoring in Danish firms. We find that emissions embodied in imports of intermediate inputs are lower in magnitude than 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.

Figure 1: Production, offshoring and emissions in Danish manufacturing and imports of Chinese final goods



Notes: The figure shows aggregate emissions reported from Statistics Denmark as well as offshoring, production and imports of final goods from China calculated from micro data. The micro data consists of observations on all Danish manufacturing firms with 20 or more employees. We follow DST's requirements for discretion including checking that no two observations are 'dominating'. All monetary variables are deflated.Production is measured as sales with 2015 as the base year. Offshoring measures the imports of products that firms could likely have produced themselves. Final goods are imports by non-manufacturing firms. The emission index is calculated based on the aggregate domestic emissions from manufacturing excluding biomass.

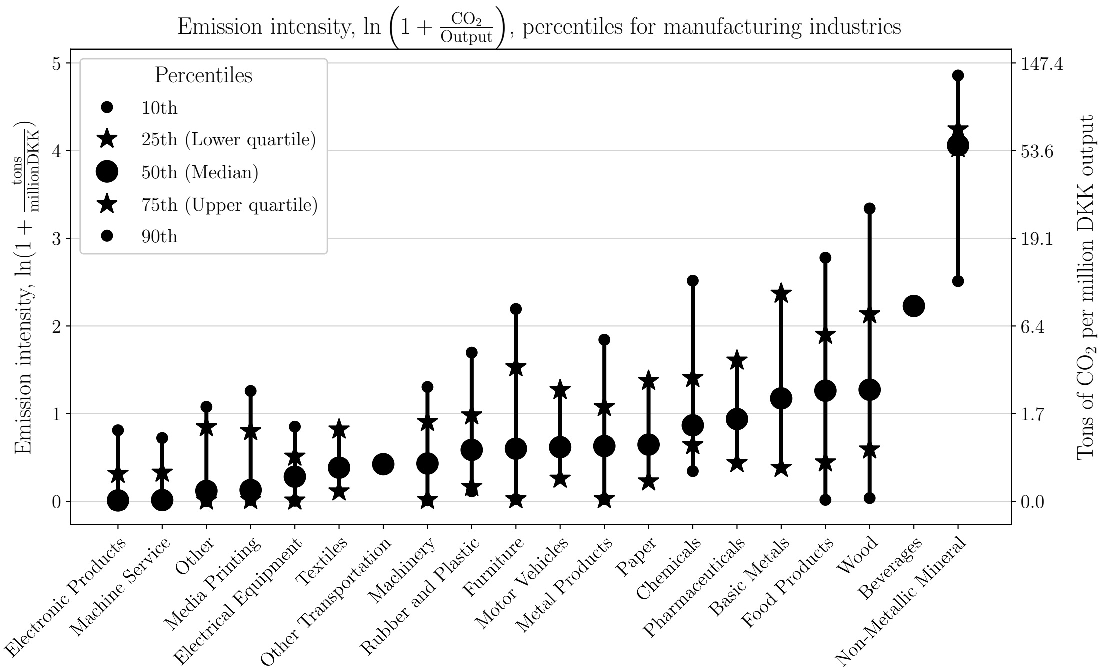
Thus, overall, offshoring contributes to reducing global carbon emissions, while import competition from China substantially increases global carbon emissions.

The rest of the paper is structured as follows. Section 2 presents summary statistics and performs the decompositions of the change in Danish manufacturing emissions. Section 3 defines offshoring and import penetration and introduces the regression sample. Section 4 present the econometric methodology including our identification strategies. Section 5 presents the results and section 6 concludes.

2 Carbon Emissions from Danish manufacturing

In this section we investigate the heterogeneity in emission intensities in Danish manufacturing. As we find large heterogeneity across firms even within narrow industries, we perform a decomposition of the change in emissions from Danish manufacturing at the firm level. These descriptive exercises motivate our subsequent regression analysis.

Figure 2: Heterogeneity in emission intensity, across and within industries (2016)



Notes: The industries 'Tobacco', 'Wearing Apparel', 'Leather' and 'Coke and Refined Petrolium' have too few non-dominant observations to have any percentiles displayed.

2.1 Heterogeneity

We add to the insights of the current literature by documenting the heterogeneity present in Danish manufacturing. We calculate industry-specific emission intensity percentiles for 2016 in Figure 2. The emission intensities are calculated as $\log(1+\frac{CO_2}{\text{Output}})$ with CO_2 emissions measured in tons and output measured in million DKK. To aid interpretation, the secondary y-axis converts the intensities back into $\frac{CO_2}{\text{Output}}$. The figure illustrates vast heterogeneity in emission intensities between and across firms within 2-digit NACE-industries. The across-industry average ratio between the 90th and 10th percentile is 382. Implying 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, when ever they produce the same amount of output.

A justified concern with this figure is that 2-digit industries after all are quite broad. However, the heterogeneity persists when one changes the industry classification to even the 6-digit level; the average 90/10 percentile ratio is 248. We also find that the heterogeneity in emission intensities is larger than the heterogeneity in e.g. capital and labor intensities (**??** in **??** summarizes these results). The vast heterogeneity across firms within narrowly defined industries suggests that costs related to carbon taxes are not the primary driver behind firms' input choices and that raising carbon taxes in Denmark would potentially cause substantial reallocations between firms.

Besides illustrating that analyses on emission intensities should ideally be performed at the firm level, the large dispersion has two implications. First, industry-level regulations that fail to incorporate firm-level differences will cause potentially large inefficiencies (Lyubich, Shapiro, and Walker 2018). One example of such a policy is border carbon adjustment e.g. taxes on imports based on their carbon content. If the carbon content of a particular good is based on an industry-level average, many firms will face a tax far from the optimal Pigouvian tax.

Second, this result questions the 'representative firm' assumption often employed in macroeconomic models such as large-scale CGE models. While heterogeneity in the underlying distribution does not invalidate the 'representative firm' assumption per se, it does warrant caution, especially in models designed to predict environmental outcomes of manufacturing industries.

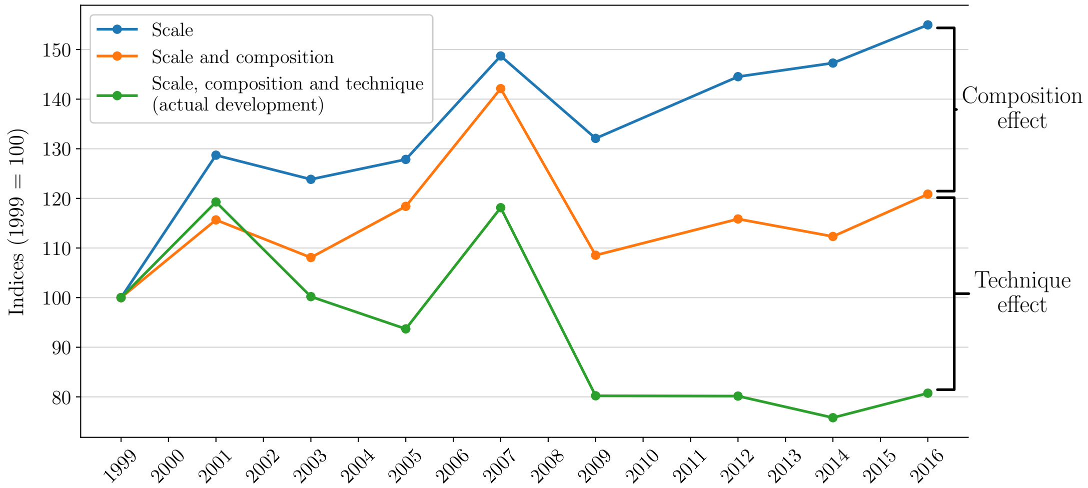
2.2 Decomposition of the historical development of emissions

We decompose the development of emissions from 1999 to 2016 into scale, composition and technique effects, that reflect changes in aggregate output, changes in market shares and changes in emission intensities respectively. The scale effect measures what the development of emissions would have been if only aggregate output changed while the composition of firms and their emission intensities were kept fixed at the initial values. The composition effect measures what the development of emissions would have been if only the composition of firms changed while aggregate output and emission intensities were fixed. Finally, the technique effect measures what the development of emissions would have been if only emission intensities changed while the outputs of all firms stayed fixed.

Our method builds on the decomposition in Shapiro and Walker (2018), with two important differences.[1] First, their decomposition is carried out at the product level, whereas ours uses the firm level dimension in our data. This implies that reallocations between firms producing the same product would be characterized as composition in our methodology, but technique in their methodology. Second, Shapiro and Walker (2018)

[1]See **??** for the exact decomposition method applied.

Figure 3: Decomposition of the historical development of emissions into scale, composition and technique effects

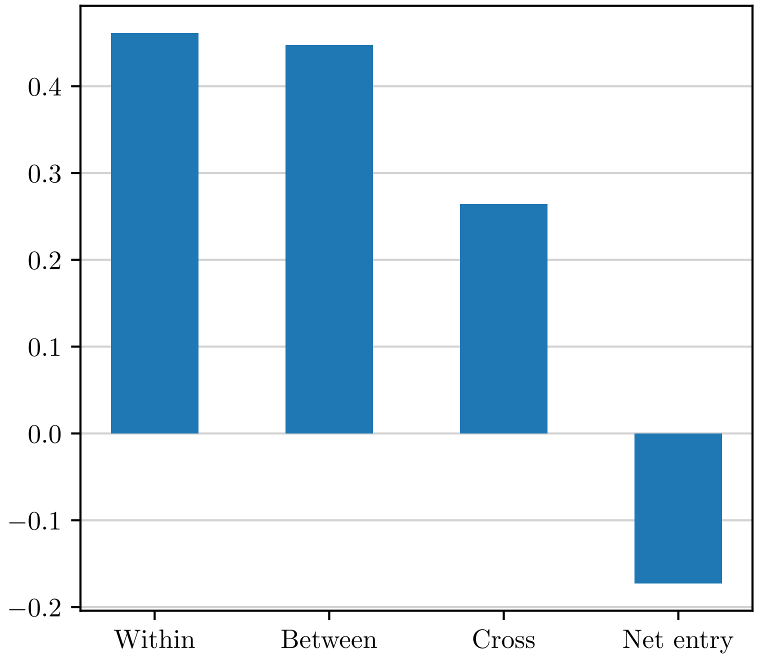


Notes: The figure shows a statistical decomposition of the historical emission development in Danish manufacturing, see **??**.

assign entering products an initial emission intensity based on adjacent products that existed in the baseline year. We assign each firm its own emission intensity in its first year of existence, hence we label entry effects as composition rather than technique, as they effectively do. We believe this is a more appropriate label for extensive margin effects, especially when the spread in emission intensities between firms within even narrowly defined industries is substantial, as documented earlier.

Figure 3 shows the results of the decomposition analysis and depicts the composition and technique effects which are measured as differences between the series. The figure shows that the scale effect contributed to rising emissions of 55.0 percent, the composition effect decreased emissions by 34.1 percent and the technique effect decreased emissions by 40.1 percent. Our analysis characterizes the composition effect as quantitatively more important than in Levinson (2009) and Shapiro and Walker (2018). This likely reflects the fact that we characterize within-industry and within-product inter-firm reallocations as composition where they do not. However, it could also reflect that compositional effects simply have been more prevalent in Danish manufacturing compared to US manufacturing, which is more sheltered from international trade.

Figure 4: Effects sizes in the FHK decomposition



Notes: The figure presents of the decomposition of the aggregate log emission intenisty which is an across-firm average. The decomposition follows Foster, Haltiwanger and Krizan (2001), as presented in Melitz and Polanec (2015). All calculations comply with the rules of Statistics Denmark.

2.3 FHK decomposition

Alternatively we can decompose the 48 percent decline in the aggregate emission intensity from 1996 to 2016 using the Foster, Haltiwanger and Krizan (2001) decomposition approach to account for entry, exit and cross term effects in addition to the technique and composition effects, see figure 4.

3 Offshoring and Import Penetration

The technique and composition effects are both quantitatively important for Danish Manufacturing. This motivates the main objective of our paper, which is to explain the importance of offshoring and import competition for the technique and composition effect.

Offshoring allows a firm to substitute domestic intermediate production and associated emissions with foreign inputs, potentially lowering the emission intensity of its production process. Import competition will affect some industries and firms more than others, and especially emission intensive firms might be disproportionately impacted, consistent with a negative composition effect. By providing casual estimates of the effects of offshoring and Chinese import competition on emission intensities and market shares respectively, we open the black boxes of the technique and composition effects.

The measure of offshoring, following the definition from Hummels et al. (2014), is the imports of goods that the firm could realistically have produced itself:

Definition 1. In year t, the products that firm i can offshore are all the 4-digit HS product categories which firm i has or will sell in any year τ. Offshoring for firm i in year t is then the total value of imports among this group of products.

One can think of offshoring as the subset of imported products that are part of the firm's core business. Consequently, these goods are more likely to be subject to considerations regarding the trade-off between producing at home generating emissions or importing. For example, it is not realistic that a cement producer will consider producing computers rather than source them from actual computer producers. So even though imported computers embed emissions from their production process, they do not realistically introduce an emit-or-import decision for cement producers.

A concern with the measure is whether a product is simply resold and not produced. We do not deem this a serious concern because the share of goods sold without value-added is very low for Danish manufacturing firms (Hummels et al. 2014).

Following e.g. Autor, Dorn, and Hanson (2013) we consider Chinese import competition an industry measure:

Definition 2.

$$\text{ImpPen}_{jt}^{CN \to DK} \equiv \frac{\text{FinalGoods}_{jt}^{CN \to DK}}{\text{Imports}_{jt}^{World \to DK} + \text{Sales}_{jt}^{DK}}, \tag{1}$$

where t indexes time and all firms in industry j share the same import penetration measure. $\text{FinalGoods}_{jt}^{CN \to DK}$ 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 it is for immediate reselling as final goods, and not for use as inputs, and hence competes with Danish manufacturing firms producing the same products. The denominator measures the total market size of these same products by summing domestic production 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.

To construct our regression sample, we require firm-years to have positive emissions, more than twenty employees, more than 300.000 DKK offshoring, positive sales, positive world export supply (WES) instrument and defined Chinese export supply (CES) instrument.[2] The resulting number of firm-years is 9337 across 1541 unique firms.

Table 1: Summary statistics

			Absolute		Natural log		
	Obs.	Firms	Average	Median	Average	Standard dev.	Dev. from firm mean
CO2	11,889	2042	5087.68	244.71	5.78	1.85	0.41
CO2 int.	11,889	2042	1.18	0.22	-1.47	1.46	0.45
Sales	11,889	2042	438,985.68	119,391.74	11.86	1.19	0.23
Offshoring	11,889	2042	86,030.25	17,358.29	9.77	1.72	0.49
ImpPen$^{CN \to DK}$	11,889	2042	0.02	0.01	-	-	-
Employment	11,889	2042	184.61	71.89	4.45	1.03	0.19
WES	11,889	2042	3,906,375.53	1,916,382.88	14.38	1.33	0.19
CES$^{CN \to OC}$	11,889	2042	0.13	0.08	-	-	-

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. All calculated statistics have been checked for compliance with the rules of Statistics Denmark, e.g. medians are calculated from at least five non-dominant observations.

Table 2: Share of Economic Acitivity in Sample

Annual Emissions	% of VA	% of Employment	% of Sales	% of Import	% of CO_2
7,130,090.91	65.06	59.97	66.30	78.80	77.60

Table 1 reports key summary statistics for the regression 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 2900 tons of CO_2.

3.1 Summary statistics regarding offshoring

Table 3 reports additional summary statistics related specifically to offshoring, e.g. that offshoring covers 80 percent of imports.

Table 3 presents important summary statistics of the importing and offshoring behavior of the firms in our 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 central statistics.

[2]Both instruments will be formally defined in the next section.

Panel A calculates the total number of HS6 codes as well as the total and across-year average of origin-product combinations. This shows that the firms (of which there are 1390 unique ones of throughout the entire sample) import 21,127 unique origin-products in an average year. When considering offshoring flows only, this number is reduced to 14,762 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: It reports that the average origin-product is imported only by 2.51 firms or 1.87 firms when considering offshoring flows. For the median product, the number is 1 for both imports and offshoring. This reflects an important fact about the importing behavior of Danish manufacturing firms: It is highly dispersed across different origin countries and products. This is useful for our identification strategy, see Section 4.1, because it means that a supply shock to a particular origin-product only affects very few Danish firms directly.

Panel C calculates the number of origin-products in all firms and reports the median and average firm respectively. It shows that the median firm imports 35 origin-products for all imports but only 14 origin-products for offshoring flows. This limits the amount of overlap between the origin-products that firms import. This is magnified by the calculations in panel D. The first two rows calculate how large a share of imports/offshoring flows that the 2 or 5 most imported products cover for each firm individually, and then reports the median firm share. For the median firm, the 5 most important origin-products cover 91 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, these shares are large, reflecting a relatively stable importing behavior of firms. This stability is an important reason why the instrument, presented later in Section 4.1, is a strong predictor of offshoring.

Finally, panel E reports that offshoring flows cover 73 percent of the aggregate import flows and 72 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 37 percent.

Table 3: Summary statistics regarding importing behavior

	All import flows	Offshoring flows only
Panel A: Totals		
Total unique products (HS6-codes)	5533	5115
Avg. yearly unique origin-products	23,324	20,093
Total unique origin-products	73,961	63,985
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	2.60	2.24
Panel C: Firm-level number of products		
Number of origin-products, median firm	34.57	22.15
Number of origin-products, average firm	58.61	43.50
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
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 the number of unique origin-products that a firm has in a given year, and then reports the median and average firm respectively. As with the remainder of the calculated statistics, the presented number is the yearly average.

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

Panel D takes 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.

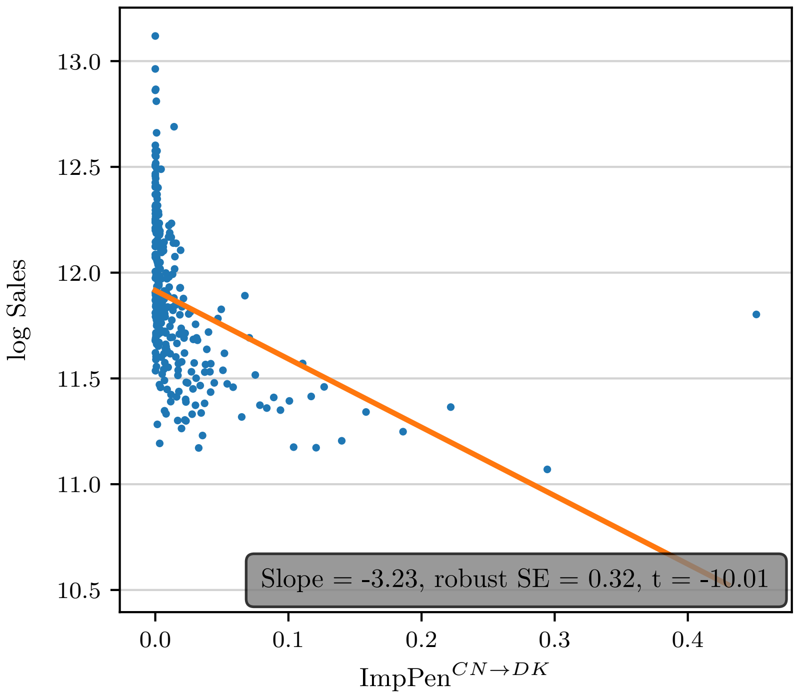
Panel E calculates the fraction of total imports (either at the aggregate or inside each firm-year) that offshoring flows constitute.

All calculations comply with the rules of Statistics Denmark (including dominance criterion).

3.2 Scatterplots

See figures 5, 6, 7, 8, 9 and 10.

Figure 5: Scatterplot of ImpPen$^{CN \to DK}$ versus log sales.



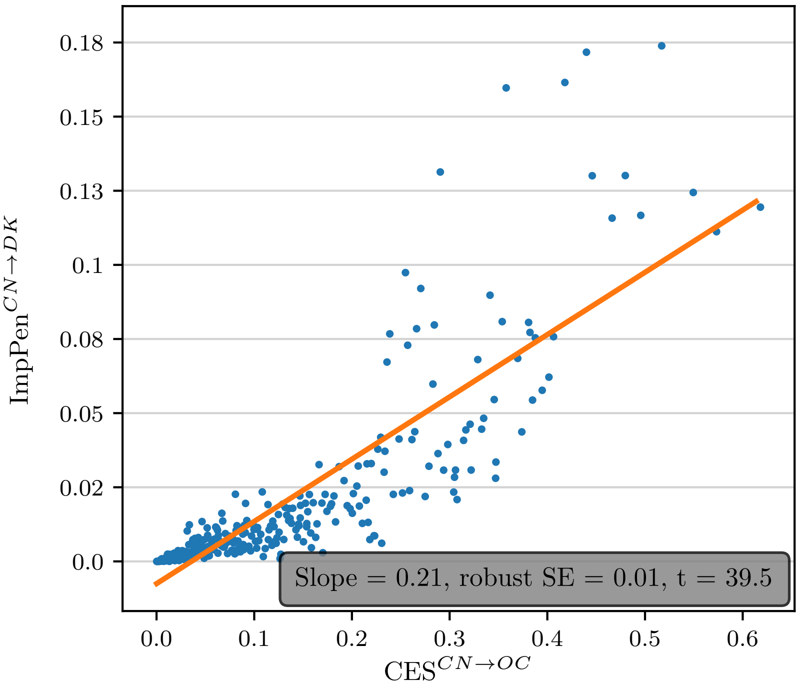
Notes: The scatterplot shows binned values. Each bin contains at least 5 different firms and no two observations account for more than 85 percent of turnover/sales for that bin. The regression line is based on all underlying observations.

4 Econometric methodology

As our decomposition showed, both the composition effect and the technique effect are quantitatively important. The remainder of the paper estimates the importance of import competition from China for the composition effect and of offshoring for the technique effect.

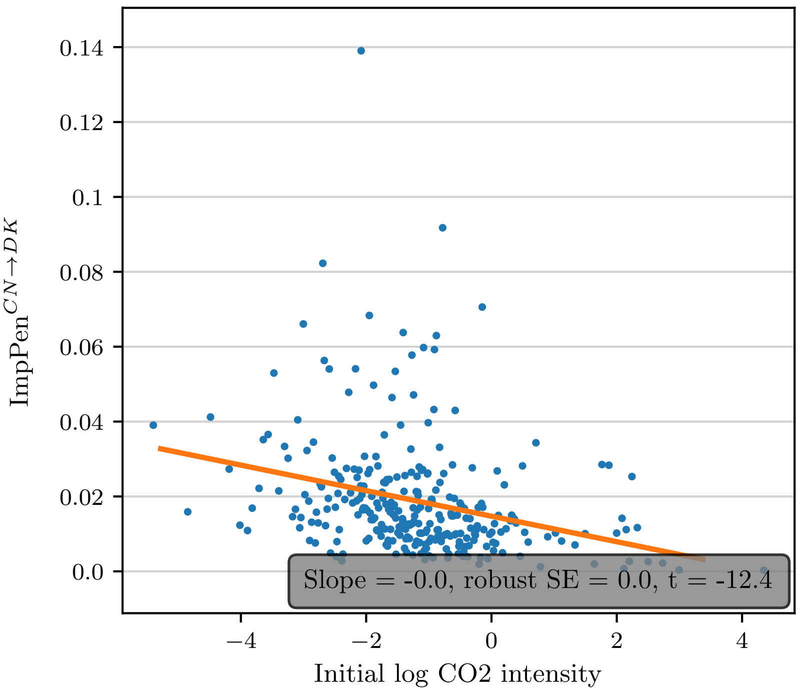
Import competition, in this case from China, is a prime candidate for a quantitatively important mechanism for driving the composition of Danish manufacturing. China's exports to Denmark have drastically increased throughout our sample, and presumably their comparative advantage has not been uniform across industries. If Chinese exporters have primarily won market shares in Denmark at the expense of relatively emission intensive firms, it would result in a negative contribution to the composition effect. To establish

Figure 6: Scatterplot of $\text{CES}^{CN \rightarrow OC}$ versus $\text{ImpPen}^{CN \rightarrow DK}$.



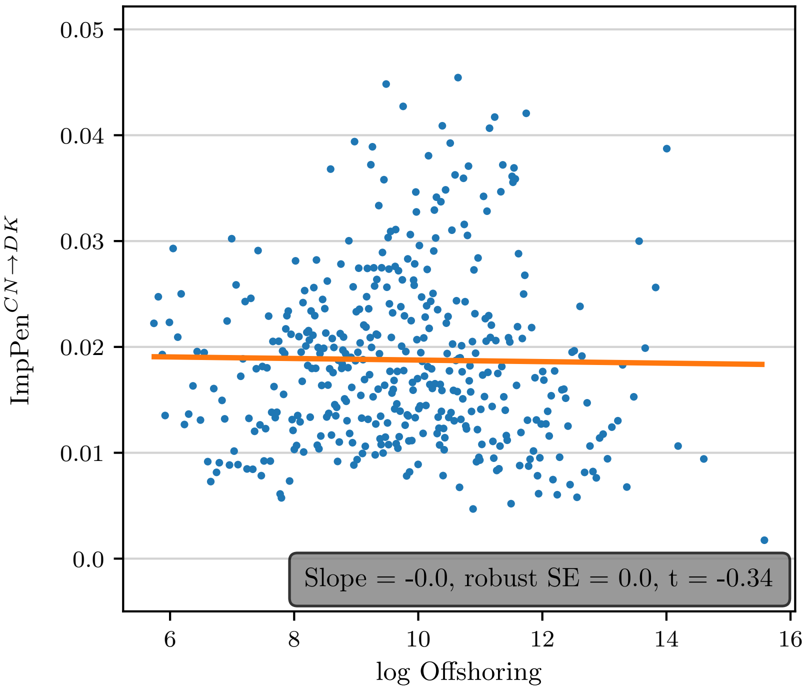
Notes: The scatterplot shows binned values. Each bin contains at least 5 different firms and no two observations account for more than 85 percent of turnover/sales for that bin. The regression line is based on all underlying observations.

Figure 7: Scatterplot of Initial log CO2 intensity versus $\text{ImpPen}^{CN \rightarrow DK}$.



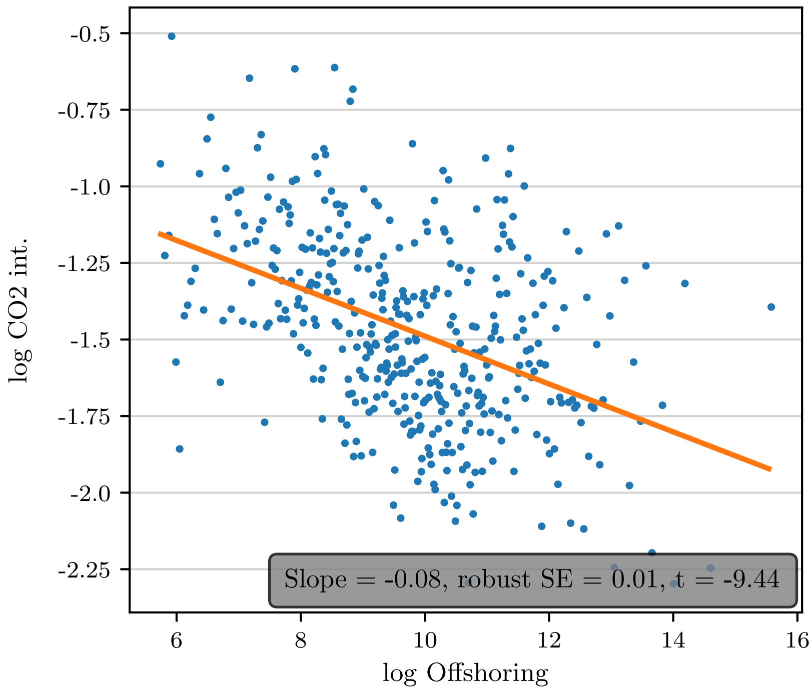
Notes: The scatterplot shows binned values. Each bin contains at least 5 different firms and no two observations account for more than 85 percent of turnover/sales for that bin. The regression line is based on all underlying observations.

Figure 8: Scatterplot of log offshoring versus ImpPen$^{CN\rightarrow DK}$.



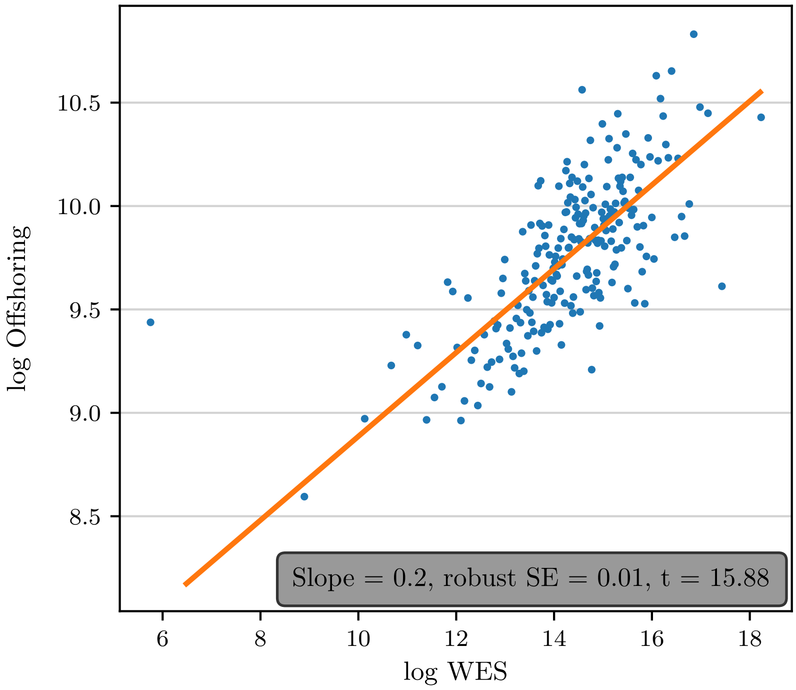
Notes: The scatterplot shows binned values. Each bin contains at least 5 different firms and no two observations account for more than 85 percent of turnover/sales for that bin. The regression line is based on all underlying observations.

Figure 9: Scatterplot of log offshoring versus log CO2 int..



Notes: The scatterplot shows binned values. Each bin contains at least 5 different firms and no two observations account for more than 85 percent of turnover/sales for that bin. The regression line is based on all underlying observations.

Figure 10: Scatterplot of log WES versus log offshoring.



Notes: The scatterplot shows binned values. Each bin contains at least 5 different firms and no two observations account for more than 85 percent of turnover/sales for that bin. The regression line is based on all underlying observations.

this link, we estimate the following regression equation;

$$\log\left(\text{Sales}_{it}\right) = \phi_i + \vartheta \text{ImpPen}_{jt}^{CN \to DK} + \gamma_t + \varepsilon_{it} \tag{2}$$

where i indexes firm, j indexes industry and t indexes year, ϕ_i is a firm fixed effect, γ_t is a year fixed effect and ε_{it} is an error term. The parameter of interest is ϑ, the semi-elasticity of firm-level sales with respect to Chinese import competition.[3]Apart from potential measurement error, there could be endogeneity issues if firms are able to affect the market shares of their Chinese competitors, e.g. in smaller industries where price setting power is stronger. To correct for possible endogeneity, we employ an instrumental variables strategy.

Offshoring is a prime candidate for a quantitatively important mechanism for driving the technique effect of Danish manufacturing. It allows firms to substitute domestic processes that require energy and cause emissions for inputs produced abroad, resulting

[3]Note that the left hand side does not explicitly include the market share as in the decomposition. Because the denominator would be identical across all firms, the two formulations are equivalent when year fixed effects are included and we use the logarithm of sales. Thus regressions of sales and market share would yield the same estimate of ϑ by construction.

in a lower emission intensity. To establish this link, we estimate the following regression equation;

$$\log\left(\frac{\text{Emissions}_{it}}{\text{Output}_{it}}\right) = \phi_i + \delta \log \text{Offshoring}_{it} + \gamma_t + \varepsilon_{it} \tag{3}$$

where the elasticity of the emission intensity with respect to offshoring, δ, is the parameter of interest. The primary reason for endogeneity issues in this equation is the existence of firm-specific productivity shocks that affect the use of inputs in production simultaneously. **??** makes this claim formally by manipulating a production function where both emissions and offshoring enter as inputs. When a firm is hit by a total factor productivity shock it is induced to decrease inputs for a given output, generating a positive correlation between inputs. In other words δ is likely biased upwards in ordinary least squares regressions.

4.1 Identification strategies

To generate exogenous variation in the Chinese import penetration measure, we employ a 2SLS procedure. The instrument that we construct, Chinese export supply, captures China's comparative advantage relative to producers from 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. [4] Formally, we define it as

$$CES_{jt}^{CN\rightarrow OC} = \frac{\text{Imports}_{jt}^{CN\rightarrow OC}}{\text{Imports}_{jt}^{World\rightarrow OC}} \tag{4}$$

where CN, DK and OC refer to China, Denmark and a group of other countries. The instrument is measured at the same industry level as the Chinese import competition measure, $\text{ImpPen}_{jt}^{CN\rightarrow DK}$. The identifying assumption, the validity criterion, is that the import share of China in the 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. For the instrument to be defined for industry j, at least one of its products must be exported from China to one

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

of the other countries.

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 used in Hummels et al. (2014). Formally, the instrument is calculated as

$$WES_{it} = \sum_{p}^{\mathcal{P}} \sum_{c}^{\mathcal{C}} \left(s_{ipc,t_0} \times X_{cpt} \right), \qquad \sum_{p}^{\mathcal{P}} \sum_{c}^{\mathcal{C}} s_{ipc,t_0} = 1 \tag{5}$$

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 and X_{cpt}, the "shifts", denote 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 very detailed HS6 level that features specific products such as cement bricks and waterproof footwear. The pre-sample years are firm-specific and are 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, therefore they are constantly hit indirectly by different supply shocks through their foreign business partners. 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 exactly the "shift" part of the Bartik instrument. Whether a firm is exposed indirectly to productivity shocks to German cement brick producers depends on, among other things, whether the firm is already tied to those producers. Therefore, a natural measure of this exposure is simply whether the firm already imports cement bricks from Germany. This is the idea behind the "share" part of the Bartik 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. ?? states the necessary and sufficient conditions formally and argues that they are likely upheld in our setting. To do so, it draws on Section 3.1, which provides descriptive evidence about the importing behavior of firms. This appendix shows, among other things, 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.

With this instrument, one might be worried that increased exports of foreign firms is driven by shocks to the demand for their product rather than supply shocks to their production process. If the export flows are driven mainly by demand shocks, it could be that those demand shocks affect Danish firms simultaneously, introducing an omitted variable bias in the offshoring equation where demand shocks partly determine emission outcomes at the (Danish) firm level as well as the export outcomes at the (foreign) firm level. Since we measure emissions relative to output, such demand shocks would only be a problem if emissions did not scale proportionally with output, e.g. because of fixed cost investments in clean technologies.

A second concern is that multi-product firms might change their optimal output mix when hit by non-uniform demand shocks (for example due to global shocks to tastes or simply from changes in its output market competition), potentially causing changes to emissions. We cannot rule out that such output mix changes play a role, but it simply means that the effect of offshoring, to the extent that importing facilitates product-switching, can also run through product switching.

A third threat to identification is the concern that the importing behavior of Danish firms could directly or indirectly drive the aggregate exporting numbers of foreign producers, essentially introducing reversed causality between offshoring and world export supply. Since we disregard export flows from foreign countries directly to Denmark in the construction of our instrument, the only possibility for this connection to be a problem is if the importing behavior of Danish firms affects exports indirectly. For example, if Danish firms increase imports of an intermediate input produced by firms in Canada that in turn use intermediate inputs produced by firms in the US, the export flow from the US to Canada is part of the instrument, potentially violating the exogeneity of the shocks.

We do not however deem this a very large concern, since Denmark is a small country and constitutes only minor parts of the export flows of any particular country.

Finally, one could be worried that import competition plays a role for emission intensities and that offshoring plays a role for firm sales. To examine such effects, we also perform regressions where the other factor is included as a control and check whether our estimates of interest change.[5]

5 Results

In this section we examine if firms rely on offshoring to become cleaner and if it contributes to the technique effect. We then examine whether import competition affects clean and polluting firms differently, and if it has affected the composition of Danish manufacturing.

5.1 Offshoring

To investigate the association between offshoring and emission intensity we rely on the linear regression model specified in (3).

The estimated elasticity in column 1 of Table 4 shows that an increase in offshoring of 1 % is associated with a fall in emission intensity of roughly 0.14 %. The parameter estimate potentially suffers from a positive bias due to omitted variables that correlate with both the emission intensity and offshoring such as productivity shocks. To remove this bias we turn to IV-regression, where we instrument offshoring using world export supply.

Column 2 shows the first main result: When offshoring increases by 1 % the emission intensity falls by 0.52 %, all else equal. This result is statistically significant at the 5 % level and economically important at the firm level. As we showed in Table 1, the average yearly deviation in offshoring from its firm mean is 0.49 percent and so such an average change in offshoring would lead to a fall in the emission intensity of around -0.25 percent. Given that an average yearly deviation in emissions intensity is 0.45 percent, offshoring is important in explaining changes in emissions at the firm level.

Columns 3 and 4 examines robustness by including the Chinese import penetration variable as a control or by including the corresponding IV as a control variable. Chinese

[5] In future work, we will estimate regressions where both endogenous variables are instrumented simultaneously.

Table 4: CO2 Intensity and Offshoring

	log CO_2 Intensity				
	(1)	(2)	(3)	(4)	(5)
	OLS	IV	IV	IV	IV
log Offshoring	-0.136***	-0.517**	-0.630**	-0.552**	-0.697*
	(0.01)	(0.24)	(0.28)	(0.26)	(0.42)
$\text{ImpPen}^{CN\rightarrow DK}$			-1.463**		-2.324
			(0.64)		(2.78)
$\text{CES}^{CN\rightarrow OC}$				-0.257	
				(0.29)	
F-stat (Off.)		14.07	11.35	12.25	12.25
F-stat (IP)					17.64
Observations	11889	11889	11889	11889	11889

Notes: All specifications include year and firm fixed effects. Standard errors are heteroscedasticity-robust. In column 3 $\text{ImpPen}^{CN\rightarrow DK}$ is included as a control, i.e. not instrumented. Column 4 includes the CES-instrument as a control. In column 5 we include two instruments for the two endogenous variables. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments, and the central first-stage coefficients.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

import penetration has a negative correlation with the emission intensity (column 3), but the estimated offshoring effect is largely unaffected in both cases. Finally, in column 5 we examine the importance of jointly estimating the impact of Chinese import competition and offshoring on firm-level sales and emission intensities in a demanding specification where both variables are instrumented. It is well known that handling two endogenous regressors jointly in a 2SLS framework often presents a challenge as there are stronger demands on the instruments and standard errors may be inflated. We find that the effect of offshoring is borderline significant and still negative with an estimated coefficient somewhat larger than in our main specification in column 2.

To examine if there is heterogeneity in the estimated offshoring effect, we split firms in two groups. A firm is labelled "dirty", if its' CO_2 intensity in the first year we observe that firm is above the median intensity among firms that year. Appendix table X shows results where we interact this dummy variable with our offshoring measure. When offshoring increases by 1 %, the CO_2 intensity drops by 0.42 % percent for the clean firms, while the intensity for the dirty firms falls by 0.67 %. Thus changes in offshoring affects dirty firms' CO_2 intensity more than clean firms.

5.2 Import Competition

We investigate the association between import competition and sales based on the regression model specified in (2). Table 5 presents results.

The estimated semi-elasticity in column 1 suggests that an increase in Chinese import penetration by 1 percentage point is associated with a fall in firm sales of 0.006 %, although the estimate is insignificant.

Table 5: Import Penetration and Sales

	log Sales				
	(1)	(2)	(3)	(4)	(5)
	OLS	IV	IV	IV	IV
$\text{ImpPen}^{CN \rightarrow DK}$	-0.637	-5.465**	-4.441**	-5.284**	-3.840
	(0.56)	(2.23)	(1.78)	(2.23)	(2.49)
log Offshoring			0.225***		0.356
			(0.01)		(0.36)
log WES				0.035	
				(0.04)	
F-stat (IP.)		18.81	18.70	17.64	17.64
F-stat (Off.)					12.25
Observations	11889	11889	11889	11889	11889

Notes: All specifications include year and firm fixed effects. Standard errors are clustered at the industry level (NACE4). In column 3 log Offshoring is included as a control, i.e. not instrumented. Column 4 includes the WES-instrument as a control. In column 5 we use two instruments for two endogenous variables. The lower panel shows information on the first-stage regressions: F-statistic for test of weak instruments, and the central first-stage coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To remove endogeneity concerns we apply the IV-strategy outlined above. Column 2, shows that when Chinese import penetration exogenously increases by one percentage point sales fall by 0.05 percent, all else equal. This is a statistically significant effect and it is economically important. The parameter obtained through IV-regressions differs in magnitude from our OLS estimate indicating endogeneity.

To show that our import penetration measure is not confounded by offshoring, we include offshoring as a control in column 3 and we include the offshoring instrument in column 4. The estimation appears to be robust as the estimated import competition effect is roughly in line with that of column 2. We also note that offshoring correlates positively with the sales in column 3 suggesting a productivity effect akin to Grossman and Rossi-Hansberg (2008). Finally in column 5 we also instrument the offshoring variable where we lose significance, but the estimated parameters do not change substantially compared with those of column 3.

In Appendix table Y we again include an interaction term for firms in the highest quarter of CO_2 intensity. The effect of import penetration on these highly polluting firms is large, at -10.5, such that dirty firms are more affected by competition from China. The effect of import penetration on least polluting firms is, on the other hand, only -4.1. This indicates that Chinese import penetration has contributed to the cleanup of Danish manufacturing, because it particularly affects the size of the most polluting firms. The estimated parameters are statistically significant, but the economic importance is also large given the substantial increase in final good imports from China, as shown in Table 1.

5.3 Reduced form counterfactual

We can now 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 and Chinese import competition are held fixed at their initial 1996 level. Table 6 shows that the overall decline in the emission intensity of 48 percent would have only been 30.5 percent if offshoring had not changed since 1996. In other words offshoring accounts for roughly a third of the decline in the manufacturing emission intensity. It is also evident that this decline is driven by the within-firm technique effect.

Table 6: Decomposition of change in log CO2 intensity: 1996 to 2016

	Total	Within	Between
Observed development	-48.0	-22.1	-21.5
Initial offshoring	-30.5	-11.5	-20.9
Initial import comp.	-64.9	-31.0	-28.9

Notes: The decomposition follows Foster, Haltiwanger and Krizan (2001), as presented in Melitz and Polanec (2015). The numbers are percentages.

By contrast, if Chinese import competition is held unchanged at its initial level, there would have been a larger decline in the emission intensity. This result covers two opposing forces. On the one hand, Chinese import competition reduces firm-level emissions through lower firm sales and the effect is larger for the dirtiest firms as discussed above. On the other hand, the firms in the cleanest industries such as textiles and electronics experienced the largest increases in import competition, see Figure XX, and this effect dominates such that Chinese import competition increases the overall manufacturing emission intensity.

5.4 Leakage

We then 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 tons of carbon created abroad for each ton removed domestically:

$$L \equiv -\frac{\Delta E_t^{ROW}}{\Delta E_t^{DK}} \tag{6}$$

As outlined in the appendix, we can calculate the leakage rate for offshoring by taking the estimation equation at face value, totally differentiate and rearrange to obtain

$$L_i^O = -\frac{1}{\beta}\frac{E_i^O}{E_i^Y} \tag{7}$$

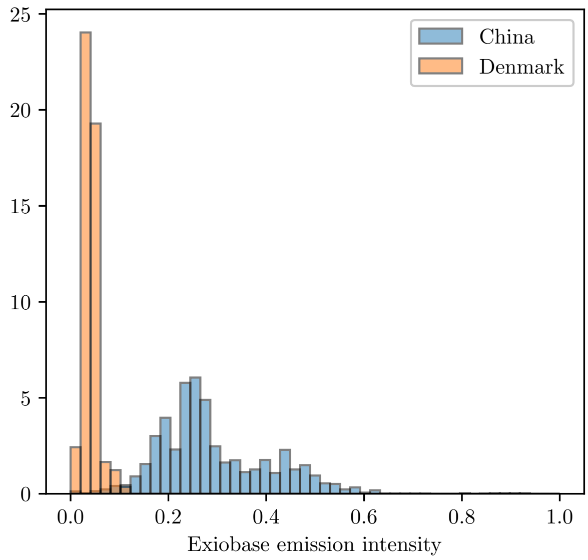
Likewise, the leakage rate for Chinese import competition is

$$L_j = -\frac{1}{\gamma}\frac{e_j^{CN} Y_j^{DK}}{\sum_{i \in j} E_i}. \tag{8}$$

Combining the above equations with the regression estimates, Exiobase emission intensities capturing both direct and indirect emission rates and firm data we can calculate these leakage rates. We find that the average offshoring leakage rate is 0.81. That is, when offshoring reduces emissions from the average firm by 1 ton in Denmark, emissions increase by 0.81 ton abroad. In other words, emissions embodied in imports of intermediate inputs are lower in magnitude than the domestic emission reduction caused by the import flows such that offshoring contributes to reducing global emissions.

The average import competition leakage rate is substantially higher at 6.90, such that when Chinese import competition reduces emissions (through sales) in Denmark by 1 ton, emissions in China increase by 6.9 ton. That is, import competition from China substantially 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 for Denmark, see Figure 11.

Figure 11: Density (unweighted)



6 Conclusion

In a globalized world, where countries participate in international trade, it is often a concern that reductions in domestic emissions come at the cost of increased foreign emissions, either due to offshoring of polluting inputs or through imports of polluting final goods.

We decompose the historical development of CO_2 emissions into scale, composition and technique effects. The decomposition departs from previous studies, Levinson (2009) and Shapiro and Walker (2018), by being performed at the firm level, something we, to the best of our knowledge, are the first to do. Similarly to the related papers we find that the technique effect is larger than the composition effect, but the split is not as skewed towards the technique effect as in the related papers.

The causal part of our paper explores the components of the decomposition by estimating the causal relationship between offshoring and emission intensities and between Chinese import penetration and sales.

To estimate causal effects we rely on two-stage least squares estimation. Exogenous variation in offshoring is obtained using a shift-share Bartik instrument constructed by following Hummels et al. (2014). The "shares" are pre-sample origin-product import shares at the firm level, and the "shifts" are origin-product export flows, which are plausibly exogenous to the Danish firm. We argue that the instrument is valid, drawing on the formal requirements from Borusyak, Hull, and Jaravel (2021). We obtain exogenous variation in Chinese import penetration to Denmark, by using Chinese import penetration in other similar countries as an instrument. We choose countries that are rich and far from Denmark, such that they are affected similarly by Chinese import competition, but it is unlikely that Danish firms are affected indirectly in through these markets.

The first main regression finds that the elasticity of the emission intensity with respect to offshoring is -0.52. The average yearly variation in firm-level offshoring is 0.49 percent, thus this estimate is economically important at the firm level. In the aggregate offshoring has increased by 189 percent in our sample period from 1995 to 2016. Hence offshoring has contributed to a substantial reduction of the emission intensity, to one third of its initial level. Thus offshoring is important at the aggregate level, but there are other, counteracting factors that affect the technique effect as well.

In the second set of results we estimate the semi-elasticity of sales with respect to Chinese import penetration. We find that it is -5.4 implying that when a firm faces more Chinese import penetration it shrinks in size. We then show that this effect is heterogeneous across firms; the most polluting firms see a decrease of 10.5 % from the same change, whereas clean firms only see a reduction of 4.1 %. Polluting firms are affected the most and they have also seen the largest increase in Chinese import penetration, implying that Chinese import penetration can play an important part in the composition effect.

Our results shed new light on the reduction of Danish manufacturing emissions by showing what we believe to be the first decomposition of emission changes at a firm level, and then providing causal evidence on mechanisms in the technique and composition effects. Namely that offshoring significantly reduces the emission intensity of manufacturing firms and that Chinese import competition changes the composition towards cleaner firms.

References

Akerman, Anders, Rikard Forslid, and Ossian Prane (2021). "Imports and the CO2 Emissions of Firms". Working paper. CEPR Discussion Paper 16090.

Autor, David, David Dorn, and Gordon H. Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". *American Economic Review* 103.6, pp. 2121–68.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2021). "Quasi-Experimental Shift-Share Research Designs". *The Review of Economic Studies* 0, pp. 1–33. ISSN: 0034-6527.

Cherniwchan, Jevan and Nouri Najjar (2021). "Environmental Regulations and the Cleanup of Manufacturing: Plant-Level Evidence". *The Review of Economics and Statistics* 103.3, pp. 476–491.

Copeland, Brian R, Joseph S Shapiro, and M. Scott Taylor (2021). "Globalization and the Environment". Working Paper 28797. National Bureau of Economic Research.

Dussaux, Damien, Francesco Vona, and Antoine Dechezleprêtre (2020). "Carbon Offshoring: Evidence from French Manufacturing Companies". Working paper. Sciences Po.

Foster, L, John Haltiwanger, and C Krizan (2001). "Aggregate productivity growth: Lessons from Microeconomic Evidence". *New Directions in Productivity Analysis.*

Hummels, David, Rasmus Jørgensen, Jakob R. Munch, and Chong Xiang (2014). "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data". *American Economic Review* 104.6, pp. 1597–1629.

Klimapartnerskab, Energitung industri (2020). "Regeringens klimapartnerskaber, partnerskabet for energitung industri, afrapportering".

Levinson, Arik (2009). "Technology, international trade, and pollution from US manufacturing". *American Economic Review* 99.5, pp. 2177–92.

Lyubich, Eva, Joseph Shapiro, and Reed Walker (2018). "Regulating mismeasured pollution: Implications of firm heterogeneity for environmental policy". *AEA Papers and Proceedings* 108, pp. 136–42.

Melitz, Marc J and Sašo Polanec (2015). "Dynamic Olley-Pakes productivity decomposition with entry and exit". *The Rand journal of economics* 46.2, pp. 362–375.

Shapiro, Joseph S (2021). "The Environmental Bias of Trade Policy*". *The Quarterly Journal of Economics* 136.2, pp. 831–886. ISSN: 0033-5533.

Shapiro, Joseph S. and Reed Walker (2018). "Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade". *American Economic Review* 108.12, pp. 3814–54.

Appendices

A Appendices

A.1 Emission coefficients

To calculate fuel-industry-year specific emission coefficients, we rely on two datasets supplied by Statistics Denmark.

The first of these data sets is an *energy matrix* which includes industry-level data on energy use across a wide range of energy goods. The split of energy use between industries is performed by Statistics Denmark using energy data from the Danish Energy Agency.

The second data set is an *emission matrix* and includes industry-level emissions from a wide range of energy goods - the same as those from the industry-level energy use data. Statistics Denmark calculates emissions using technology-specific emission coefficients supplied by DCE (Danish Centre For Environment And Energy) who is also responsible for reporting the official emission accounts for Denmark to e.g. the UNFCCC. Alongside emissions directly related to specific energy goods are also industry-level process emissions. We divide these process emissions onto firms in the relevant industry proportionally with the individual firm's share of the total turnover in that industry. Lastly, the emission matrix includes a residual; emissions which Statistics Denmark could not place. We distribute this residual to each energy good in that industry according to its share of total emissions in the industry. Hence, the total number of emissions is preserved.

We wish to calculate emission coefficients essentially by dividing each emission matrix by its corresponding energy matrix. Practically, this means dividing e.g. carbon dioxide emissions from coal usage (in some industry in some year) by the coal usage itself. The result is a number which states how many emissions that a gigajoule of coal usage generates in an industry in a specific year.

Before dividing the emission matrix by the energy matrix however, we aggregate energy goods, such that they correspond to the energy goods asked about in the industrial energy use survey.[6] After this final aggregation, we divide the two matrices.

[6] One example is natural gas. In the survey, firms are simply reporting their use of natural gas. In the energy and emission matrices however, natural gas is divided into multiple categories. We combine two of these, 'Large users and export' and 'Commercial and households'. Statistics Denmark provided us with the most appropriate aggregations.

For each firm in the energy use survey, we multiply its energy uses by the relevant emission coefficients. Then, as mentioned, we add that firm's share of its industry's process emissions, based on its share of sales in the industry. Finally, total emissions of CO_2 of that firm is the sum of these two; the energy-related emissions and the process emissions. Energy emissions cover the vast majority of emissions.

While calculating emissions from emission coefficients is standard, the method has potential drawbacks, each of which we address in turn.

First, it assumes that one gigajoule of energy from e.g. coal emits the same number of CO_2 units across firms within the same industry and in the same year. The amount of gigajoules that a kilogram of coal can generate through combustion might change over time as technologies improve, but that is exactly what the time dimension of the emission coefficients reflects. At the same time, the industry dimension reflects differences in combustion technologies across industries. In practice the emission coefficients between industries are rather similar, reflecting that such technological differences are small. This assumption does not imply that firms in the same industry and year will have the same firm-level emission intensities, because their fuel mixes can be vastly different.

Second, if firms employ so-called end-of-pipe abatement technologies which reduce the emissions for given fuel inputs, this would pose a problem for our measure of emissions, because we do not observe such abatement. Anecdotal evidence suggests that carbon capture and storage technologies are currently too costly to be economically feasible in our setting (source in Danish: Klimapartnerskab 2020).

B Offshored and Imported Emissions

B.1 Offshored Emissions

Whenever a Danish Firm increases offshoring, emissions in Denmark decrease as emission intensity falls (holding total sales constant, for now). This is, however, associated with increasing emissions abroad. There are two approaches to this, either we calculate year to year differences and how this affects emissions, or we calculate the counterfactual where there is no offshoring and compare. Hence, the Δs can be interpreted either as the change from $t-1$ to t or from the current value to zero.

For any specific firm, i, we are interested in the change in global emissions, consisting reduction in Danish emissions and increase in foreign emissions:

$$\Delta E_t^G = \Delta E_t^{DK} + \Delta E_t^{ROW} \tag{9}$$

Note this could also be in the form of a leakage rate $\left(-\frac{\Delta E_t^{ROW}}{\Delta E_t^{DK}}\right)$.

B.1.1 Foreign emissions

Emissions in rest of world, associated with the Danish firm's offshoring is simply the change in the value of offshored inputs at the country-product-time level multiplied by the corresponding emissions coefficient:

$$\Delta E_{it}^{ROW} = \sum_c \sum_p \Delta O_{cpit} e_{cpt} \tag{10}$$

where e_{cpt} refers to the emission intensity of product p as given from the exiobase-database. Since the products in exiobase are more aggregated than the product in imports (hs6), we aggregate import flows from hs6 into exiobase-products before making the calculation.

Now, since ΔO_{cpit} is only defined for firms that exist in both period t and $t-1$, the set of continuing firms S, to aggregate the firm-level "foreign emissions" into one number, we sum over these:

$$\text{Foreign emissions} = \sum_{i \in S} \Delta E_{it}^{ROW}. \tag{11}$$

This is the number we report in the leakage table.

B.1.2 Offshoring

A way of calculating the leakage rate is to take the estimating equation at face value and totally differentiate.

First some notation. We want to calculate the leakage rate, $-\Delta E_i^O/\Delta E_i$, where ΔE_i^O is the change in emissions embodied in offshoring. These emissions 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. Notice, for later use, the total differential of that equation, keeping emission intensity fixed, is $\Delta E_i^O = e_i^O \Delta OFF_i$.

We start from the estimated coefficient, which is an elasticity:

$$\delta = \frac{\Delta \log e_i^Y}{\Delta \log OFF_i} = \frac{\Delta e_i^Y/e_i^Y}{\Delta OFF_i/OFF_i}, \tag{12}$$

where $e_i^Y = E_i/Y_i$ is the emission intensity in firm i's output (i.e. the LHS in the estimated equation). Keeping (initial) output fixed we can write this in terms of changes in overall emissions, $\Delta e_i^Y = \Delta E_i/Y_i$. We can then substitute and rewrite the elasticity in terms of emissions:

$$\delta = \frac{\frac{\Delta E_i}{Y_i}\frac{Y_i}{E_i}}{\frac{\Delta E_i^O}{e_i^O}\frac{e_i^O}{E_i^O}} = \frac{\frac{\Delta E_i}{E_i}}{\frac{\Delta E_i^O}{E_i^O}} = \frac{\Delta E_i}{\Delta E_i^O}\frac{E_i^O}{E_i}, \tag{13}$$

We can now rearrange to get the leakage rate

$$L_i^O = -\frac{\Delta E_i^O}{\Delta E_i} = -\frac{1}{\delta}\frac{E_i^O}{E_i}. \tag{14}$$

The equation is only an approximation for the entire dataset used for the regressions, so dropping subscripts, we have

$$L^O = -\frac{\Delta E^O}{\Delta E} = -\frac{1}{\delta}\frac{E^O}{E}. \tag{15}$$

That is, the leakage rate is a function of the parameter estimate and observable emissions for the firms in the sample. As an extension we could calculate leakage rates separately for emission intensive firms vs. non-emission intensive firms (using the interacted version of the model) etc.

B.1.3 Import competition

We want to calculate the leakage rate between emissions generated in China and the subsequent causally predicted emissions generated in Denmark, from import penetration. Since this is an industry measure, we define a leakage rate for each industry k. Suppose we want to calculate the LR between some period t and $t+1$, defined as:

$$L_k = -\frac{\Delta E_k^C}{\sum_{i \in k} \Delta E_i} \tag{16}$$

where the numerator comes from the exogenous variation and the denominator consists of predicted values from the regression coefficients. The change in emissions from China, under the assumption that the emission intensity of the average import flow stays fixed, is:

$$\Delta E_k^C = e_k^C \Delta Imports_k^{CN}. \tag{17}$$

Next, assume that the denominator in the import penetration measure ImpPen stays fixed, implying

$$\Delta ImpPen = \frac{\Delta Imports^{CN}}{\text{Imports}_{jt}^{World \rightarrow DK} + \text{Sales}_{jt}^{DK}} \tag{18}$$

where we will now define the market size $Y_k^{DK} \equiv \text{Imports}_{jt}^{World \rightarrow DK} + \text{Sales}_{jt}^{DK}$.

Next, for the change in Danish firm-level emissions, we use the regression equation (approximating the logs with percentage change). Under the assumption that the emission intensity of firm i (e_i^Y) stays fixed, we have:

$$\nu \Delta ImpPen = \frac{\Delta Y_{it+1}}{Y_{it}} = \frac{e_i^Y \Delta Y_{it+1}}{e_i^Y Y_{it}} = \frac{\Delta E_i}{E_{it}} \Leftrightarrow \tag{19}$$

$$\Delta E_i = \nu E_{it} \frac{\Delta Imports^C}{Y_k^{DK}} \tag{20}$$

We can now plug these expressions into the definition of the leakage rate

$$
\begin{aligned}
L_k &= -\frac{\Delta E_k^C}{\sum_{i \in k} \Delta E_i} && (21) \\
&= -\frac{e_k^C \Delta Imports_k^{CN}}{\sum_{i \in k} \nu \frac{\Delta Imports^C}{Y_k^{DK}}} && (22) \\
&= -\frac{1}{\nu} \frac{e_{kt}^C Y_k^{DK}}{\sum_{i \in k} E_i} && (23)
\end{aligned}
$$

which is identical to Jakob's expression except we sum over firms and define LR at the industry level.

C Decompositions using the Foster, Haltiwanger, and Krizan (2001) method

The FHK (Foster, Haltiwanger, and Krizan 2001) decomposition method presented here follows Melitz and Polanec (2015). The decomposition is performed between some start year ($t = 1$) and some end year ($t = 2$). We divide firms into three groups:

S : Survivors/continuing firms, i.e. firms who exist in $t = 1, 2$.

X : Exiters, i.e. firms who exist only in $t = 1$.

E : Entrants, i.e. firms who exist only in $t = 2$.

Denote by Φ_t the aggregate emission intensity in some time period, defined as the market-share weighted sum of (log) emission intensities across all firms:

$$\Phi_t = \sum_i s_{it}\phi_{it} \tag{24}$$

where i indexes firms, s denotes market shares and ϕ denotes firm-level logarithms of emission intensities.

The FHK decomposition decomposes the change in aggregate the emission intensity $\Phi_2 - \Phi_1 \equiv \Delta\Phi$ as

$$\begin{aligned}
\Delta\Phi &= \sum_{i\in S} \left[\left(s_{i2}\left(\phi_{i2} - \Phi_1\right) - s_{i1}\left(\phi_{i1} - \Phi_1\right)\right)\right] + \sum_{i\in E} s_{i2}\left(\phi_{i2} - \Phi_1\right) - \sum_{i\in X} s_{i1}\left(\phi_{i1} - \Phi_1\right) \\
&= \underbrace{\sum_{i\in S} s_{i1}\left(\phi_{i2} - \phi_{i1}\right)}_{\text{Within-firm}} + \underbrace{\sum_{i\in S}(s_{i2} - s_{i1})(\phi_{i1} - \Phi_1)}_{\text{Between-firm (given ems. int.)}} + \underbrace{\sum_{i\in S}(s_{i2} - s_{i1})(\phi_{i2} - \phi_{i1})}_{\text{Cross/interaction}} \\
&\quad + \underbrace{\sum_{i\in E} s_{i2}(\phi_{i2} - \Phi_1)}_{\text{Entry}} - \underbrace{\sum_{i\in X} s_{i1}(\phi_{i1} - \Phi_1)}_{\text{Exit}}
\end{aligned} \tag{25}$$

C.1 Counterfactual decompositions

We wish to perform the decomposition in a way that allows us to say "how would the aggregate emission intensity have evolved if offshoring had stayed fixed at its initial value". To do so, we calculate counterfactual data series. For offshoring, we replace actual values of firm-level emission intensities by ones predicted by the regressions:

$$\tilde{\phi}_{it} = \phi_{it,\text{data}} - \delta \left(\ln \text{Offshoring}_{it} - \ln \text{Offshoring}_{i1996} \right) \tag{26}$$

where $\tilde{\phi}_{it}$ denotes the counterfactual emission intensity and $\phi_{it,\text{data}}$ denotes the actual emission intensity.

Similarly for import competition, we replace actual values of sales by their predicted value when import penetration is kept fixed:

$$\widetilde{\text{Sales}}_{it} = \text{Sales}_{it,\text{data}} - \vartheta \left(\ln \text{ImpPen}_{jt}^{CN \to DK} - \ln \text{ImpPen}_{j1996}^{CN \to DK} \right). \tag{27}$$

After calculating counterfactual sales, we can calculate the counterfactual market shares $\widetilde{s}_{it}$ used in the decomposition.