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The Role of Firm Heterogeneity and Intermediate Inputs in Carbon Leakage

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The Role of Firm Heterogeneity and Intermediate Inputs in Carbon Leakage *

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Abstract

How effective are climate policies in reducing emissions? Although this issue is becoming more pressing, standard models largely ignore the role of heterogeneity in firms' responses. Using administrative German firm data, I show that two determinants of carbon leakage, the emission intensity of production and the import intensity of intermediates, vary significantly across firms. I incorporate this heterogeneity into a model of heterogeneous firms to introduce two new adjustment channels to carbon pricing: the reallocation of production towards firms with a lower emission intensity or a higher import intensity. I calibrate the model to the German manufacturing sector and simulate an increase in the domestic carbon price. A model with firm heterogeneity predicts greater emission reductions, smaller welfare losses, and a higher leakage rate. Production reallocation towards less emission-intensive firms offsets increased emissions from offshoring. Combining a domestic carbon price with a carbon tariff would further reduce leakage and welfare losses. However, it would not yield additional emission reductions since it limits the reallocation of domestic production towards clean firms. These results suggest that optimal carbon taxes and tariffs derived from models without firm heterogeneity may be set at an excessively high level to achieve a specified emission target.

Keywords: Firm Heterogeneity, International Trade and the Environment, Intermediate Inputs, Emissions, Leakage.

JEL Codes: F12, F18, F64, Q56.

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1 Introduction

Without a globally coordinated effort to harmonize carbon pricing, countries rely on domestic policies to reduce carbon emissions. However, rising domestic carbon prices can lead to dirty imports displacing clean domestic production, resulting in leakage. A growing literature proposes to address this leakage problem by combining a domestic carbon price with a carbon tariff (Campolmi et al., 2024; Farrokhi and Lashkaripour, 2021; Kortum and Weisbach, 2021).

These papers commonly use industry-level data and assume that firms differ only in their productivity. This, however, limits within and between firm adjustments to climate policies and is at odds with empirical evidence, documenting pronounced heterogeneity in two measures of leakage risk at the firm level: a firm's international activity and emission intensity. Firms select into importing, source from different partner countries, and import different products (Antràs et al., 2017; Bernard et al., 2009). In the context of trade liberalization, this heterogeneity has important implications for aggregate welfare, productivity, and employment (Blaum et al., 2018; Halpern et al., 2015; Hummels et al., 2014). Similarly, there is significant heterogeneity in firms' emission intensities within and across industries and fuel mix (Barrows and Ollivier, 2018; Lyubich et al., 2018; von Graevenitz and Rottner, 2020). Despite these findings, the role of firm heterogeneity for aggregate outcomes of climate policy has received limited attention (Jo and Karydas, 2023; Kim, 2023; Sogalla et al., 2024) and its implications for carbon leakage remain unexplored.

In this paper, I ask how important firm heterogeneity is for the effectiveness and welfare effects of climate policies. I study this question empirically and theoretically in the context of the German manufacturing sector. First, I show that German firms vary along two dimensions of heterogeneity that shape carbon leakage: their sourcing strategy for intermediate inputs and their emission intensity. Next, I incorporate these two dimensions of heterogeneity into a standard Melitz model with intermediate inputs. Compared to the standard model, this introduces a new adjustment channel: the reallocation of production to firms less affected by climate policies, i.e., lower production cost increases. I find that ignoring both sources of heterogeneity leads to an underestimation of the reduction of emissions and an overestimation of the welfare losses associated with an increase in domestic carbon prices. Adding a carbon tariff does reduce the leakage rate but not the total emissions in a model with heterogeneity in emission intensity and import intensity. A domestic carbon price reallocates production towards low emission-intensity firms that are import-intensive, decreasing domestic emissions but causing leakage through an increase in imports. Combining a carbon tax and carbon tariff, however, reallocates production towards high emission-intensity firms compared to the carbon-tax-only scenario. This increases domestic emissions more than it decreases foreign emissions since the most emission-intensive domestic firms produce dirtier than foreign firms.

The German manufacturing sector provides a significant setting for this analysis. Germany is the largest emitter in the European Union, with the manufacturing sector alone emitting 300 million tons of CO_2 in 2018, which is equivalent to one-fourth of Germany's total emissions (Rottner and von Graevenitz, 2022). Through the EU ETS, the sector is also subject to stringent environmental regulations aimed at substantially decreasing emissions in the coming decade. At the same time, German firms are highly integrated into global supply chains, with more than 70% of firms sourcing intermediates from foreign countries. Together, these factors create ideal conditions for carbon leakage to occur.

I combine German administrative firm-level data on emissions, trade and balance sheet information for the manufacturing sector from 2011 to 2018. I first provide direct reduced-form evidence for the carbon leakage mechanism by demonstrating that emissions and foreign inputs are substitutes. To estimate the effect of offshoring on emission intensity, I use exogenous variation in foreign prices caused by country-specific trade costs and productivity shocks. Consistent with other studies (Akerman et al., 2021; Dussaux et al., 2023; Leisner et al., 2022), offshoring, defined as the use of foreign inputs, reduces a firm's domestic emission intensity. If offshoring increases by 10 %, a firm's emission intensity goes down by 0.26%. Moreover, the effect varies across firm-size bins, with larger firms reducing their emission intensity more. Differences in sourcing strategies can explain this variation, as large firms have access to a broader set of partner countries and, consequently, more imported varieties.

Next, I use the German data to document that differences in firms' sourcing strategies introduce significant variation in the import intensity and the emission intensity of imported intermediate inputs across firms. Large firms use relatively more and dirtier foreign intermediate inputs. This finding is explained by an extensive margin effect. Larger firms source foreign intermediate inputs from more countries, including those with higher emission intensity of production, resulting in a higher emission intensity of their imports.

However, even though large firms use more and dirtier foreign inputs, they also have a higher domestic emission intensity than their smaller counterparts. This finding contrasts with the literature (Barrows and Ollivier, 2018). Still, it can be explained by the composition of the German manufacturing sector, which has a high share of output from the most emission-intensive industries, which include steel, aluminum, cement, paper, and glass. Large firms operating in these industries benefit from several policies to gain access to cheap energy, making them relatively more emission-intensive.

Motivated by this empirical evidence from German firm-level data, I build a heterogeneous firm model to quantify the general equilibrium effects of climate policy changes. The model extends the firm-level input trade framework of Blaum et al. (2018) to include emissions as an additional factor of production. Sourcing intermediate inputs is subject to fixed costs, but through love-of-variety and quality differences, foreign intermediate inputs reduce the production costs of a firm. Large firms import from more countries and have a higher import intensity. Independently of a firm's sourcing strategy, I assume that firms differ in their relative efficiency in using emissions. I call this emission-specific productivity the emission bias. This introduces variation in the emission intensity of firms.

My model differs from the standard environmental Melitz model with input trade in two dimensions. First, firm heterogeneity in import intensity and emission intensity introduces variation in firm exposure to climate policies. This gives rise to a reallocation of output. Second, I depart from the standard assumption of a Cobb-Douglas production function, limiting the elasticity of substitution between different production factors to one. Peter and Ruane (2022) show that this restriction biases aggregate gains from trade liberalization.

To take the model to the data, I first estimate the elasticity of substitution between intermediate inputs and emissions. This elasticity is crucial for understanding carbon leakage, as it indirectly influences the elasticity between domestic and foreign emissions. I follow Oberfield and Raval (2021) and estimate the elasticity using information on factor costs and a shift-share instrument based on international energy price variation. My findings indicate that emissions and inputs are substitutes, with the estimated elasticity ranging from 1.4 to 1.8 depending on the choice of weights for the shift-share instrument and the sample period.

Next, I estimate the parameters of the joint distributions of productivity, emissions bias, and fixed costs of imports using a Simulated Method of Moments (SMM) approach. This method estimates the endogenous parameters of the joint distribution to minimize the distance between selected empirical and data moments. I use the observed firm-level distributions of value-added, emissions intensity, and foreign shares as empirical counterparts for the productivity, emission bias, and fixed costs of importing. The estimated model matches all moments of the data. This stands in contrast with more aggregate versions of the model. Ignoring (i) heterogeneity in sourcing strategy, (ii) heterogeneity in emission bias, or (iii) heterogeneity in sourcing strategy and emission bias shows that introducing an emission bias is crucial to not only capture the correlation of firm size and emission intensity but also necessary to achieve the dispersion in emission intensity. Similarly, without fixed import costs, all firms would have the same foreign share. Hence, none of these aggregate models can fully capture all the features of the data.

To further evaluate the ability of my model to fit the data, I estimate the effect of a 1% increase in the aggregate emission price by firm decile on emission intensity, output, offshoring, and the emission intensity of imports using (i) the German firm-level data and (ii) my calibrated baseline model. The predicted treatment effects of my baseline model match the estimated treatment effects of the data, even though my calibration did not target this result. Furthermore, this result sheds light on the heterogeneity in firms' responses to climate policy. Large firms decrease their emission intensity and increase their output, their imports, and their emission intensity of imports relative to smaller firms.

To quantify the emission and welfare effects of future increases in the domestic carbon price, I use the estimated model to simulate a counterfactual increase in domestic carbon prices for Germany, both with and without a carbon tariff. Specifically, I simulate an increase in the domestic carbon price from 10 to 100 €/tCO_2. My baseline model predicts an 11% decrease in emissions and welfare declines by 56 billion €. The leakage rate is 25 %: for every ton of domestic CO_2 saved, foreign emissions increase by 0.25 tons CO_2. More aggregate versions of the model predict a smaller decrease in emissions and a higher decrease in welfare. For emissions, their bias is between 2 and 20%, and for welfare, their bias is between 40 and 44 %. The sign of the bias depends on whether the reallocation towards less emission-intensive firms or the offshoring of emissions is more prominent. This depends on the parametrization of the elasticities of substitution, the demand elasticity, and the joint distribution of parameters. In the calibrated version of my model, the reallocation channel dominates. Hence, the heterogeneous emission bias model has the smallest bias.

To better understand how a domestic carbon price increase affects leakage, I decompose leakage into four channels: changes in emission intensity, production, offshoring, and the emission intensity of imports. I find that global emission reductions are primarily driven by a decrease in the domestic emission intensity and output of firms and reallocation towards clean firms. This is partially offset by an increase in importing and, hence, an increase in foreign emissions.

Next, I study the effectiveness of carbon tariffs in limiting carbon leakage. Carbon tariffs are one solution to mitigate carbon leakage without a globally coordinated policy (Farrokhi and Lashkaripour, 2021; Kortum and Weisbach, 2021). These tariffs impose a carbon price on the emissions embodied in imports, helping to offset domestic cost disadvantages. The tariff corresponding to pricing emissions embodied in imports at the domestic carbon price is 8.5%. In the aggregate models, carbon tariffs reduce emissions by an additional 23 - 30 %. In my baseline model, however, emissions increase because a carbon tariff reallocates production towards emission-intensive domestic firms with a low import intensity. In all models, welfare substantially increases compared to the scenario without a carbon tariff. This additional reduction is highest in the baseline model, where the welfare loss more than doubles.

Literature Review This paper is related to several strands of the literature. First, it relates to the literature studying carbon leakage and carbon tariffs in the absence of a global carbon tax. To mitigate leakage associated with the introduction of a domestic carbon price, governments can employ capacity-based subsidies (Meunier et al., 2014), output-based subsidies (Fowlie and Reguant, 2022), industry exemptions (Gerster and Lamp, 2020), or carbon border tariffs (Fischer and Fox, 2012; Fowlie et al., 2021). Even though most world trade is in intermediate goods, almost all studies focus on leakage in final goods. The exception is Artuc and Sommer (2024), who introduce trade in intermediates in a multi-country model with perfectly competitive firms. I follow a different approach and focus on one country to highlight the role of firms in carbon leakage and welfare.

Second, the paper relates to the literature quantifying the environmental effects of offshoring, which can be split into empirical and theoretical contributions. Recent empirical studies using firm-level data have demonstrated that offshoring can lead to a reduction in the domestic emission intensity of firms (Akerman et al., 2021; Cole et al., 2021; Dussaux et al., 2023; Leisner et al., 2022; Li and Zhou, 2017).[1] Yet, the reason why emission intensity decreases is unclear, with evidence pointing to imports becoming more emission-intensive and productivity-enhancing effects. Complementing theoretical papers that study offshoring in the presence of environmental policy are Cherniwchan et al. (2017); LaPlue and Erickson (2020); Schenker et al. (2018). Closest to my research is Lim (2021), who studies the effect of offshoring on US air pollution and calibrates her model using sectoral data. However, evidence on the role of firm heterogeneity is sparse, with several theoretical papers focusing only on heterogeneity in productivity (Chang et al., 2022; Kreickemeier and Richter, 2014; Shapiro and Walker, 2018; Sogalla, 2023; Sogalla et al., 2024; Von Graevenitz et al., 2024). I contribute to this literature by quantifying the general equilibrium effect of firm heterogeneity on

[1] Imbruno and Ketterer (2018) find the same holds for energy intensity in Indonesia

carbon leakage and welfare. By using firm-level data, I can document the importance of reallocation across firms.

Third, an emerging literature focuses on the dispersion of heterogeneity in environmental performance across firms (Barrows and Ollivier, 2018; Leisner et al., 2022; Lyubich et al., 2018). While existing papers focus on the role of product and within- and across-sector dispersion in emission intensity, I focus on the role of firm size and emission intensity. In contrast to the literature, I document a positive correlation between firm size and emission intensity when using value-added as a measure for size. This is driven partially by the composition of the manufacturing sector in Germany and energy subsidies for large firms.

Methodologically, this paper relates to the literature modeling the importing behavior of heterogeneous firms (Blaum et al., 2018; Blaum, 2022; Gopinath and Neiman, 2014; Halpern et al., 2015; Ramanarayanan, 2020) and the role of firm heterogeneity for aggregate outcomes (Arkolakis et al., 2012; Blaum et al., 2018; Blaum, 2022; Brinatti and Morales, 2021). I extend Blaum et al. (2018) to incorporate firm heterogeneity in two input factors of production: intermediate inputs and emissions. Introducing firm heterogeneity, besides productivity, leads to the reallocation of production across firms. I contribute to this literature, by documenting the importance of firm heterogeneity for aggregate emissions, carbon leakage and welfare when studying climate policies.

The rest of the paper is structured as follows. Section 2 contains a description of the data and empirical evidence, while Section 3 presents the theoretical model. Sections 4 and 5 contain the quantitative exercise and the counterfactual analysis. Section 6 concludes.

2 Descriptive Evidence

In this section, I establish empirical evidence on (i) the effect of trade in intermediate inputs on domestic CO_2 emission intensity, (ii) firm heterogeneity in emission intensity, and (iii) differences in sourcing strategies across firms. I start with a description of the data and the construction of the variables before presenting my results.

2.1 Data

German administrative data I use rich administrative data ("Amtliche Firmendaten für Deutschland") provided by the Federal Statistical Office of Germany from 2011 to 2019. For my analysis, I combine several data sources. The first dataset is the German manufacturing census at the firm level. Participation is mandatory for all establishments with more than 20 employees. The data include information on sales, employment, investment, and sectoral affiliation. Additional information on value-added and expenditure on labor, energy, capital, and intermediate inputs is available for a sample of firms. I combine this information with plant-level data on energy consumption. Again, all plants with more than 20 employees must provide information on their energy consumption by energy type, electricity procurement, and electricity from self-generation.

After aggregating the data to the firm level, I can construct CO_2 emissions at the firm level. Lastly, I use customs data, which provide information on quantity, value, and partner country for each firm's six-digit product-level imports and exports.

Emission Intensity The dataset on energy consumption contains information on consumption for 14 different fuel types and electricity in kWh. Each fuel type and electricity can be matched to an annual emission factor provided by the German Environmental Agency (see Appendix A.2 for a list of energy types and emission factors). I calculate total CO_2 emissions for each firm by multiplying energy consumption by fuel type with its emission factor and summing up all energy types. Unless otherwise noted, I define emission intensity as emissions divided by the value added to measure the dirtiness of a firm's production. I use value added instead of sales to account for the emission-offshoring effect of intermediate inputs.

Offshoring Measure I use several measures to measure a firm's offshoring activity. I follow Hummels et al. (2018) and define offshoring as imports that belong to the same industry as the firm. I distinguish between narrow offshoring (measure 1) and wide offshoring (measure 2). Narrow offshoring is offshoring within the firm's four-digit industry, while wide offshoring is offshoring within the firm's two-digit industry. As a third measure, I characterize all non-raw material imports (measure 3) as offshoring. Unless otherwise noted, the third measure of offshoring is used.
Firms will use more foreign intermediate inputs solely because they are larger. However, to determine the leakage and welfare effect of policy, the key measure is a firm's relative import intensity. I define a firm's import intensity as the foreign share, which is the value of foreign intermediates divided by the sum of the value of domestic and foreign intermediates. Foreign intermediate inputs are the value of all non-raw material imports (measure 3).

Instrument for Offshoring Since my measures of international sourcing activity are not exogenous (e.g., there could be unobserved productivity shocks that reduce a firm's emissions intensity and increase its international sourcing), I follow the literature and construct a shift-share instrument following Hummels et al. (2014) using aggregate trade flows at the HS6 level from Comtrade. The instrument is constructed as follows:

$$WES_{it} = \sum_{ck} X_{ckt} s_{ick}^{pre} \tag{1}$$

X_{ckt} denotes aggregate exports of product k from country c in year t to all countries except Germany. s_{ick} is the import share of product k from country c for firm i in a pre-sample period. Intuitively, the instrument uses exogenous supply-side variation uncorrelated with firm-specific productivity shocks. The pre-sample year for all firms is 2011. Thus, for the instrument to be defined, a firm must continue to import a specific product from at least one country during the sample period. Borusyak et al. (2022)'s condition for consistency of the 2SLS estimator allows the variation in shares to be endogenous as long as the variation in shocks is exogenous. This requires shocks to be as good as randomly assigned and that firms are exposed to many small independent shocks. Exposure shares in this setting can be viewed as endogenous, as (unobserved) differences in firm characteristics affect which products firms source from different countries. Variation in world exports of product k from country c may, for example, arise from country-specific productivity or trade cost shocks, which can be viewed as a quasi-experimental variation. Since firms, on average, import from nearly twelve different import partners, the exposure to each shock should be small enough and independent of each other.

Emission Intensity of Imports To measure the emissions embodied in a firm's imports, I need the emission intensities of foreign production. This information is available through environmentally extended multi-regional input-output (EE MRIO) tables. Following the literature, I use EXIOBASE (Stadler et al., 2018).[2] EXIOBASE combines data from national accounts, energy accounts, and input-output tables, among other sources, to cover about 90% of global GDP. Data for 200 products across all sectors are available for 44 countries plus five aggregate regions. The original dataset covers 1995-2011 but has been extended to 2022. EXIOBASE reports emissions from combustion and non-combustion activities. I convert emission intensity measures to 2015 Euros and merge them with HS6 trade flows. In cases where an exact match between EXIOBASE products and HS6 codes and products is impossible, I use an unweighted average over all matched products.

For my analysis, I keep all firms that report information on their cost structure and positive sales. This reduces my sample to 134,123 observations. Although I drop more than 50% of the observations, more than 80% of emissions, production, and trade are covered, as summarized in Table 2. Due to the wave structure of the cost survey, which rotates smaller firms in and out of the survey every four years, the sample is not balanced. Table 1 presents summary statistics for the sample. There is considerable heterogeneity across firms in value-added, emission intensity, and offshoring activity.

Table 1: Summary Statistics

	Mean	SD	p25	p50	p75	p90	p99
CO_2 emissions	19,106.43	315,016.78	207.42	721.50	3,123.52	12,176.97	205,980.66
Emission intensity	0.25	0.94	0.04	0.09	0.20	0.47	2.76
Employees	306.69	2206.76	47.00	94.00	223.00	548.00	2661.00
Export status	0.71	0.45	0.00	1.00	1.00	1.00	1.00
Foreign share	0.22	0.30	0.00	0.08	0.34	0.71	1.00
Implicit emission price	410.49	475.01	256.24	318.60	411.45	609.66	2285.68
Import status	0.78	0.41	1.00	1.00	1.00	1.00	1.00
Number import partners	10.16	11.83	1.00	7.00	15.00	26.00	51.00
Offshoring (millions)	19.93	290.74	0.00	0.52	4.56	20.88	230.80
Sales (millions)	107.34	1,319.10	5.85	15.27	49.02	148.81	1,113.98
Sales per worker	242,077.59	548,654.56	104,213.17	160,160.77	255,715.56	426,078.19	144,0636.12
Value added (millions)	45.50	446.96	3.25	7.72	22.44	64.92	465.72

Notes: The table shows summary statistics for firms in the manufacturing sector from 2011-2018. The sample consists of 134,123 observations with 31,529 distinct firms. All nominal variables are expressed in Euros. CO_2 emissions are measured in tons. Emission intensity is measured in kg CO_2 per € value added. The implicit emission price is measured in €/tCO_2. For about 2% of the observations, no information on emissions is available. A firm is defined as an importer if it has a positive offshoring value. The number of import partners includes trade in raw material imports.

[2]See Shapiro (2021) for a comparison of different EE MRIOs.

Table 2: Representativeness of data sample

	Full data	Sample
CO_2 Emissions (thousand t)	324,816.58	298,930.19
Offshoring (millions)	292.99	266.76
Sales (millions)	1,798.23	1,537.54
Energy use (GWh)	1,071.11	997.33
Emission intensity (kg/€)	0.18	0.19
Number firms	36,187	15,031

Notes: The table compares selected outcomes in 2014 for the full data consisting of all firms with more than 20 employees and a subsample of these data used in the analysis. CO_2 emissions, offshoring, sales, and energy use are the sum of all firms. Emission intensity is the average firm-emission intensity weighted by firm sales.

2.2 Stylized Facts

Fact 1 *Offshoring decreases domestic emission intensity and increases emissions of a firm.*

A canonical trade-environment model assumes that as a firm's offshoring activity increases, its emission intensity decreases. The assumption is that emission offshoring, specifically the offshoring of dirty production stages and positive productivity effects of intermediates, leads to a decrease in emission intensity. To confirm that this relationship holds for Germany, I regress the emission intensity EI of a firm i in year t, defined as emissions from direct fuel and electricity consumption embodied in production divided by the value added or sales, on a variable measuring firm i's offshoring activity in year t and a set of firm δ_i and year γ_t fixed effects. Offshoring is defined here as all non-raw material imports and is instrumented using World Export Supply.

$$\log(EI_{it}) = \beta_0 + \beta_1 \log(Offshoring_{it}) + \delta_i + \gamma_t + \epsilon_{it} \tag{2}$$

I find that a 10% increase in offshoring reduces emissions intensity by 0.264 %, all else being equal (see Table 3, column (2)), using value-added as the denominator. The effect is slightly larger than the OLS estimate in column (1). I use the foreign share, defined as offshoring divided by total intermediate use, as an alternative measure. Here, the estimate of -0.0758 is statistically significant. To explore the role of firm heterogeneity, I add an interaction of the offshoring measure with firm size, measured by the number of employees (column (4)). Once I have added the interaction term, the effect of offshoring becomes much smaller and insignificant. However, the effect of the interaction is statistically significant, negative, and economically relevant. The larger the firm, the more negative the effect of offshoring on emission intensity. Repeating the regression with emissions as the dependent variable shows that offshoring reduces firm emissions only for small firms (see column (5)). Large firms increase their emissions. These findings indicate that offshoring reduces firms' emission intensity. This reduction may occur directly through offshoring previously in-house,

Table 3: Offshoring, emission intensity, and emissions

	Log Emission Intensity				Log Emissions
	VA	VA	VA	VA	
	(1)	(2)	(3)	(4)	(5)
log Offshoring	-0.0211***	-0.0264**		-0.0145	-0.1044***
	(0.0021)	(0.0129)		(0.0173)	(0.0145)
log Offshoring X Log Size				-0.0027*	0.0243***
				(0.0015)	(0.0013)
Foreign share			-0.0758***		
			(0.0128)		
First Stage					
log WES		0.1057***		0.0047	0.0047
		(0.0069)		(0.0142)	(0.0142)
log WES X Log Size				0.0181***	0.0181***
				(0.0023)	(0.0023)
F-Stat		236.8736		87.2161	87.2161
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	57,604	57,604	57,604	51,079	51,079

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. This table presents the results of regressing a firm's emission intensity on its offshoring activity, controlling for firm and year-fixed effects. For the regression, the years 2012-2018 are used.

emission-intensive production stages or indirectly through productivity gains from substituting foreign intermediates for domestic ones. The idea is that offshoring can replace domestic intermediate inputs or domestic emissions. If imported intermediates replace mostly domestic intermediates, the effect on emission intensity will be smaller. The replacement of domestic with foreign intermediate is most likely happening during the sample period.[3]

In Appendix B, I show that the result is invariant to the choice of offshoring measure. For both narrow and wide offshoring, the estimates are more negative. Looking at the effect heterogeneity across firm deciles, the largest firms experience a larger decrease in their emission intensity, but these results are not statistically significant.

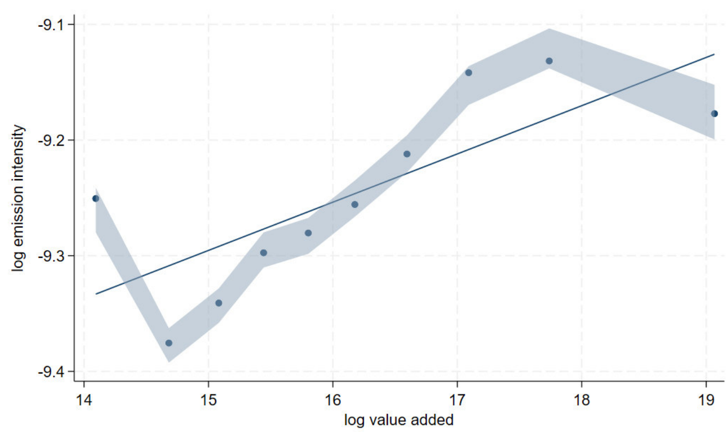
Fact 2 *The relationship between firm size and emission intensity is nonlinear.*

To assess the general equilibrium effect of trade in intermediate inputs, it is crucial to know how

[3]Compared to the literature (Akerman et al., 2021; Dussaux et al., 2023; Leisner et al., 2022), which finds an elasticity around 0.5, my elasticity is very small. Other studies include China's accession to the WTO and the EU's Eastern enlargement. A significant increase in trade in intermediate inputs with partner countries with high emission intensities characterizes both events.

firm size and emission intensity are correlated. It is commonly assumed that large, more productive firms use a cleaner production technology than small firms (Shapiro and Walker, 2018).
Figure 1 reveals a non-linear relationship between firm size and emission intensity. At first, emission intensity decreases with size, but the sign reverses after reaching a threshold size. This finding also holds when using sales as a measure of firm size.
The composition of the German manufacturing sector drives the non-linear relationship between firm size and emissions. Heterogeneity in emission intensity varies across two-digit industries: the most emission-intensive industries display a positive correlation between firm size and emission intensity. In contrast, in less emission-intensive industries, large firms are also less emission-intensive (Figure 16). Since many large German firms produce in emission-intensive industries, such as chemicals, the correlation between firm size and emission intensity is, on average, positive.
Several possible explanations exist for why large firms have a higher emission intensity. First, large firms are more likely to pay lower taxes on their energy consumption and emissions Gerster and Lamp (2020). Second, in Germany, large electricity consumers can buy electricity at a lower rate. Both conditions can result in large firms in emission-intensive industries facing a relatively lower emission price, making their production relatively dirty to small firms.

Figure 1: Emission intensity and firm size

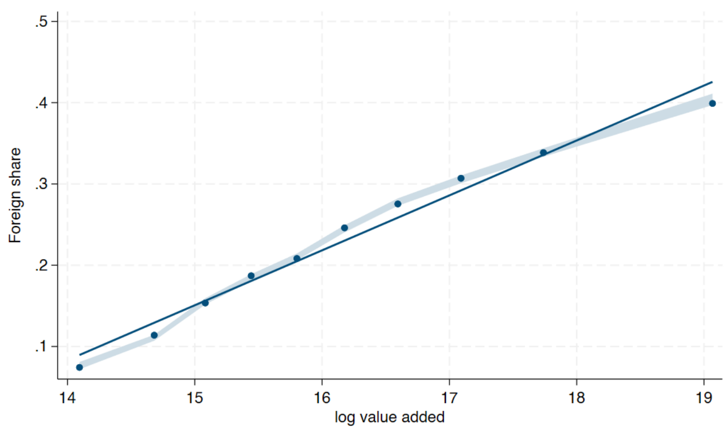


Notes: This figure shows a binscatter plot of log(emission intensity) as the dependent variable and log(VA) as the independent variable, controlling for four-digit industry and year fixed effects. Observations are divided into ten equally sized bins using the independent variable. For each bin, the mean of the independent variable and the mean of the dependent variable are calculated. Data for the dependent variable are residualized. Emission intensity is defined as emissions produced by the firm divided by VA. The plot uses the years 2011-2018.

Fact 3 *Large firms use relatively more and dirtier foreign intermediates.*

The amount of carbon leaked per firm depends on the amount of foreign intermediate inputs and their emission intensity. Both vary with firm size. Focusing on the importance of imported intermediates for firms of different sizes, Figure 2 shows that large firms use relatively more imports in their production. The foreign share, defined as offshoring expenditures divided by total intermediate expenditure, measures the relative importance of foreign intermediates. The foreign share increases with firm size. Heterogeneity across firms is pronounced. The largest firms spend almost four times as much on foreign intermediates as the smallest firms.

Figure 2: Foreign share and firm size



Notes: This figure shows a binscatter plot of foreign share as the dependent variable and log (VA) as the independent variable, controlling for four-digit industry and year fixed effects. Observations are divided into ten equally sized bins using the independent variable. For each bin, the mean of the independent variable and the mean of the dependent variable are computed. Data for the dependent variable are residualized. The foreign share is defined as imports excluding raw materials divided by expenditures on intermediate inputs. The plot uses the years 2011-2018.

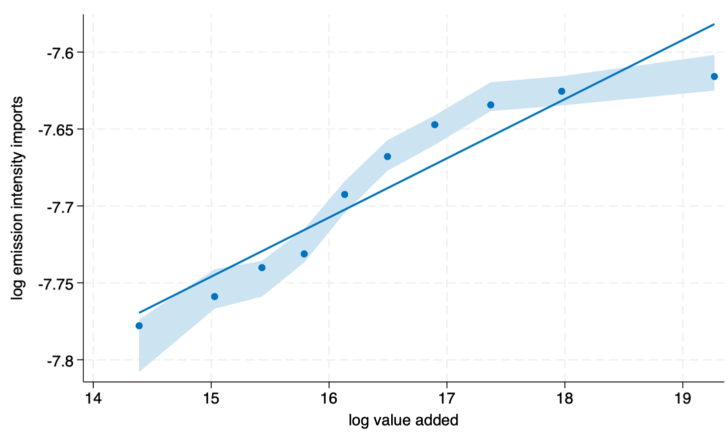
Variation in the foreign share can be driven by an extensive or an intensive margin effect. Firms can increase their foreign share by starting to import from additional countries. Then, different foreign shares can be explained by the extensive margin. Alternatively, all firms import from the same set of partner countries, but some firms import more from each country. Then, different foreign shares can be explained by the intensive margin effect. Table 4 shows the foreign share, the share of importers, and the number of partner countries for different firm size deciles. The foreign share is increasing with the share of importers and the number of partner countries. Small firms, with a lower foreign share, are less likely to be importers and import from relatively few partner countries compared to large firms. This evidence is consistent with an extensive margin effect and, hence, a fixed cost to import from each additional country. If the intensive margin were the driver, then the share of importers and the number of partner countries would be more similar across deciles.

Table 4: Extensive and intensive margin of importing

VA decile	1	2	3	4	5	6	7	8	9	10
Foreign share	0.11	0.13	0.18	0.22	0.24	0.28	0.30	0.28	0.31	0.42
Share importers	0.38	0.54	0.66	0.75	0.81	0.88	0.91	0.94	0.97	0.99
# Partner countries	1.48	2.59	3.72	5.12	6.60	8.83	11.37	14.04	19.11	30.12

Because sourcing locations differ across countries, the emission intensity of imports varies with firm size, as the emission intensity is dispersed at the country level. Large firms source from a different set of partner countries. In general, they have more trading partners and source from farther away countries. These faraway countries are usually dirtier (see Figure 8).
Figure 3 shows how the emission intensity of imports and firm size correlate. Large firms not only produce more emission-intensive products; they also import more emission-intensive products. The effect seems to be at least partly driven by their sourcing strategy. Compared to domestic emission intensity, the emission intensity of imports is less dispersed across firms. Lower implicit emission costs do not deter firms from importing emission-intensive intermediates. One possible explanation could be that the cost share of emissions is relatively low, while differences in labor or capital costs are the main determinants of a firm's sourcing strategy. Appendix B provides complementary regressions of the emission intensity of imports on firm size and further evidence of the role of products.

Figure 3: Emission intensity of imports and firm size



Notes: This figure shows a binscatter plot of log import emission intensity (EII) as the dependent variable and log (VA) as the independent variable, controlling for four-digit industry and year. Observations are divided into ten equally sized bins using the independent variable. For each bin, the mean of the independent variable and the mean of the dependent variable are computed. Data for the dependent variable are residualized. The emission intensity of imports is defined as direct and indirect emissions using Exiobase data divided by value added. The years 2011-2018 are used for the plot.

Summary This section presented facts highlighting the heterogeneity in emission intensity and sourcing strategy across firms. In Section 3, I build a model incorporating firm heterogeneity in sourcing strategy and emission intensity of production to quantify the effect of a change in domestic carbon prices and a carbon tariff on carbon emissions and welfare.

3 Model

In this section, I introduce a quantitative model to study the role of firm heterogeneity on emission intensity in a globalized world. To achieve this, I extend the sourcing model by Blaum et al.

(2018) to include emissions. The model features multiple sectors linked by input-output linkages, a firm-specific sourcing strategy that generates differences in the share of foreign inputs across firms, and firm differences in emission prices driven by technological choices.

3.1 Environment

Firms live in a small, open economy and produce differentiated varieties. The set of firms is fixed. A representative consumer is endowed with L units of labor. The supply of emissions is perfectly elastic, and one unit of emissions can be purchased at a price of pE. Consumers allocate their income between a tradable manufacturing good and a non-tradable outside good.

Consumer preferences I model the preferences of a representative agent as a two-tier utility function. The upper level is a Cobb-Douglas aggregator over sector aggregates. Let C_s denote the industry aggregate of sector s, consisting of domestic varieties produced within the sector. There is one outside sector that is non-tradable. Expenditure shares $\alpha_s \in (0, 1)$, with $\sum_{s=1}^{max} \alpha_s = 1$, are constant and depend only on their price and income.

$$U = \prod_{s=1}^{S} C_s^{\alpha_s} \tag{3}$$

The lower-tier utility function is a CES composite of domestic varieties produced by firms within sector s, which are imperfect substitutes. The parameter $\sigma_s > 1$ represents the sector-specific elasticity of substitution.

$$C_s = \left[\int_{\omega_s \in \Omega_s} q_s(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} \, d\omega \right]^{\frac{\sigma_s}{\sigma_s - 1}} \tag{4}$$

Production Each sector of the economy is populated by a set of heterogeneous firms denoted as Ω_s. Each firm produces a different variety indexed by ω_s. In the following, I will replace ω with the index i. I treat the number of firms N_s within each sector as fixed. Competition is monopolistic. Firms employ four factors of production: capital K_i, labor L_i, emissions E_i, and intermediate inputs X_i. I restrict the production technology to a nested Cobb-Douglas-CES production function with nests driven by the allocation to primary and secondary production factors. Nest one contains a labor-capital aggregate combined according to technology F(.), which I assume to be Cobb-Douglas. Nest two consists of the intermediate input bundle and emissions. Elasticities of substitution are allowed to vary across sectors. ϕ_i represents productivity.

$$q_i = \phi_i \left((1 - \beta_i) X_i^{\frac{\theta - 1}{\theta_s}} + \beta_i E_i^{\frac{\theta_s - 1}{\theta_s}} \right)^{\frac{\theta_s}{\theta_s - 1} \gamma_s} F(K, L)^{1 - \gamma_s} \tag{5}$$

Firms can use domestic and foreign intermediate inputs, which are imperfect substitutes. q_{Di} and z_{Di} are the quantity and quality of the domestic input. The foreign input bundle is X_{Fi}. β_i is the emission bias of a given firm.

$$X_i = \left[q_{Di} z_{Di}^{\frac{\epsilon_{Xs}-1}{\epsilon_{Xs}}} + X_{Fi}^{\frac{\epsilon_{Xs}-1}{\epsilon_{Xs}}} \right]^{\frac{\epsilon_{Xs}}{\epsilon_{Xs}-1}} \tag{6}$$

Sectoral linkages are modeled using a roundabout production structure (Caliendo and Parro, 2015), with each sector consuming a distinct input bundle composed of the output from all other sectors Y_j. The parameters $\nu_{js} \in [0,1]$ and $\sum_{j=1}^{S} \nu_{js} = 1$ specify the sector-specific input-output linkages.

$$z_{Ds} = \prod_{j=1}^{S} Y_{js}^{\nu_{js}} \tag{7}$$

$$Y_{js} = \left(\int_0^{N_j} y_{vjs}^{\frac{\sigma_j - 1}{\sigma_j}} \, dv \right)^{\frac{\sigma_j}{\sigma_j - 1}} \tag{8}$$

Sourcing Strategy The foreign input bundle is a function of quality-adjusted q_c quantities z_c sourced from a firm-specific set of partner countries Σ_i, which is referred to as the sourcing strategy. c indicates the country from which inputs are imported. I assume that the foreign bundle is specified by a CES function with an elasticity of substitution κ.

$$X_{Fi} = \left(\int_{c \in \Sigma_i} (q_c z_c)^{\frac{\kappa-1}{\kappa}} \, dG(q) \right)^{\frac{\kappa}{\kappa-1}} \tag{9}$$

I further assume that firms face a firm-specific fixed cost f_i of importing inputs that are constant across countries. I also assume that the price of the input bundle is the same for all firms. Thus, the sourcing strategy is a function of quality. Then, the import price index is given by:

$$P_F(\Sigma_i) = \left(\int_{q \in \Sigma_i} p(q)/q^{1-\kappa} \, dG(q) \right)^{\frac{1}{1-\kappa}} = \left(\int_{q \in \Sigma_i} q^{\kappa-1} \, dG(q) \right)^{\frac{1}{1-\kappa}} \tag{10}$$

I assume the country quality parameter follows a Pareto distribution characterized by shape parameter $\theta > 0$ and scale parameter q_m.

$$P_F(\Sigma_i) = \theta q_{min}^{\theta} \left(\int_{q \in \Sigma_i} q^{\kappa-1} \theta^{-\theta-1} \, dG(q) \right)^{\frac{1}{1-\kappa}} \tag{11}$$

Because of the assumption of constant fixed costs across countries, firms will source from countries whose quality lies above a cut-off $\bar{q}_i$. Hence, the price index simplifies to:

$$P_{Fi}(n) = q_{i,min}^{-1} \left(\frac{\theta_s}{\theta_s - (\kappa - 1)} \right)^{\frac{1}{1-\kappa}} n^{\frac{-1}{\kappa-1}} = z n^{-\eta} \tag{12}$$

where n is the mass of countries firm i is sourcing. z and n are functions of $(\kappa, \theta, q_{min})$. Restricting $\theta > min[1, \kappa - 1]$, the price index P_F decreases in the number of partner countries.

Unit cost Using the CES properties of the production function, the unit cost of a given firm can be expressed as a function of parameters and prices. w is the price of the capital-labor bundle, p_E is the price of emissions consisting of the price of energy and a carbon tax t, p_M is the price index of materials, consisting of intermediate inputs and emissions, $Q(\Sigma_i)$ is the price index of intermediate inputs, p_D is the price of the domestic input bundle, and $P_F(\Sigma_i)$ is the price index of the foreign input bundle.

$$u_i = \frac{1}{\phi_i} \left(\frac{w}{1-\gamma_s} \right)^{1-\gamma_s} \left(\frac{p_{Mi}}{\gamma_s} \right)^{\gamma_s} \tag{13}$$

where

$$p_{Mi} = \left((1-\beta_i)^{\theta_s} Q(\Sigma_i)^{1-\theta_s} + \beta_i^{\theta_s} p_E^{1-\theta_s} \right)^{\frac{1}{1-\theta_s}} \tag{14}$$

and

$$Q(\Sigma) = \left((p_D/q_D)^{1-\epsilon_{Xs}} + P_F(\Sigma)^{1-\epsilon_{Xs}} \right)^{\frac{1}{1-\epsilon_{Xs}}} \tag{15}$$

Standard calculations imply that the domestic share, defined as expenditure on domestic intermediate inputs divided by total intermediate input spending, is given by

$$s_{Di} = \frac{(p_D/q_D)^{1-\epsilon_{Xs}}}{(p_D/q_D)^{1-\epsilon_{Xs}} + P_F(\Sigma)^{1-\epsilon_{Xs}}} = (p_D/q_D)^{1-\epsilon_{Xs}} \, Q(\Sigma_i)^{\epsilon_{Xs}-1} \tag{16}$$

The foreign share is defined as

$$s_{Fi} = 1 - s_{Di} \tag{17}$$

Plugging in Equation 12, the domestic share can be expressed as a function of partner countries.

$$s_{Di}(n) = \left(1 + \left((p_D/q_D) \, \frac{1}{z} n^{\eta} \right)^{1-\epsilon_{Xs}} \right)^{-1} \tag{18}$$

It follows that the unit cost can then be expressed as a function of the number of partner countries and the emission bias.

$$u_i(n) = \frac{1}{\phi_i} \left(\frac{w}{1-\gamma_s} \right)^{1-\gamma_s} \left(\frac{1}{\gamma_s} \right)^{\gamma_s} \left((1-\beta_i)^{\theta_s} s_{Di}(n)^{\frac{1-\theta_s}{\epsilon_{Xs}-1}} (p_D/q_D)^{1-\theta_s} + \beta_i^{\theta_s} p_E^{1-\theta_s} \right)^{\frac{\gamma_s}{1-\theta_s}} \tag{19}$$

Pricing Decision and Profit Maximization Given their sourcing strategy and emission bias, firms choose their price to maximize their profits. Since consumer preferences are CES, the price equals a firm's unit cost u_i multiplied by a constant markup.

$$p_i = \frac{\sigma_s}{\sigma_s - 1} u_i \tag{20}$$

The consumer price index is then given by:

$$P_s = \left(\int p_i^{1-\sigma_s} di \right)^{\frac{1}{1-\sigma}} \tag{21}$$

The profit maximization problem of a firm is given by

$$\pi_i = \max_n \left\{ u_i(n)^{(1-\sigma_s)} B - w(nf + f_I I(n > 0)) \right\} \tag{22}$$

where f denotes the country-specific fixed cost, and f_I is the fixed cost of importing. $B = \frac{1}{\sigma_s} \frac{\sigma_s}{\sigma_s - 1}^{1-\sigma_s} P_s^{\sigma_s - 1} S$ is defined as a function of the general equilibrium object P and S where S is aggregate spending. $u_i(n)$ is defined as above.

3.2 Changes in trade and environmental policy

The following section presents theoretical results on how changes in the domestic emission price and carbon tariffs, specifically an increase in the price of the foreign intermediate good, affect emission intensity at the firm level in partial equilibrium. For tractability, I study firm responses in an economy with one sector and set w as the numéraire.

I show that an increase in the domestic emission price decreases the emission intensity of a firm, while a carbon tariff increases the emission intensity of a firm. Hence, if both instruments are combined, it is ex-ante unclear whether the emission intensity of a firm and the aggregate emission intensity will increase or decrease. In the aggregate model without reallocation across firms, the aggregate and firm emission intensity coincide. Hence, the result can also be applied to the aggregate emission intensity. In models with additional firm heterogeneity, this conjecture does not hold. Differences in emission intensity and sourcing strategy introduce reallocation of production across firms, which will affect the aggregate emission intensity. Depending on the underlying distribution of these variables, the change in aggregate emission intensity is either upward or downward-biased.

Firm emission intensity Emission intensity is defined as firm emissions divided by value added. Using standard CES calculations, I get:

$$z_i = \left(\frac{\sigma_s - 1}{\sigma_s} \right) \left(\frac{\gamma_s}{1 - \gamma_s} \right) \beta_i^{\theta_s} p_E^{-\theta_s} \left((1 - \beta_i)^{\theta_s} Q(\Sigma_i)^{1-\theta_s} + \beta_i^{\theta_s} p_E^{1-\theta_s} \right)^{-1} \tag{23}$$

Emission intensity, measured in terms of output value, does not directly depend on productivity. Productivity influences emission intensity indirectly through a firm's domestic share and emission bias, both of which are correlated with productivity.

Proposition 1: *An increase in the domestic emission price decreases emission intensity conditional on emissions and intermediate inputs being substitutes* $(1 - \theta) < 0$.

Proof.

$$\frac{\partial z_i}{\partial p_E} = \left(\frac{\sigma_s - 1}{\sigma_s}\right)\left(\frac{\gamma_s}{1-\gamma_s}\right)\frac{-\theta_s \beta_i^{\theta_s}(1-\beta_i)^{\theta_s} Q(\Sigma_i)^{1-\theta_s} p_E^{-\theta_s - 1} - \beta_i^{2\theta_s}\left(\theta_s p_E^{-\theta_s} + (1-\theta_s) p_E^{-2\theta_s}\right)}{\left((1-\beta_i)^{\theta_s} Q(\Sigma_i)^{1-\theta_s} + \beta_i^{\theta_s} p_E^{1-\theta_s}\right)^2} < 0 \quad (24)$$

If the government increases the emission price through a carbon tax increase, firms substitute other factors of production for emissions, leading to a cleaning up of domestic firms. This can be either labor or intermediate inputs. In the case of foreign intermediate inputs, this, however, will come at the cost of relocating domestic emissions abroad.

In general, the response of a firm's emission intensity to an increase in the emission price depends on two components—the change in emissions and the change in value-added. Suppose value-added is more sensitive to a change in the emission price, e.g., a high demand elasticity σ. In that case, the value added will decrease more, and the reduction in emission intensity will be stronger. This affects all firms the same. On the other hand, the change in emissions depends on the elasticity of substitution between emissions and intermediate inputs in addition to the distribution of emission bias and fixed costs. Intuitively, large firms are hit harder by an increase in the emission price but can compensate for this effect by having easier access to foreign intermediate inputs. Ex-ante, it is unclear whether large, emission-intense firms reduce their emission intensity more than small firms.

Proposition 2: *A carbon tariff increases domestic emission intensity conditional on emissions and intermediate inputs being substitutes* $(1-\theta) < 0$.

Proof.

$$\frac{dz_i}{dP_{Fi}} = -\left(\frac{\sigma_s - 1}{\sigma_s}\right)\left(\frac{\gamma_s}{1-\gamma_s}\right)\beta_i^{\theta_s} p_E^{-\theta_s} \cdot \frac{(1-\beta_i)^{\theta_s}(1-\theta_s) Q(\Sigma_i)^{\frac{1}{1-\epsilon_{Xs}} - 1 - \theta_s} P_F^{-\epsilon_{Xs}}}{\left((1-\beta_i)^{\theta_s} Q(\Sigma_i)^{1-\theta_s} + \beta_i^{\theta_s} p_E^{1-\theta_s}\right)^2} > 0 \quad (25)$$

Hence, under the fairly general assumption that all production factors are substitutes, a carbon tariff increases the emission intensity of domestic firms as firms substitute away from foreign intermediates towards domestic inputs, including emissions. Conversely, trade liberalization, which corresponds to a decrease in the foreign price, reduces firm emission intensity through emission offshoring. This, however, will come at the cost of relocating domestic emissions abroad.

Similar to the reaction of the emission intensity to the emission price, the magnitude of the change in emission intensity is not obvious. It depends on the relative change in value-added and emissions. Additionally, the elasticity between foreign and domestic emissions becomes more important and determines how much emissions will change. Large firms using (relatively) more foreign intermediates are hit harder by a carbon tariff.

3.3 Carbon Leakage

Emission Intensity of Imports To compute carbon leakage, I need to take a stance on how the emission intensity of imports is correlated with firm size. Larger firms source from more countries than smaller firms. Adding a country to a firm's sourcing strategy can either increase or decrease the emission intensity of imports. To express emission intensity as a function of the number of partner countries, I assume that the emission intensity of countries follows a Pareto distribution. Similar to the expression for the foreign price index, I derive the following expression:

$$EEI(n) = r_{min}^{-1} \left(\frac{\nu}{\nu - (\kappa - 1)} \right)^{\frac{1}{1-\kappa}} n^{\frac{-1}{\kappa-1}} = vn^{-\iota} \tag{26}$$

n is the mass of countries from which the firm is sourcing. v and ι are functions of elasticity of substitution between foreign varieties κ and the shape ν and scale parameter r_{min} of the Pareto distribution.

Leakage Rate I use the leakage rate to measure carbon leakage, which is the amount of emissions offset by an increase in emissions abroad. The leakage rate is defined by dividing the change in foreign emissions by the change in domestic emissions.

$$L = -\frac{\Delta \text{Foreign Emissions}}{\Delta \text{Domestic Emissions}} \tag{27}$$

A leakage rate smaller than one implies that overall emissions decrease, while a leakage rate larger than one implies that overall emissions increase. The literature reports leakage rates between 10 to 40 % for final goods (Fowlie and Reguant, 2022; Sogalla, 2023) and 75 % for intermediate goods (Leisner et al., 2022).

Decomposition of Change in Global Emissions Building upon the leakage rate, I want to dissect the channels contributing to the change in domestic and foreign emissions and, hence, the leakage rate. I decompose the change in global emissions, the sum of domestic and foreign emission changes, into four parts: i) the change in domestic emissions due to emission substitution, ii) the change in domestic output, the change in foreign emissions due to iii) offshoring, and iv) the emission intensity of imports.

$$\begin{aligned}\Delta E^{Global} = & \underbrace{\underbrace{\int_i^{N_s} (z_i' - z_i)\, va_i \, di}_{\text{Emission substitution}} + \underbrace{\int_i^{N_s} (va_i' - va_i)\, z_i \, di}_{\text{Output}}}_{\Delta \text{Domestic emissions}} + \\ & \underbrace{\underbrace{\int_i^{N_s} \left(X_{Fi}' - X_{Fi}\right) z_i(X_{Fi}) \, di}_{\text{Offshoring}} + \underbrace{\int_i^{N_s} \left(z_i(X_{Fi})' - z_i(X_{Fi})\right) X_{Fi}) \, di}_{\text{Emission Intensity Imports}}}_{\Delta \text{Foreign emissions}}\end{aligned} \tag{28}$$

Domestic emissions can decrease either if firms become cleaner and reduce their emission intensity or through changes in firm output. Changes in output include the effect of output reduction and

output reallocation towards cleaner/dirtier firms. Influenced by the changes in the input mix and output, firms' offshoring will also change. This happens through an extensive margin effect. Firms add or drop countries from their sourcing set, which either increases or decreases their importing activity. As a by-product of this extensive margin effect, the average emission intensity of imports will change as well if we assume that foreign countries differ in their emission intensity.
The contribution of the different channels depends on the underlying joint distribution of productivity, fixed costs of importing, and the emission bias, together with the parameters governing the elasticity of substitution between inputs and the demand elasticity.

3.4 Welfare

To account for the disutility of emissions for consumers, I follow Shapiro (2021) by modifying the utility function of the consumer as follows:

$$U = \prod_{s=1}^{S} C_s^{\alpha_s} f(E^{Global}) = \prod_{s=1}^{S} C_s^{\alpha_s} \left[1 + \delta \left(E^{Global} - E_0^{Global}\right)\right] \tag{29}$$

Damages from global emissions, denoted as E^{Global}, enter utility in a multiplicative way through the function $f()$, whose specification is chosen so that an increase in one ton of global emissions compared to a baseline emission level, causes damages equal to the social cost of carbon. However, consumers ignore the effect of emissions on their utility, treating emissions as an externality.
After modifying the utility function to include environmental damages, the change in welfare can be decomposed into two components: real income and the disutility of emissions. Real income depends on the price index and nominal income, while nominal income is determined by labor income and the aggregate resource loss due to fixed costs. I assume income from emission prices and carbon taxes is lost to rent-seeking activities Shapiro and Walker (2018). The disutility of emissions increases with global emissions and the social cost of carbon.

$$d \log W = \underbrace{d \log \frac{Y}{P}}_{\text{Real Income}} - \underbrace{d \log f(E^{Global})}_{\text{Disutility Emissions}} \tag{30}$$

3.5 Equilibrium

I assume that firms maximize profits and consumers maximize their utility, subject to their budget constraints. Moreover, the goods and labor markets clear, and trade is balanced. Additionally, I assume that the rest of the world (RoW) has the same CES demand structure as domestic consumers and firms. The supply of foreign intermediates and emissions is perfectly elastic. For more details, see the Appendix.

4 Estimation of the Model

As shown in the previous sections, firm heterogeneity has implications for both domestic and global emissions. I calibrate a one-sector version of my model using German microdata to quantify the impact of emission subsidies and the increase in global trade of intermediate inputs. In Section 4.1, I estimate the key parameters of the model, followed by an outline of the calibration procedure in Section 4.2. In Section 4.3, I present the calibration results and evaluate the model fit.

4.1 Estimation of Parameters

Elasticity of Demand I use German microdata to compute the elasticity of substitution σ. I follow Oberfield and Raval (2014) and infer σ from firms' markups. Markups are defined as the ratio of total revenue to costs. Following my model, I compute costs as the sum of wages, capital costs, and material expenditures.

$$\frac{revenue}{costs} = \frac{\sigma}{\sigma - 1} \tag{31}$$

I obtain an average markup of 1.36, corresponding to an elasticity of substitution of 3.8. This value is on the higher end of the estimates featured in the literature.

Elasticity of Substitution for Intermediates and Emissions Minimizing costs implies that, for a firm i, factor prices equal their marginal products. Using the first-order condition, it is possible to express the factor-cost ratio as a function of the elasticity of substitution and factor prices. See Raval (2019) for a more detailed derivation. Equation 32 identifies the elasticity of substitution between the intermediate input bundle and emissions using variation in the two-digit industry emission price $\bar{p}E, s$. I construct $\bar{p}E, s$ by taking a weighted average of the firm-specific emission prices. G_i includes controls for the four-digit industry, year, and a multi-plant dummy. $X_{i,s}$ is the quantity of intermediate inputs, while E_{is} is the quantity of emissions. The coefficient of interest is $\beta_1 = \eta - 1$.

$$log\left(\frac{p_X X_{is}}{p_E E_{is}}\right) = \beta_0 + \beta_1 log\left(\bar{p}_E, s\right) + \zeta_s G_{is} + e_{is} \tag{32}$$

Instruments I use differences in factor prices across two-digit industries to identify the elasticity of substitution. If these prices are correlated with unobserved industry characteristics, such as market power or productivity, the OLS estimator of β will be biased. To address this endogeneity issue, I propose a version of the shift-share instrument by Hummels et al. (2014), which utilizes differences in the energy-input composition combined with foreign prices for energy. Variation in energy prices captures supply-side shocks independent of German firms' demand. Since Germany is a small, open economy, it does not have the power to influence market outcomes. I use pre-sample shares of energy inputs from 2011 to measure a firm's exposure to energy-supply shocks. I construct firm-level instruments for input prices and then take a weighted average to obtain industry-level instruments.

Hence, the instrument for the energy input price EIP_{it}^E at the firm level is defined by:

$$EIP^E_{it} = \Sigma_j s_{ikt_0} P^W_{jt} \tag{33}$$

j denotes the set of different energy inputs a given firm can use. s_{ijt_0} represents firm i's share of energy input j in year $t_0 = 2011$, while P^W_{jt} is an unweighted average of the price of energy input j, calculated using data from all countries except Germany in year t. I obtain data on energy input prices from the International Energy Agency (IEA).

Table 5: Elasticity of substitution between emissions and intermediates

	Log input cost ratio			
	(1)	(2)	(3)	(4)
Log Average Emission Price	0.460***	0.486***	0.760***	0.815***
	(0.0327)	(0.0199)	(0.0377)	(0.0235)
Multi-plant dummy	0.0652***	0.0407***	0.0691***	0.0560***
	(0.0192)	(0.0121)	(0.0184)	(0.0118)
First Stage				
log EIP	0.111***	0.107***	0.113***	0.108***
	(0.0059)	(0.0058)	(0.0034)	(0.0035)
F-Stat	198.2	596.6	406.3	1203.0
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
N	42,116	90,887	42,124	90,898

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. This table presents the results of regressing a firm's intermediate input-energy factor-cost-ratio on its emission price controlling for firm and year fixed effects. Columns (1) and (2) construct shares based on energy consumption, while columns (3) and (4) use emissions to construct shares. Columns (1) and (3) use the period 2012-2015, while columns (2) and (4) use the period 2012-2019.

Table 5 shows the estimated elasticity of substitution between emissions and intermediate inputs. The estimates for this elasticity are between 1.5 and 1.8. Thus, both inputs can be classified as substitutes. For my calibration, I set the elasticity to 1.46.

Elasticity of Substitution for EII and Sourcing Strategy I need an estimate for the elasticity ι to calculate the emission intensity of imports and leaked emissions. Using Equation 26, the theory predicts a log-linear relationship between the number of sourcing locations n and the emission intensity of imports EEI, which can be estimated using German microdata and information on foreign emission intensities from Exiobase. I estimate the following regression:

$$\log(EII_i) = \delta_s + \delta_t + \phi \log(n_{ist}) + u_{ist} \tag{34}$$

n denotes the firm's average number of countries per product sourced. δ_s and δ_t are sector and year fixed effects. I measure products at the 6-digit level.

The results of the regression are displayed in Table 6. The emission intensity of imports increases with

Table 6: Elasticity of substitution between imported emission intensity and imported Varieties

	Log emission intensity imports				
	(1)	(2)	(3)	(4)	(5)
Log Number Varieties	0.146***	0.188***	0.189***	0.177***	0.0894***
	(0.00136)	(0.00268)	(0.00270)	(0.00398)	(0.00435)
Export Status			-0.0195***	-0.000686	0.00619
			(0.00502)	(0.00784)	(0.00823)
Log Capital/Worker				-0.00879***	-0.00763***
				(0.00182)	(0.00178)
Year FE	✓	✓	✓	✓	✓
Number Products		✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
N	219,903	219,816	219,816	102,706	91,958

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. The calculation of emission intensity of imports is based on Exiobase. Column (5) considers only firms that import more than one variety.

the number of imported varieties, measured as the number of foreign partner countries. Controlling for export status, the number of products, or the log capital-to-worker ratio changes the coefficient only slightly. However, restricting the sample to firms with more than one partner country nearly halves the coefficient. In my calibration, I use the smallest estimate of 0.0894.

Other Parameters Table 7 provides an overview of the parameter estimates I use to calibrate my model. To identify γ, I divided material spending by the firm's total costs. As for the carbon tax, I take the EU ETS price from 2014. ϵ_X and η are taken from Blaum et al. (2018).

Table 7: Calibrated model parameters

Description	Parameter	Estimate	Source
Demand elasticity	σ	4.10	German data
Output elasticity materials	γ	0.48	German data
EoS between emissions and intermediates	θ	1.46	German data
EoS between dom. and foreign intermediates	ϵ_X	2.38	Blaum et al. (2018)
Sensitivity P_F to mass sourcing countries	η	0.38	Blaum et al. (2018)
Sensitivity EII to mass sourcing countries	ι	0.09	German data
Price for one unit of emissions	t	10	EU ETS Price

Notes: This table reports the value of the calibrated parameters. The calibrated parameters are estimates using German firm-level data, aggregate data, or data taken from the literature.

4.2 Estimation Procedure

I allow for three dimensions of heterogeneity in my model: productivity ϕ_i, average fixed costs f_i, and emission bias β_i. I parameterize the distribution of the three parameters (ϕ_i, f_i, β_i) as a joint log-normal with means μ_ϕ, μ_f and μ_β, variances σ_ϕ^2, σ_f^2 and σ_β^2 and correlations $\rho_{f,\phi}$, $\rho_{\phi,\beta}$ and $\rho_{f,\beta}$.[4] I normalize average productivity to one. To solve the model, I use the simulated method of moments (SMM). The objective of the SMM is to minimize the distance between data and model moments by picking values for the endogenous model parameters. Intuitively, the distribution of value-added, the emission intensity, and the domestic share are the data equivalent of the distribution of ϕ_i, β_i, and f_i. Hence, the SMM estimates all parameters of (ϕ_i, f_i, β_i), the fixed costs of importing, and the minimum emission intensity of imports. To estimate the parameters, I must match each model moment with a moment from the data. The model with full heterogeneity targets nine data and model moments. I use the dispersion in value added to identify the dispersion in productivity σ_ϕ. The aggregate emission intensity and the dispersion in firm emission intensity identify the mean and the dispersion of the emission bias β_i. The aggregate foreign share and the dispersion of the foreign share identify the mean and the dispersion of the firm-specific fixed to import from a country. The share of importing firms identifies the fixed costs of importing all firms have to pay to start importing. The correlation between value-added, emission intensity, and foreign share identifies the correlation between productivity, emission bias, and fixed costs. Lastly, I use the minimum emission intensity of imports to identify the average emission intensity of imports in the model.

Table 8: Overview heterogeneity models

	Aggregate	Het. Bias	Het. Sourcing	Baseline
Productivity	✓	✓	✓	✓
Emission bias	✗	✓	✗	✓
Fixed costs	✗	✗	✓	✓

Notes: This table introduces the naming convention for different versions of the model.

4.3 Model Fit

I calibrate four different versions of the model, differing in the degree of firm heterogeneity (see Table 8). First, the aggregate model features only heterogeneity in productivity, with all firms having the same foreign share and emission bias. Next, I allow firms to differ either in terms of their emission bias in the heterogeneous bias model or in terms of their sourcing strategy in the heterogeneous sourcing model. Finally, in my baseline model, I incorporate both heterogeneous emission bias and heterogeneous sourcing strategy, in addition to heterogeneous productivity.
Table 9 shows the fit of the four different models. Overall, my baseline model can fit the sign of all targeted moments of the data. As expected, the heterogeneous bias model matches the distribution

[4] For consistency across the different models, I calibrate all models to feature variation along the intensive instead of the extensive margin. To do so, I introduce a home bias into the model to replace heterogeneity in fixed costs. See C.2 for details. As shown in Blaum et al. (2018), both approaches are nearly equivalent.

of emission intensity better than the distribution of the foreign share. The heterogeneous sourcing model cannot fit the dispersion of emission intensity, which can only be generated through variation in sourcing strategy, and predicts a positive correlation between the domestic share and emission intensity. The aggregate model neither matches the distribution of emission intensity nor that of the foreign share. Table 10 displays the parameter estimates for the baseline model.

Table 9: Moments of different models

		Aggregate	Het. Bias	Het. Sourcing	Baseline
Moments	Data	Simulated			
Dispersion in ln va	1.42	1.42	1.42	1.41	1.42
Agg. domestic share	0.65	0.65	0.65	0.64	0.64
Share of importers	0.78	1.00	1.00	0.78	0.78
Dispersion in ln sD	0.51	0.00	0.00	0.51	0.50
Corr ln va - ln sD	-0.26	0.00	0.00	-0.25	-0.25
Agg. log z	-8.55	-8.55	-8.55	-8.54	-8.55
Dispersion in ln z	1.27	0.00	1.27	0.01	1.27
Corr ln va - ln z	0.12	0.00	0.12	-0.25	0.11
Corr ln sD - ln z	-0.03	-1.00	0.00	0.98	-0.03
Agg. log EII	-7.07	-7.07	-7.07	-7.08	-7.07
Domestic/Foreign Emissions	1.32	1.32	1.32	1.32	1.32

Notes: The table reports the data and model moments for the calibrated models using the SMM approach.

Table 10: Parameter estimates of baseline model

Parameter Description	Parameter	Estimate
Average home bias	μ_h	3.4773
Average emission bias	μ_β	5.9347
Dispersion emission bias	σ_β	1.0616
Correlation emission bias and efficiency	$\rho_{\phi,\beta}$	-0.1061
Fixed costs of importing	f_I	0.0001
Dispersion fixed costs	σ_f	1.6772
Correlation fixed costs and efficiency	$\rho_{f,\phi}$	0.2560
Correlation emission bias and fixed costs	$\rho_{\beta,f}$	0.1134
Minimum Emission Intensity Imports	-	-9.3835
Emission price	p_E	1.3240

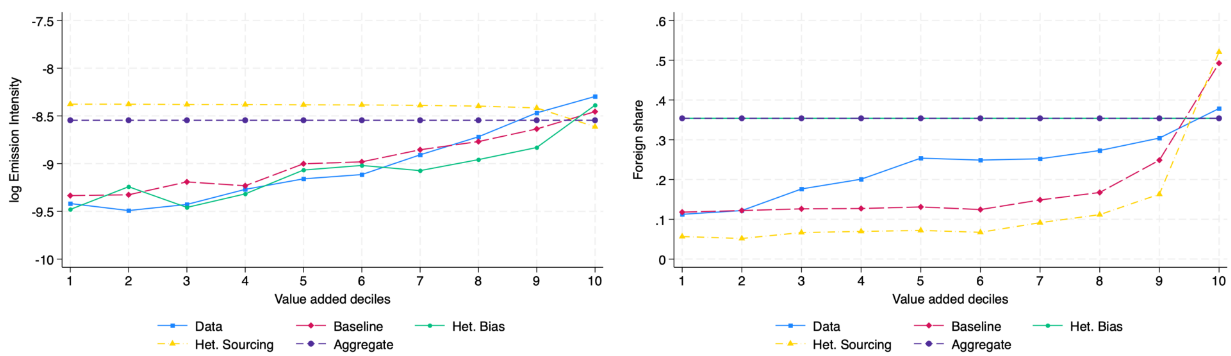
Notes: The table reports the parameter estimates for the baseline model using the SMM for calibration.

In Figure 4, I plot the distributions of the emission intensity and the foreign share for the data and all four versions of the model to verify that the model matches not only the moments but also the distribution of the variables.

Figure 4a shows the distribution of the emission intensity for the four models and the data. Not surprisingly, the aggregate model does not feature any dispersion in emission intensity and cannot match the data. In the heterogeneous sourcing model, large firms have a lower emission intensity caused by the variation in the foreign share. Both models overpredict the emission intensity of small firms and underpredict the emission intensity of large firms. The baseline and heterogeneous bias models match the distribution of log emission intensity fairly well. Similar to the other models, they overpredict the emission intensity of small firms and underpredict the emission intensity of large firms, but to a lesser extent.

Figure 4b shows the distribution of the foreign share for the four models and the data. The aggregate and heterogeneous sourcing models do not feature any dispersion in the foreign share and overpredict the foreign share for all but the largest firms. The baseline and heterogeneous sourcing models match the positive correlation between foreign share and firm size. However, they underpredict the foreign share for all but the largest firms and feature a jump in the foreign share for the largest firms.

Figure 4: Distribution of emission intensity and foreign share: data vs model



(a) Emission intensity

(b) Foreign share

4.4 Model Validation

To study the heterogeneity in firms' responses to climate policy and to validate the model, I compare the predicted treatment effects of my baseline model with the estimated treatment effects. In both cases, I study a 1% increase in the aggregate emission price. Building on the decomposition of global emissions change in Section 3.3, the focus is on output, emission intensity, offshoring, and the emission intensity of imports. Both my model and the data predict that large firms are more responsive to a carbon price shock. Large firms decrease their emission intensity and increase their output, their imports, and their emission intensity of imports relative to smaller firms.

4.4.1 Empirical Specification

For my model validation, I closely follow Brinatti and Morales (2021). Using the German firm-level data, I estimate the following regression:

$$\log(y_{i,t}) = \beta_0 + \beta_1 \log(pE^{Agg}_{s,t}) + \beta_2 \log(pE^{Agg}_{s,t}) \log(L_{i,t}) + \delta_i + \delta_s + \delta_t + \epsilon_{i,t} \tag{35}$$

$y_{i,t}$ is the output, emission intensity, offshoring, or emission intensity of imports for firm i in year t. $pE^{Agg}_{s,t}$ is the average implicit price of emissions firms pay in the two-digit industry s in year t. L is the size of firm i measured by employment. δ_i, δ_s, and δ_t are firm, industry and year fixed effects. I construct an industry-level instrument for the emissions price, using variation in the energy-input composition combined with foreign energy prices to capture exogenous energy-supply shocks. To measure the exposure of an industry to energy supply shocks, I use pre-sample shares of energy inputs from 2011 for each industry. The instrument is defined as:

$$Z_{s,t} = \Sigma_j s_{j,s,t_0} P^W_{jt} \tag{36}$$

s_{j,s,t_0} is the share of energy input j in industry s in the pre-sample year t_0. P^W_{jt} is the average price of energy input j in all OECD countries excluding Germany. The validity of the instrument relies on the industries being exposed to small, independent, and random shocks. For example, variations in world market prices may arise from technology shocks or production shocks.

Results Table 11 presents the average change in a firm's output (column 1), emission intensity (column 2), offshoring (column 3), and the emission intensity of imports (column 4) in response to an emission price shock. Panel A shows the OLS estimates, and Panel B the 2SLS estimates. The OLS and 2SLS estimates have the same signs, but the OLS estimates are downward biased. The 2SLS estimates in column (1) suggest that, on average, firms increase their output measured by value added. The estimates in column(2) and column (3) show that firms simultaneously decrease their emission intensity and increase their use of imported intermediates. Column (4) suggests that firms use more imported intermediates and dirtier imported intermediates. These estimates can be taken as evidence for emission offshoring, which, as a by-product, increases firm productivity. However, only the estimates for emission intensity and offshoring are statistically significant. My findings are similar to Fontagné and Schubert (2023), who study energy shocks of French firms. They find firms decrease their emission intensity and increase their import of intermediate inputs. However, the effect on output is insignificant and close to zero during 2012-2019.[5]

These average effects mask firm heterogeneity. In Table 12, I present the estimates where I allow the effect to vary with firm size. Again, the OLS estimates in Panel A have the same sign as the 2SLS estimates in Panel B but are downward biased. Starting with the estimate for output in column (1), I find a negative and statistically significant effect of the industry emission price on output. Still, the estimate for the interaction of the industry emission price with firm size is positive and statistically significant. The overall effect is positive for all firms with more than 16 employees. An increase in the industry emission price increases the output of all firms but more so for large firms.

[5] Colmer et al. (2024) study firms' responses to the EU ETS and find that regulated firms decrease their emission intensity but find no significant effect on output and offshoring.

Table 11: Effects of an emission price increase

	Output	Emission Intensity	Offshoring	EII
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates				
Log(Industry Emission Price)	0.0614	-0.1313	0.1657	0.0642
	(0.0530)	(0.0785)	(0.1459)	(0.0827)
Panel B: 2SLS Estimates				
log(Industry Emission Price)	0.1692	-0.2484*	0.2880*	0.2550
	(0.1182)	(0.1330)	(0.1644)	(0.2363)
F-Stat	28.9	28.9	31.4	31.4
Firm FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
N	69,616	69,616	54,935	54,935

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. This table presents the results of regressing a firm's output, emission intensity, offshoring, and emission intensity of imports on the industry emission price; the industry emission price interacted with employment and year, industry, and firm fixed effects. Standard errors are clustered at the industry level.

Columns (2) to (4) show the estimates for emission intensity, offshoring, and emission intensity of imports. While the estimates for the interaction term are highly statistically significant, the estimate for the industry emission price is not. Overall, the estimates suggest that firms decrease their emission intensity and increase their intermediate imports and their emission intensity of imports. The response of large firms is more pronounced for all three dependent variables.

Table 13 shows the average firm response for different firm size deciles. To compute the effect, I multiply the estimates by the average emission price and the average number of employees for each firm decile. Overall, the effects are relatively large. A 1% increase in the aggregate emission price decreases emission intensity by around -1.3% for the median firm. The change in importing of intermediates and output depends strongly on firm size. The largest firms increase their imports and output approximately four times more relative to the smallest firms. Overall, the effect for the median firm is smaller when accounting for firm heterogeneity. Without heterogeneity, firms would increase their output by 1.02%, while with heterogeneity, the median firm would increase their output by approximately 0.8%. Hence, aggregate estimates overestimate the median response.

4.4.2 Firm Response: Model and Data

Next, I want to compare the firm response predicted by the data and the model. I re-estimate Equation 35 using the calibrated model and simulate a 1% increase in the aggregate emission price, which equals a carbon tax increase from 10 to 14 €. I compute the average response for each firm decile by multiplying the estimates with the aggregate emission price and the average employment for each firm decile.

Figure 5 compares the model response with the data. The model matches the predicted effects

Table 12: Heterogeneous effects of an emission price increase

	Output	Emission Intensity	Offshoring	EII
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates				
Log(Industry Emission Price)	-0.2942***	-0.0665	-0.3860**	0.0315
	(0.0523)	(0.0835)	(0.1553)	(0.0816)
log(Industry Emission Price) × log(L)	0.0732***	-0.0133***	0.1106***	0.0066**
	(0.0042)	(0.0042)	(0.0135)	(0.0028)
Panel B: 2SLS Estimates				
log(Industry Emission Price)	-0.2272*	-0.1517	-0.2758	0.2009
	(0.1303)	(0.1277)	(0.1742)	(0.2365)
log(Industry Emission Price) × log(L)	0.0834***	-0.0204***	0.1157***	0.0111**
	(0.0073)	(0.0062)	(0.0184)	(0.0047)
F-Stat	28.9	28.9	31.4	31.4
Firm FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
N	69,616	69,616	54,935	54,935

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. This table presents the results of regressing a firm's output, emission intensity, offshoring, and emission intensity of imports on the industry emission price; the industry emission price interacted with employment and year, industry, and firm fixed effects. Standard errors are clustered at the industry level.

of the data well. Similar to the data, it predicts emission intensity to decrease and output and offshoring to increase. In the model, only the largest firms increase the emission intensity of imports. The model correctly predicts that large firms react more strongly to an increase in the emission price for all four outcome variables and matches the slope of the data response fairly well. Still, the effect size between the data and the model differs. However, this discrepancy in levels between the model and data estimates is expected since the effects estimated using the German firm data cannot consider the general equilibrium effect on prices.

5 Policy Experiment

Using the calibrated model, I want to study the effects of a change in the domestic carbon tax, both with and without a carbon tariff, on domestic and foreign emissions and welfare. The increase in the domestic emission price is calibrated to match a price increase from 10 of 100 €/tCO_2, simulating the rising prices of the EU ETS. The increase in the foreign price is calibrated to match a carbon tariff applying the domestic carbon tax to emissions embodied in imports. I find that an increase in the domestic carbon price decreases emissions and welfare in all models. In general, a carbon tariff reduces emissions further unless the most import-intensive firms are more emission-intensive than foreign producers.

Table 13: Firm response to a 1% emission price increase by firm decile

VA decile	1	2	3	4	5	6	7	8	9	10
Output	0.33	0.43	0.54	0.64	0.75	0.85	0.99	1.15	1.39	1.84
Emission Intensity	-1.21	-1.23	-1.26	-1.28	-1.30	-1.32	-1.35	-1.39	-1.44	-1.54
Offshoring	0.67	0.81	0.96	1.10	1.25	1.39	1.58	1.80	2.13	2.77
EII	1.31	1.32	1.33	1.34	1.35	1.35	1.37	1.39	1.41	1.47

Notes: The table reports the mean % change for output, emission intensity, offshoring, and the emission intensity of imports in response to a 1% change in the aggregate emission price for different firm deciles. Firms are ranked based on their value-added, with decile 1 being the firms with the lowest value added. The effects are computed using the estimates reported in Table 12.

5.1 Counterfactual 1: Increase in the Domestic Carbon Price

Context The European Union Emission Trading System (EU ETS) came into force in 2005 to reduce greenhouse gas emissions in the EU. While the social cost of carbon (SCC) is estimated to be at least 40 €, with estimates reaching over 400 €, the carbon price in the EU ETS remained below 35 € until 2020.

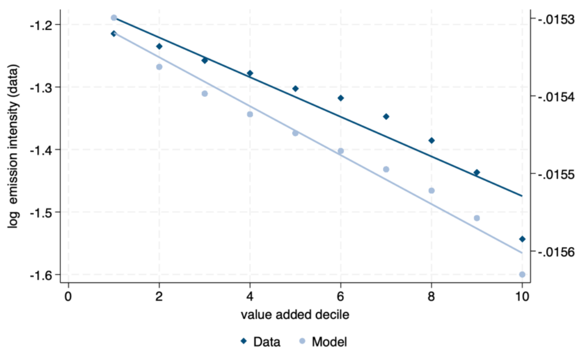
To slow climate warming, the carbon price in the EU ETS will have to increase significantly in the future. The absence of a carbon tariff may have a detrimental effect on the domestic manufacturing sector due to the relocation of production. It may also lead to significant carbon leakage. To examine a moderate increase in carbon prices, I simulate a change in the carbon price to 100 €/tCO_2. Such a price increase has already been observed temporarily in 2023 and is also in line with projected carbon prices needed to meet EU emissions targets.

Results As shown in Table 14, all four models predict a decrease in emissions and feature carbon leakage. However, there are significant differences between the models. Aggregate models underestimate the emission reduction and either under- or overestimate leakage.

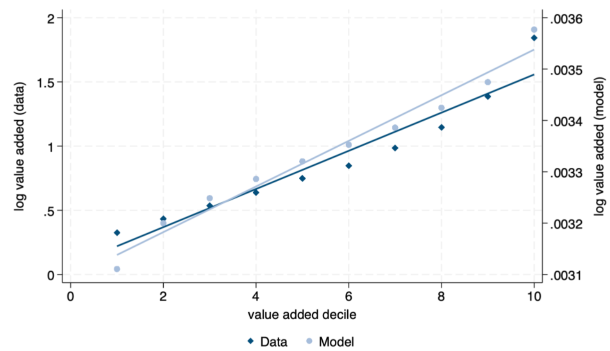
In the baseline model, domestic emissions would fall by 10.7% in response to the increase in the carbon price from 10 to 100 €/tCO_2. Consistent with the concept of emissions offshoring, foreign emissions increase by 8.1 %. Global emissions, defined as the sum of domestic and foreign emissions, decrease by approximately 10.7% overall, which is significantly less than the reduction in domestic emissions. The leakage rate is 25% and similar to estimates for final good leakage rates from the literature, which range between 10 and 50 %. However, it is smaller than the leakage rate for intermediate inputs of 75% found by Leisner et al. (2022) using reduced-form evidence.

In the three other, more aggregate models, global emissions decrease by between 8.5 - 10.5%. Hence, the bias of the aggregate models ranges between 2-20%, with the heterogeneous emission bias model being the closest. The bias is driven by different components. Models without heterogeneity in emission intensity underestimate the domestic emission reduction because they do not feature reallocation towards cleaner firms or, to a much smaller extent, in the heterogeneous sourcing model. Models without heterogeneity in sourcing strategy display lower emission offshoring because large firms increase their offshoring relative to smaller firms as they face lower costs to do so. Since these

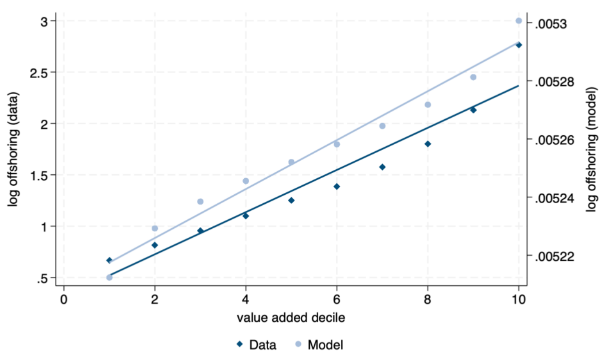
Figure 5: Firm responses: model vs data



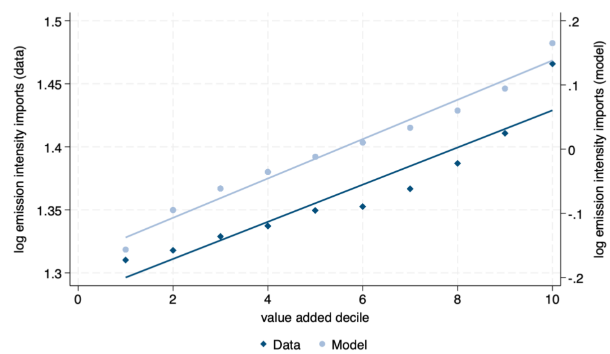
(a) Emission intensity



(b) Output



(c) Offshoring



(d) Emission Intensity of Imports

Notes: The figure shows the mean % change in emission intensity (a), output (b), offshoring (c), and the emission intensity of imports (d) in response to a 1% change in the aggregate emission price for different firm deciles, comparing the data and the model. Firms are ranked based on their value-added, with decile 1 being the firms with the lowest value added.

two effects bias the aggregate emission change in different directions, it is not clear whether the aggregate model would overestimate leakage relative to the baseline model, as the magnitude and direction of the bias depend closely on the parametrization of the model. Moreover, the bias for the global emission change and the leakage rate are not perfectly correlated. The baseline model has a higher leakage rate than the aggregate models without heterogeneity in sourcing strategy but a lower leakage rate than the heterogeneous sourcing model. Again, the absence of heterogeneity in fixed costs biases the leakage rate downwards, whereas the heterogeneity in emission bias introduces reallocation in the baseline model, mitigating leakage.

Table 15, decomposes the absolute change in emissions in million tons into the four different channels of (i) emission intensity, (ii) output, (iii) offshoring, and (iv) the emission intensity of imports. In all models, the domestic emission reduction is driven by a change in the emission intensity of the firm. All firms produce less emission-intensive after the domestic carbon price increases. The reduction is stronger in the absence of emission intensity heterogeneity. This can be explained by the relatively stronger price increase in the domestic intermediate inputs bundle,

Table 14: Counterfactual percentage change in domestic, foreign, and global emissions of a domestic carbon price increase

Model	Domestic (%)	Foreign (%)	Global (%)	Leakage Rate	Bias (%)
Baseline	-24.88	8.13	-10.68	0.25	0.00
Aggregate	-21.62	6.89	-9.35	0.24	-12.45
Het. sourcing	-22.16	9.55	-8.51	0.33	-20.29
Het. emission bias	-23.99	7.42	-10.48	0.23	-1.91

Notes: The table reports the change in domestic emissions (column 1), the change in foreign emissions (column 2), the change in global emissions (column 3), and the leakage rate (column 4) for a carbon price increase from 10 to 100 10 to 100 €/tCO_2. Column 5 reports the bias of the model in terms of change in global emissions relative to the baseline model.

limiting substitution towards intermediates. However, these two models feature a reduction in domestic emissions due to the output channel. The most mission-intensive firms shrink in absolute and relative terms. This effect is stronger than the increases in output of the clean firms and those with a low cost of sourcing. The increase in foreign emissions is driven by an increase in offshoring, with the composition of imports only marginally affecting total emissions. Overall, emissions go down by 56.06 million tons of CO_2 in my baseline model.

Table 15: Decomposing the change in emissions (million t CO_2)

Model	Emission Intensity	Output	Offshoring	EI Imports	Total
Baseline	-63.59	-13.60	18.31	0.05	-56.06
Aggregate	-67.47	3.64	15.57	0.00	-49.08
Het. sourcing	-66.49	0.39	21.52	0.05	-44.69
Het. emission bias	-64.09	-9.69	16.76	0.00	-55.00

Notes: The table reports the decomposition of the change in global emissions into the change in emission intensity (column 1), the change in output (column 2), the change in offshoring (column 3) and the change in the emission intensity of imports (column 4) for a carbon price increase from 10 to 100 €/tCO_2. All values are in million t CO_2.

In addition to leakage, I want to explore the welfare effects of an increase in the carbon price. The welfare effect can be decomposed into two components: the change in consumers' real income and the change in emissions. On one hand, the higher carbon price increases prices, resulting in a decline in real income. On the other hand, emissions decrease, which reduces the disutility associated with emissions as measured by the social cost of carbon. Ex-ante, it is not clear which of these effects is stronger. I perform a back-of-the-envelope calculation to quantify the change in welfare in €, as shown in Table 18. For this calculation, I take values for the domestic emissions from the manufacturing sector, the emissions embodied in imports, the average wages in Germany, and the number of employees from the data. Additionally, I value each tonne of emissions at its social cost of carbon (SCC), which I assume to be equal to 150 €(Rennert et al., 2022). The changes in emissions are taken from Table 17.

In the baseline model, an increase in the domestic carbon price to 100 €/tCO_2 results in an increase of the price by 2.63%, which is equivalent to a decrease of real income by 65.0 billion €. Compared

Table 16: Comparing welfare effects of the baseline and aggregate models without a carbon tariff (billion €)

Model	Real Income (€)	Emissions (€)	Change Welfare (€)	Bias (%)
Baseline	-65.00	9.06	-55.94	0.00
Aggregate	-87.50	7.93	-79.57	42.25
Het. sourcing	-87.65	7.22	-80.42	43.78
Het. emission bias	-87.18	8.89	-78.29	39.97

Notes: The table reports the change in real income (column 1), the change in the disutility of emissions (column 2), and the change in welfare (column 3) for a carbon price increase from 10 to 100 10 to 100 €/tCO_2. Column 4 reports the bias of the model in terms of welfare relative to the baseline model.

to the real income effect, consumers benefit moderately from the emissions reduction, amounting to about 9.06 billion €. However, this benefit is insufficient to offset the loss in real income, resulting in a total welfare decline of 56 billion €. This finding is consistent with the literature, which typically identifies the real income effect as being more significant than the emissions reduction effect (Shapiro, 2016, 2021). The other models overestimate the welfare losses by around 40% because they feature a larger increase in the price index, around 3.5 %. In the baseline model, small firms cannot escape the carbon price shock. In the other models, they experienced cost reduction through cheaper domestic or foreign intermediates. In the baseline model, however, domestic intermediates become more expensive, and offshoring is too costly.

5.2 Counterfactual 2: Increase in the Domestic Carbon Price with Carbon Tariff

Context The second counterfactual examines how combining a domestic carbon price and a carbon tariff can prevent carbon leakage in the baseline model. Unlike domestic emissions subsidies, carbon tariffs or a global carbon tax aim to create a level playing field for all countries in terms of carbon prices without an equivalent carbon pricing mechanism abroad.

I compare two different carbon tariffs in terms of leakage and welfare. First, I examine an aggregate carbon tariff that uses industry-level information, which is typically proposed in theoretical papers. I assume that all firms have the same emission intensity of imports. Second, I implement the Carbon Border Adjustment Mechanism (CBAM) proposed by the EU. The CBAM exactly prices a firm's imported emissions. The information requirements for this proposal are higher, as it is necessary to know the emission intensity of imports for each firm.

Results Table 17 shows that an industry-level carbon tariff of 8.5% can limit carbon leakage and reduce global emissions compared to the scenario with only a domestic carbon price for all but the baseline model. Compared to the carbon price-only scenario, emissions increase by 7% in the baseline model and decrease by an additional 23-30% in the other models. These differences are driven by the different reactions to a carbon tariff. A carbon tariff, even on its own, increases emissions in the baseline model, whereas it decreases emissions in all other models. These reactions are shaped by the existence or non-existence of emission-intensive firms with a low import intensity: emission-intensive firms with a low import intensity are growing as a response to a carbon tariff. Intuitively, the carbon tariff hurts firms with a high import intensity or a low emission intensity most. Either of these firms wants to substitute away from foreign intermediates towards emissions. This causes an increase in the domestic emission intensity. In the baseline model, high-emission intensity and low-import-intensity firms exist. Conversely, they are the least affected, and production is reallocated towards them, and they increase offshoring by relatively less than other firms. Domestic emissions increase by more than in the aggregate models, and the offshoring response is less pronounced. In the baseline model, this effect can be strengthened by the fact that some of these emission-intensive and low import-intensity firms produce dirtier than foreign producers.

The ranking of models in terms of emission reduction is changed. Now, the baseline model performs worst in terms of leakage rate and global emission reduction, whereas the heterogeneous bias models feature the largest emission reduction.

Even though emissions in three out of four models decrease, welfare drops further. In the aggregate model, welfare decreases by an additional 36%. In the baseline model, welfare losses are more than double. Additionally, welfare losses are the largest in models with heterogeneity in sourcing strategy. Large firms with a high foreign share and low price are hit relatively more, causing higher welfare losses in those models.

Lastly, I want to compare the results for a carbon tariff based on an industry measure of the emission intensity of imports and a carbon tariff based on the firm's emission intensity of imports (CBAM). For the aggregate and heterogeneous bias models, both carbon tariffs are identical. The baseline and heterogeneous sourcing model now feature additional heterogeneity in carbon tariffs. CBAM reduces emissions by more than the industry carbon tariff but by less than 1%. In the case of the heterogeneous sourcing model, CBAM is slightly improving welfare compared to the industry carbon tariff.

Table 17: Counterfactual percentage change in domestic, foreign, and global emissions of a domestic carbon price increase combined with an industry carbon tariff

Model	Domestic (%)	Foreign (%)	Global (%)	Leakage Rate	Add. reduction (%)
Baseline	-20.96	4.65	-9.94	0.17	-6.88
Aggregate	-20.85	-0.17	-11.96	-0.01	27.87
Het. sourcing	-20.86	1.84	-11.09	0.07	30.24
Het. emission bias	-22.75	0.22	-12.87	0.01	22.83

Notes: The table reports the change in domestic emissions (column 1), the change in foreign emissions (column 2), the change in global emissions (column 3), and the leakage rate (column 4) for a carbon price increase from 10 to 100 €/tCO_2 and a carbon tariff based on the emission intensity of imports. The carbon tariff prices emissions at the domestic carbon price. Column 5 reports the additional reduction in emissions compared to the scenario without a carbon tariff.

Taxing emissions embodied in imports for each firm is equivalent to an average tariff of 6.75% (see Table 26), with firm-level tariffs ranging from 5.9% to 7.9%.

Discussion Carbon tariffs on intermediate inputs are effective in reducing emissions in models without heterogeneity in sourcing strategy. However, models with heterogeneity cannot eliminate

Table 18: Comparing welfare effects of the baseline and aggregate models with an industry carbon tariff (billion €)

Model	Real Income (€)	Emissions (€)	Change Welfare (€)	Add. reduction (%)
Baseline	-133.83	8.44	-125.39	124.16
Aggregate	-118.39	10.14	-108.24	36.04
Het. sourcing	-119.11	9.41	-109.70	36.40
Het. emission bias	-118.19	10.92	-107.27	37.01

Notes: The table reports the change in real income (column 1), the change in the disutility of emissions (column 2), and the change in welfare (column 3) for a carbon price increase from 10 to 100 €/tCO_2 and a carbon tariff based on the emission intensity of imports. The carbon tariff prices emissions at the domestic carbon price. Column 5 reports the additional reduction in welfare compared to the scenario without a carbon tariff.

Table 19: Counterfactual percentage change in domestic, foreign, and global emissions of a domestic carbon price increase combined with CBAM

Model	Domestic (%)	Foreign (%)	Global (%)	Leakage Rate	Add. reduction (%)
Baseline	-20.92	4.70	-9.90	0.17	-0.47
Aggregate	-20.85	-0.17	-11.96	-0.01	0.00
Het. sourcing	-20.85	1.84	-11.09	0.07	-0.01
Het. emission bias	-22.75	0.22	-12.87	0.01	0.00

Notes: The table reports the change in domestic emissions (column 1), the change in foreign emissions (column 2), the change in global emissions (column 3), and the leakage rate (column 4) for a carbon price increase from 10 to 100 €/tCO_2 and a carbon tariff based on the emission intensity of imports. The carbon tariff prices emissions at the domestic carbon price. Column 5 reports the additional reduction in emissions compared to the scenario with an industry carbon tariff.

leakage, and they come at the cost of over-proportional welfare losses. For example, in the aggregate model, emissions decrease by an additional 28 %, but welfare decreases by 36%. In the baseline model, average CBAM tariffs are lower than industry-based carbon tariffs of 8.5 % (see Figure 6). Even though they reduce leakage for all firms, especially large firms that have high leakage rates above 30%, those firms also have the dirtiest imports and are responsible for a large share of imported emissions.

To effectively reduce leakage, one has to target those firms and try to bring down their leakage rates. Campolmi et al. (2024) propose a leakage border adjustment mechanism (LBAM) that sets import tariffs as high as necessary to eliminate leakage from the domestic carbon price. This approach could be adapted to target a specific leakage rate for each firm to maximize emission reductions. However, this approach would come at high additional welfare costs in my model, since large firms would face considerable higher carbon tariffs.

5.3 Sensitivity of leakage and welfare to carbon prices and SCC

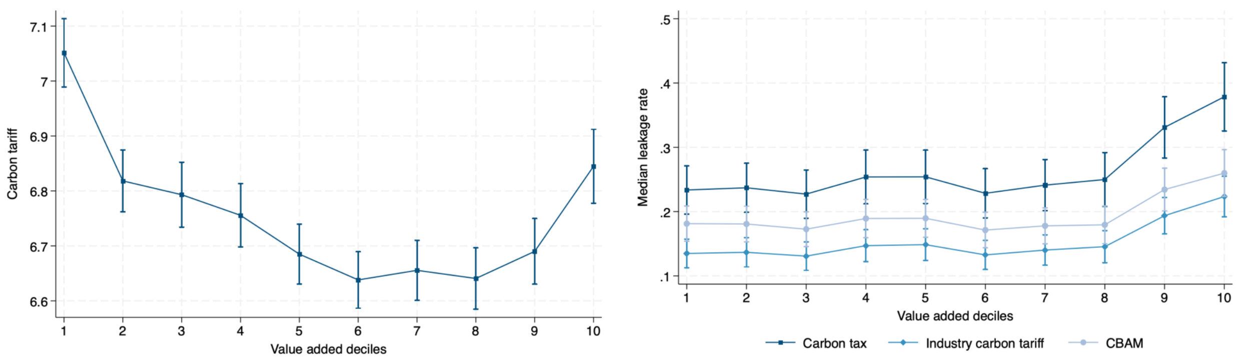
In this section, I show that the change in emissions, the leakage rate, and the change in welfare is linear in the carbon price. Additionally, I show that even for high SCC estimates, consumer welfare decreases if the domestic carbon price increases. I simulate increases in the domestic carbon price

Table 20: Comparing welfare effects of the baseline and aggregate models with CBAM (billion €)

Model	Real Income (€)	Emissions (€)	Change Welfare (€)
Baseline	-134.44	8.40	-126.04
Aggregate	-118.39	10.14	-108.24
Het. sourcing	-119.09	9.41	-109.68
Het. emission bias	-118.19	10.92	-107.27

Notes: The table reports the change in real income (column 1), the change in the disutility of emissions (column 2), and the change in welfare (column 3) for a carbon price increase from 10 to 100 €/tCO_2 and a carbon tariff based on the emission intensity of imports. The carbon tariff prices emissions at the domestic carbon price.

Figure 6: Firm Heterogeneity in Leakage and Carbon Tariffs



(a) Carbon tariff - CBAM

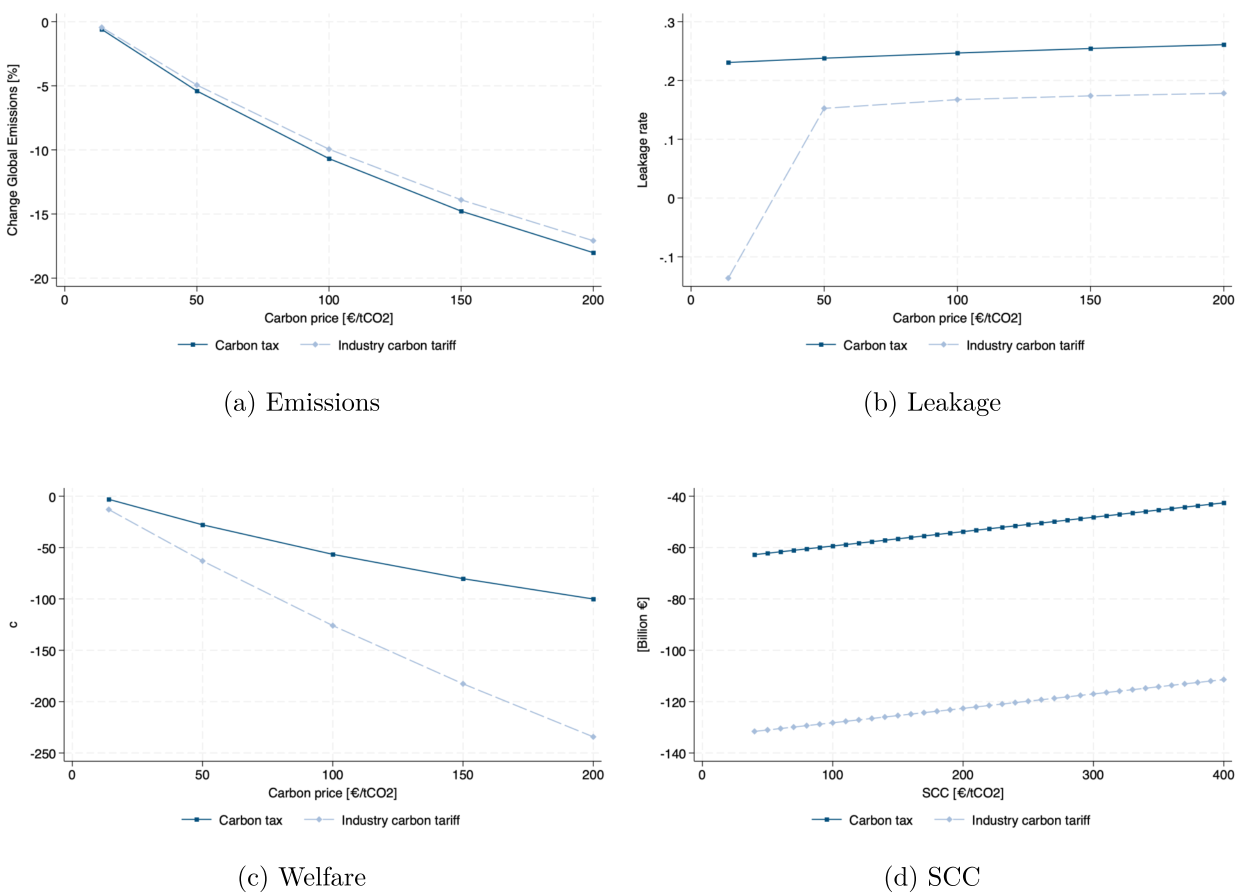
(b) Leakage rate

Notes: The left panel shows the mean carbon tariff based on the firm's emission intensity of imports for different firm deciles. The right panel shows the mean leakage rate for different firm deciles for the three scenarios of (i) an increase in the domestic carbon price, (ii) an increase in the domestic carbon price with an industry carbon tariff, and (iii) an increase in the domestic carbon price with CBAM.

for values between 10 and 500 € per ton CO_2 for my baseline model.

Figure 7a shows emission reduction of a carbon tax with and without a carbon tariff for my baseline model. Emissions decrease nearly linearly in the carbon tax with and without a carbon tariff. However, the gap between the two scenarios widens as the carbon tax and marginal emission reductions become smaller. Although global emissions decrease with the carbon price, the leakage rate increases with the carbon price (see Figure 7b). A carbon tariff equivalent to the domestic carbon price reduces the leakage rate by a constant proportion below the leakage rate of the domestic carbon tax. However, the leakage rate remains well above zero for all except for a carbon price of 14 €t CO_2. To further decrease the leakage rate, the emissions embodied in imports would have to be taxed at a higher price than domestic emissions. Figure 7c and Figure 7d focus on the sensitivity of welfare losses with respect to the carbon price and the SCC. Similarly to the trend for emissions, welfare decreases in the carbon price. However, welfare reacts more sensitively to a carbon tariff than emissions do, and the gap between the two scenarios continues to grow with the carbon price. Besides the change in consumer income, the gap in welfare losses depends on the SCC. Contrary to consumer income, measuring the SCC is less precise. The 95% confidence interval for the SCC is approximately between 40 €and 400 €per ton CO_2 (Rennert et al., 2022). Deviating from my standard assumption that the SCC is equal to 150 €per ton CO_2 can hence chance the welfare gap. For my preferred scenario of a carbon price increase to 100 €per ton CO_2, welfare losses can be as small as 40 billion €, which is approximately 15 billion €less than my benchmark result.

Figure 7: Change in welfare and emissions for different carbon prices



(a) Emissions

(b) Leakage

(c) Welfare

(d) SCC

Notes: The figure compares the change in global emissions (a), the change in the leakage rate (b), and the change in welfare (c) for different carbon prices with and without a carbon tariff. Panel (d) shows the sensitivity of the change in welfare to the SCC for an increase of the carbon price from 10 to 100 €/tCO_2.

5.4 Model extensions

This section discusses possible extensions to the baseline model. To focus on the role of firm heterogeneity, the model focuses on a one-sector economy with input substitution towards intermediates and labor as the only available abatement mechanism. This abstracts from several other factors influencing leakage and welfare. In the following, I want to focus on the implementation of a domestic carbon tax for only selected industries, trade in final goods, an additional abatement channel through clean energy/technology, and the role of EU-wide cooperation in carbon taxation.

Multi-sector In my previous analysis, I assumed that all manufacturing firms must pay a carbon tax. However, only the most emission-intensive industries in Germany are covered by the EU ETS.[6] I plan to extend my model to a two-sector economy with input-output (IO) linkages to address this limitation. In this version, I classify firms into dirty and clean sectors, where only firms in the dirty sector are subject to a carbon price. This allows me to study the spillover effects of the carbon price on untreated firms and compare the emission reductions achieved when all firms are covered.
Figure 16 and Figure 17 in the Appendix show the heterogeneity in emission intensity, foreign share, and emission intensity for a clean and dirty industry. Hereby, I classify all 4-digit industries with an above-median emission intensity as dirty. My current model parametrization aligns with the characteristics of the dirty sector, where large firms are dirtier. Including a clean sector in the analysis will increase leakage.

Trade in Final Goods Although this paper focuses on the role of firm heterogeneity in the leakage of intermediate inputs, leakage in final goods can occur simultaneously. When examining emissions embodied in imports (see Figure 15 in the Appendix), it becomes evident that more emissions are imported via intermediate goods; however, the emissions from imported final goods are only slightly smaller in magnitude. By extending the model to include trade in final goods, I can distinguish between the contributions of different channels, which will help in designing effective policies.
Intuitively, leakage in final goods will replace the production of small firms with imported goods. Since small firms are, on average, cleaner and have a lower leakage rate, allowing for trade in final goods will increase leakage under the assumption that imported goods are dirtier than the production of small domestic firms.

Abatement Clean Energy In my baseline model, the standard environmental trade abatement mechanism (Antweiler et al., 2001; Shapiro and Walker, 2018) is absent. This absence may lead to overestimating carbon leakage, as firms cannot abate emissions and can only substitute labor and intermediates to reduce their emissions. Hence, my estimates should be treated as an upper bound for leakage. To address this shortcoming, I introduce two types of energy in my model: dirty and clean, which are imperfect substitutes. All firms have access to dirty energy, which generates emissions. However, to access clean energy, firms must pay a fixed cost. In this context, I use renewable energy as a proxy for clean energy. Alternatively, one could think about including investment in clean production technology.
Figure 19 in the Appendix shows how the share of renewable energy varies with firm size.

EU ETS The EU is the most important import partner of German firms. Approximately 60% of the imported intermediates are from EU member countries. My model treats imports from EU ETS and non-EU ETS countries equally. However, this does not accurately reflect that countries covered by the EU ETS are likely to reduce their emission intensity. Moreover, they are subjected to the

[6] Industries vary widely in their emission intensity, as shown in Figure 10 in the Appendix.

CBAM. As a result, this may lead to an overestimation of leakage and firms switching to cleaner partner countries.

I introduce a further distinction between EU and non-EU imports to overcome this shortcoming of my model. EU imports are cleaner and not subject to a carbon tariff, but their prices still rise. In contrast, non-EU imports are subject to a carbon tariff, yet the pass-through is incomplete. Furthermore, EU imports are assumed to become cleaner, while the emission intensity of non-EU imports remains the same. Although I do not include a multi-country version of the model in this analysis, these modifications allow me to obtain more precise estimates of carbon leakage. They could be extended to analyze carbon clubs or a global carbon tax.

6 Conclusion

This paper documents that German manufacturing firms exhibit varying emission intensities, even after controlling for input expenditures. Contrary to common assumptions, larger firms are characterized by higher emission intensity due to lower emission prices. These lower emission prices result from differences in the underlying energy mix and firms' technologies to generate emissions. Moreover, firms differ in their shares of foreign intermediates and the emission intensities of imported intermediates. Building on these empirical facts, I propose a theoretical model of heterogeneous firms that differ in their import and emission intensities. I demonstrate that the model aligns with standard empirical results at the firm level.

In my quantitative exercise, I illustrate that models lacking heterogeneity in sourcing strategy and emission bias fail to capture the characteristics of the German data. In a counterfactual analysis, I examine the effects of an increase in the domestic carbon price from 10 to 100 €/tCO_2, with and without a carbon tariff. First, an aggregate model without firm heterogeneity would underestimate emission reduction and welfare losses. In my baseline model, an increase in the domestic carbon price from 10 to 100 €/tCO_2 reduces domestic emissions by about 25%, while foreign emissions increase by 8.1% without a carbon tariff. In contrast, the aggregate model predicts that domestic emissions decrease by only 2%, while foreign emissions also increase by 7%. A carbon tariff can reduce leakage and lower global emissions in all but my baseline model.

Even though emissions fall in response to a carbon price increase, the welfare effects are negative because real income declines more than consumers benefit from the lower disutility associated with emissions. Moreover, accounting for the non-linearity of carbon leakage in carbon prices is crucial if policymakers aim to minimize welfare losses.

The results should be viewed as an upper bound for welfare losses and a lower bound for emission reduction. My model features only input substitution as a way to reduce emissions. In reality, firms have the option to invest in abatement, switch to cleaner energy sources, or switch to cleaner import partners. Hence, the analysis can be extended along several dimensions. First, a multi-sector version could better capture the significant sectoral heterogeneity present in the data. Carbon leakage may be more or less pronounced depending on the sector, and consequently, the optimal policy might vary by industry. Second, this paper focuses solely on carbon leakage in intermediate inputs. An extended version of the model could consider carbon leakage in both final and intermediate inputs: a unilateral increase in carbon prices incentivizes emissions offshoring and exposes domestic firms to greater import competition. Third, switching to cleaner import partners or cleaner energy sources can be incorporated easily. Finally, given the varying importance of domestic and foreign emissions, carbon tariffs could be complemented by firm-specific domestic emission subsidies to achieve higher emission reductions.

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A Data

A.1 Data Cleaning

Data on energy use at the plant level is aggregated to the firm level and then combined with other datasets. While the German Statistical Agency employs several quality checks, resulting in generally good data quality, some inconsistencies persist, particularly regarding reported energy use and materials. First, I eliminate all firms that report less than €1,000 in sales or have total energy use below 1,000 kWh. Second, due to misreporting, there are often significant fluctuations in reported values within firms over time. To address this, I impute any observations that differ by more than 30% from the values reported in periods t-1 and t+1 with the average of the adjoining periods. With data available starting in 1995, this adjustment does not affect my sample. Third, I impute missing observations for firms where data for the years t-1 and t+1 are available, using the average of the adjoining periods to ensure a balanced panel.

A.2 Emission Factors

Table 21: Emission factors for different fuel types and electricity

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Coke	389,20	389,20	389,20	389,20	389,20	389,20	389,20	389,20	389,20
Light fuel oil	266,50	266,50	266,50	266,50	266,50	266,50	266,50	266,50	266,50
Heavy fuel	288,50	288,50	288,50	288,50	288,50	288,50	288,50	288,50	288,50
Other petroleum products	281,50	281,50	281,50	281,50	281,50	281,50	281,50	281,50	281,50
Natural gas	201,30	201,30	201,30	201,30	201,30	201,30	201,30	201,30	201,30
Liquified gas	236,20	236,20	236,20	236,20	236,20	236,20	236,20	236,20	236,20
Other gas products	196,50	196,50	196,50	196,50	196,50	196,50	196,50	196,50	196,50
Industrial waste and other fuels	256,00	256,00	256,00	256,00	256,00	256,00	256,00	256,00	256,00
Renewables	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Raw lignite	381,70	377,90	378,50	373,60	374,20	380,80	382,50	382,90	383,30
Hard coal	339,20	337,20	336,10	336,80	336,60	336,80	336,10	335,10	337,20
Brown coal briquettes	357,40	357,40	356,70	358,40	357,80	358,20	357,50	356,40	356,30
Other coal products	353,20	352,90	352,90	353,10	352,80	352,90	353,10	351,00	350,90
District heat	188,10	187,50	186,80	186,20	185,60	185,00	184,40	183,70	183,10
Electricity	568,00	573,00	572,00	557,00	527,00	523,00	488,00	471,00	408,00

Notes: Emission factors are taken from Umweltbundesamt (2008, 2021, 2022) reported in gCO_2/kWh.

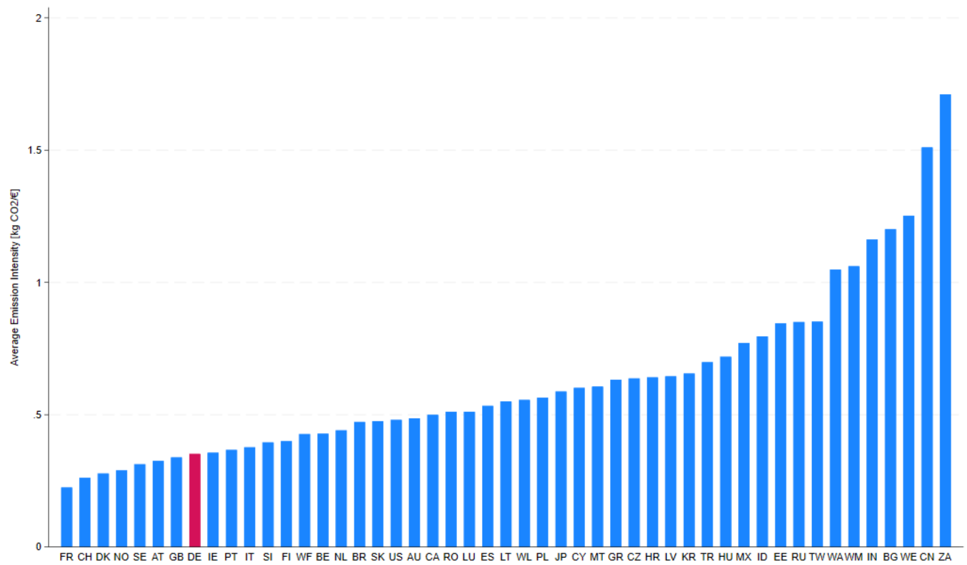
A.3 Trade Data Imputation

EU internal trade data for Germany is not collected at the firm level but for tax groups ("Organkreise"). A tax group is an amalgamation of independent firms that jointly file taxes. Only the parent company reports the monthly trade flows within a tax group. The German statistical agency has implemented an algorithm based on information from the VAT information exchange system and product-level production data to allocate imports and exports to the integrated companies within a tax group. For details on the implemented methodology and coverage of the data, see Kruse et al. (2021).

A.4 Exiobase

Figure 8 depicts the emission intensity of manufacturing for different countries using direct and indirect emissions. Germany, highlighted in red, is among the cleanest countries.

Figure 8: Emission intensity of different countries based on Exiobase



Notes:

B Empirical Evidence - Additional Results

B.1 Emission Intensity and Offshoring

Table 22 provides additional evidence on the emission offshoring channel using more narrowly defined measures for offshoring. Compared to the baseline measure, the coefficients are larger in magnitude but still smaller than estimates from the literature. Moreover, no clear raking of wide and narrow offshoring regarding effect size is possible.

Table 22: Offshoring and emission intensity

	Log Emission Intensity	
	VA	
	(1)	(2)
log Offshoring (wide)	-0.0273	
	(0.0188)	
log Offshoring (narrow)		-0.0234
		(0.0160)
First Stage		
log WES	0.0976^{***}	0.1138^{***}
	((0.0137)	(0.0163)
F-Statistics	50.5081	48.9238
Firm FE	✓	✓
Year FE	✓	✓
N	38907	38907

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. This table presents the results of regressing a firm's emission intensity on its offshoring activity, controlling for firm and year-fixed effects. For the regression, the years 2012-2018 are used.

B.2 Foreign share and imported varieties

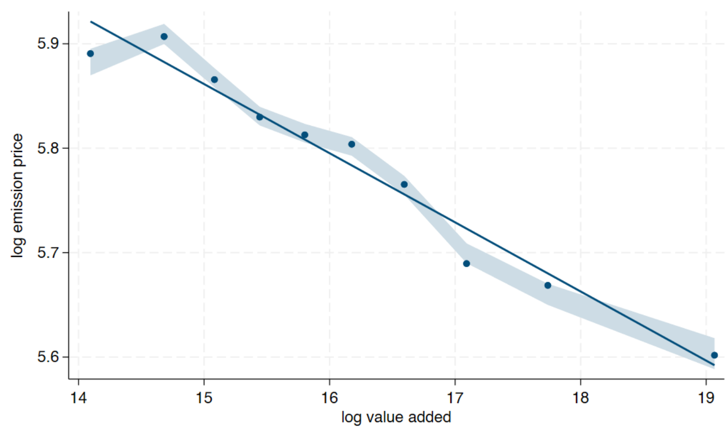
Table 23: Relative domestic share and import partners

	Log Relative Domestic Share				
	(1)	(2)	(3)	(4)	(5)
Log No. varieties	1.535***	1.056***	1.055***	1.050***	0.998***
	(0.00710)	(0.0147)	(0.0148)	(0.0150)	(0.0160)
Export status			0.0182	0.0230	0.212***
			(0.0281)	(0.0289)	(0.0326)
Log Capital/worker				-0.0151*	-0.00330
				(0.00680)	(0.00686)
Year FE	✓	✓	✓	✓	✓
No. Products		✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
N	97796	97715	97715	94972	84306

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. This table presents the results of regressing the relative domestic share of a firm, defined as foreign share divided by domestic share, on its number of imported varieties, export status, and capital per worker controlling for firm, product, and year fixed effects. For the regression, the years 2012-2018 are used.

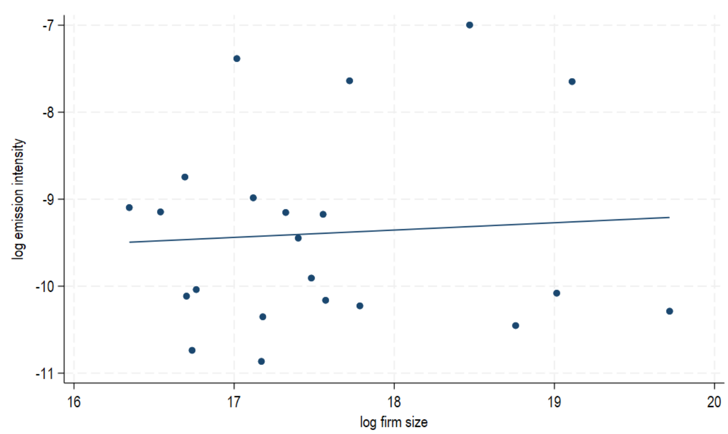
B.3 Firm size and emission intensity

Figure 9: Firm size and implicit emission price



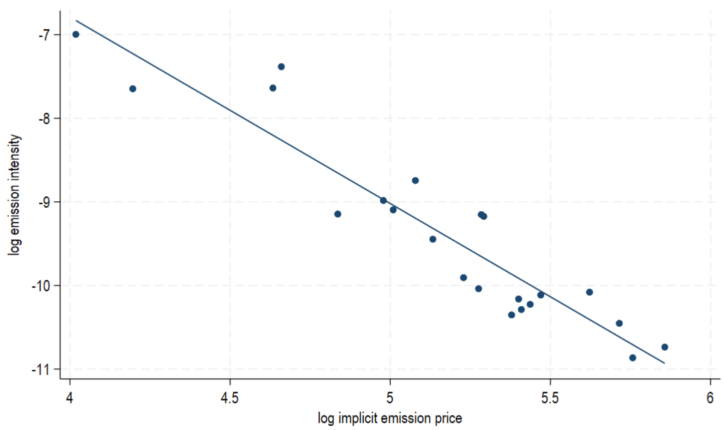
Notes: This figure depicts a binscatter plot of log implicit emission price as the dependent variable and log value added as the independent variable controlling for four-digit industry and year fixed effects. Observations are divided into ten equal-sized bins using the independent variable. For each bin, the mean of the independent variable and the mean of the independent variable is computed. The data for the dependent variable is residualized. Implicit emission price is defined as energy expenditure divided by emissions from fuel use and electricity. For the plot, the years 2011-2018 are used.

Figure 10: Emission intensity and sales per firm for 2-digit industries



Notes: This figure plots log emission intensity as the dependent variable and log average firm size as the independent variable for two-digit industries in the German manufacturing sector. Emission intensity is defined as emissions divided by sales. Firm size is measured as sales. For the plot, the years 2011-2018 are used.

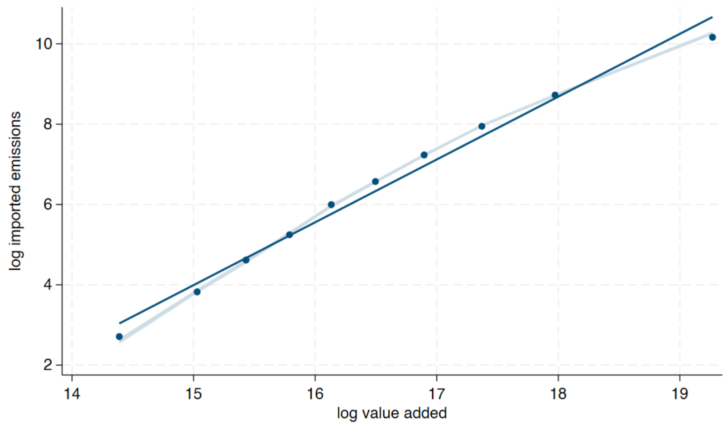
Figure 11: Emission intensity and implicit emission price for 2-digit industries



Notes: This figure plots log emission intensity as the dependent variable and log average implicit emission price as the independent variable for two-digit industries in the German manufacturing sector. Emission intensity is defined as emissions divided by sales. Implicit emission price is defined as energy expenditure divided by emissions from fuel use and electricity. For the plot, the years 2011-2018 are used.

B.4 Imported Emissions

Figure 12: Firm size and imported emissions

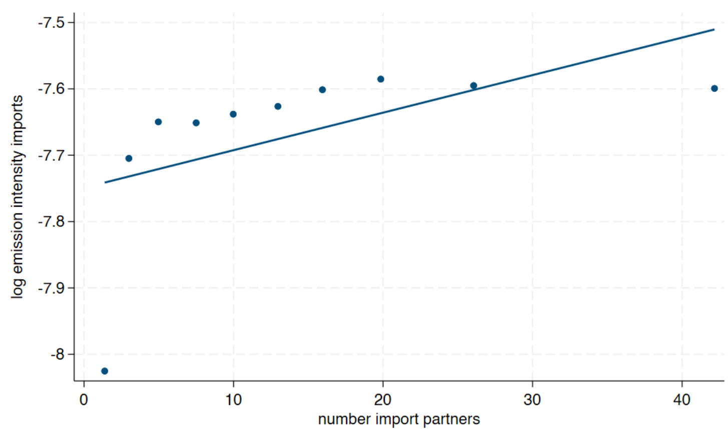


Notes: This figure depicts a binscatter plot of log imported emissions as the dependent variable and log value added as the independent variable controlling for four-digit industry and year fixed effects. Observations are divided into ten equal-sized bins using the independent variable. For each bin, the mean of the independent variable and the mean of the independent variable is computed. The data for the dependent variable is residualized. Imported emissions are defined as direct and indirect emissions of imports using Exiobase data. For the plot, the years 2011-2018 are used.

B.5 Emission Intensity of Imports

To gain additional insight into the role of sourcing strategy on imported emission intensity, Figure 13 plots the number of different import partners against the emission intensity of imports. Noticeable is a jump between the first and second decile. The firms in the first bin source from only a handful of suppliers, which are relatively clean and located in Western Europe. Starting with the second bin, imports from dirty countries gain importance.

Figure 13: Emission intensity and number import countries



Notes: This figure depicts a binscatter plot of log emission intensity of imports (EII) as the dependent variable and the number of different partner countries as the independent variable controlling for four-digit industry and year fixed effects. Observations are divided into ten equal-sized bins using the independent variable. For each bin, the mean of the independent variable and the mean of the independent variable is computed. The data for the dependent variable is residualized. The emission intensity of imports is defined as direct and indirect emissions of imports using Exiobase data divided by value-added. For the plot, the years 2011-2018 are used.

To exclude the possibility of the correlation between emission intensity of imports and firm size being driven by outliers in the Exiobase data, I use data from the United Nations Sustainable Development Goals (UNSDG) on emission intensity of VA in the manufacturing sector as a plausibility check. Compared to Exiobase, the data is more aggregated and does not allow for the distinction between manufacturing industries. Nevertheless, I find a positive and statistically significant correlation between firm size and emission intensity of imports in both cases (see Table 24 and Table 25).

Table 24: Correlation firm size and emission intensity imports: Exiobase

	Emission intensity imports			
	(1)	(2)	(3)	(4)
Log Sales	0.0522^{***}		0.0162^{***}	
	(0.000977)		(0.00432)	
Log VA		0.0378^{***}		0.0263^{***}
		(0.00129)		(0.00633)
Year FE	✓	✓	✓	✓
Firm FE			✓	✓
Industry FE	✓	✓		
N	218753	105682	214559	101215

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. The emission intensity of imports is calculated using Exiobase.

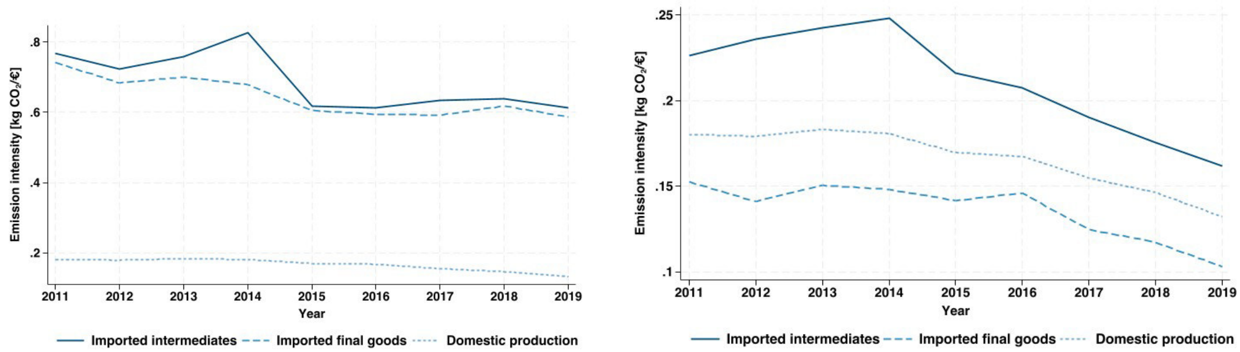
Table 25: Correlation firm size and emission intensity imports: UNSDG

	Emission intensity imports			
	(1)	(2)	(3)	(4)
Log Sales	0.0930^{***}		0.0488^{***}	
	(0.00133)		(0.00577)	
Log VA		0.0734^{***}		0.0364^{***}
		(0.00170)		(0.00795)
Year FE	✓	✓	✓	✓
Firm FE			✓	✓
Industry FE	✓	✓		
N	218301	105553	214098	101085

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. The emission intensity of imports is calculated using UNSDG data.

B.6 Trade in final goods

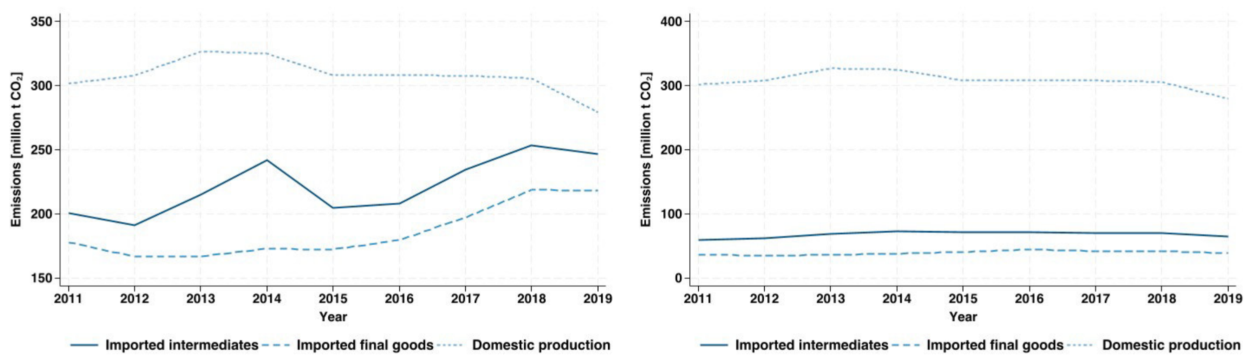
Figure 14: Emission intensity imports and domestic production



(a) Exiobase

(b) Domestic emission intensity

Figure 15: Domestic and imported emissions



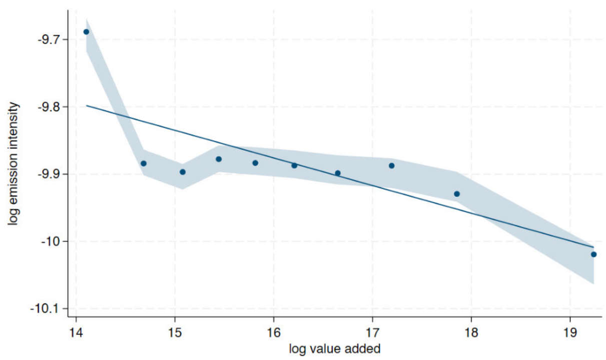
(a) Exiobase

(b) Domestic emission intensity

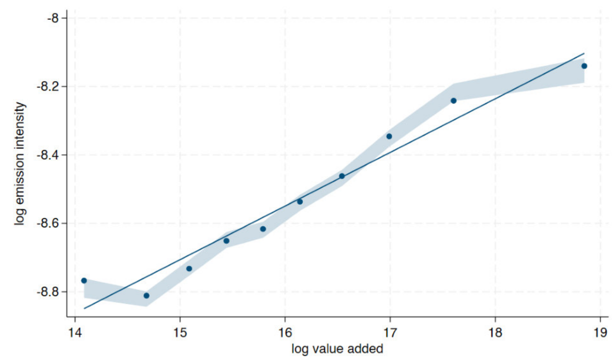
B.7 Clean and dirty industry

Divide 4-digit industries into clean and dirty industries, using the median emission intensity. Interestingly, to see which sector drives the result and spillover effects, if only the dirty industry has to pay a carbon price, with no change, foreign share and emission intensity imports increase in firm size. However, the emission intensity decreases in firm size for clean industries and increases in firm size for dirty industries.

Figure 16: Emission intensity for clean and dirty industries

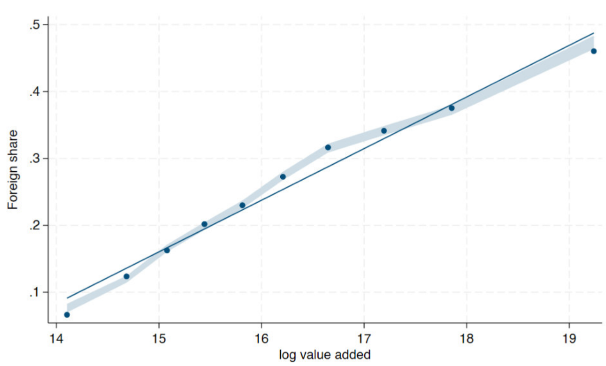


(a) Emission intensity clean

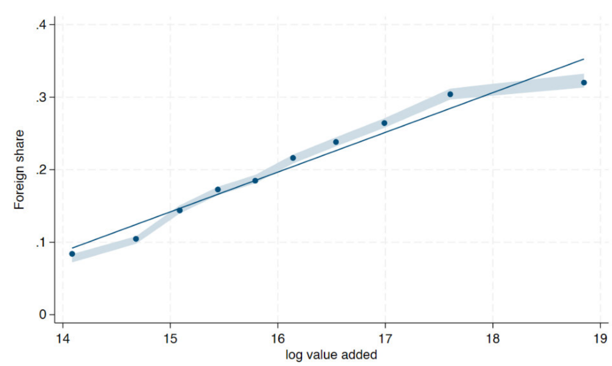


(b) Emission intensity dirty

Figure 17: Foreign share for clean and dirty industries

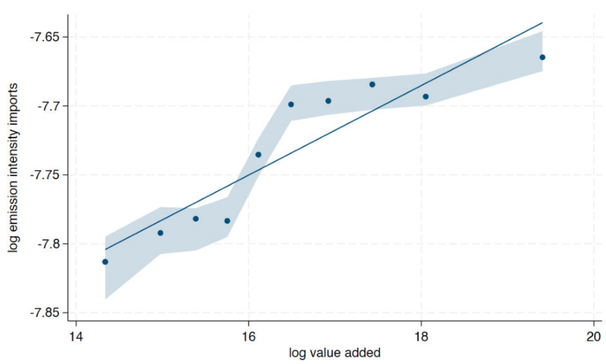


(a) Foreign share clean

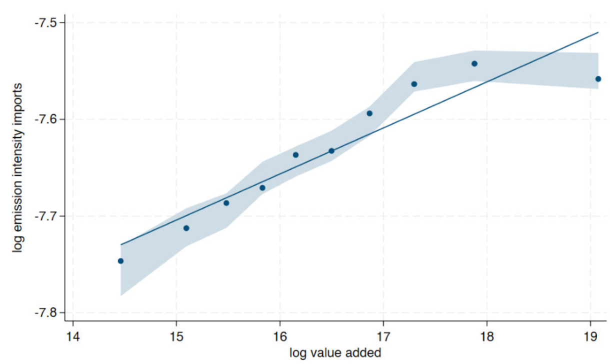


(b) Foreign share dirty

Figure 18: Emission intensity of imports for clean and dirty industries



(a) Emission intensity imports clean

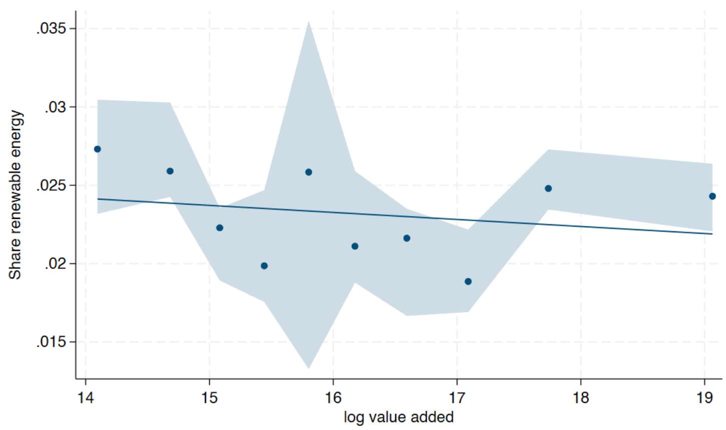


(b) Emission intensity imports dirty

B.8 Renewable energy

German firm data no information on investments in abatement/clean technology. Therefore, I use the share of renewable energy as a proxy. Figure 19 plots the share of renewable energy for different firm sizes. Overall, the share of renewable energy is low, with an average share of 2.5 %. Moreover, it seems uncorrelated with firm size. Compared to other countries, German firms do not have access to clean energy (e.g., France has nuclear power). Additionally, firms might directly buy clean electricity, which cannot be measured in the data.

Figure 19: Firm size and renewable energy share



Notes: This figure depicts a binscatter plot of the share of renewable energy as the dependent variable and log value added as the independent variable controlling for four-digit industry and year fixed effects. Observations are divided into ten equal-sized bins using the independent variable. For each bin, the mean of the independent variable and the mean of the independent variable is computed. The data for the dependent variable is residualized. The share of renewable energy is defined as the share of total energy and electricity use. For the plot, the years 2011-2018 are used.

C Model Derivations

In the following, I provide the main derivations for a one-sector economy.

C.1 Firm Problem

Consumer preferences imply that firm revenue is given by

$$R_i = p_i y_i = \left(\frac{p_i}{P}\right)^{1-\sigma} S \tag{37}$$

where the price index P is defined as $P = \left(\int p_i^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}$ and S denotes total spending. Since firms charge a constant markup over unit costs, their price is equal to $p_i = \left(\frac{\sigma}{\sigma-1}\right) u_i$ Substituting this for the firm price, the expression can be written as

$$p_i y_i = \left(\left(\frac{\sigma}{\sigma-1}\right) u_i P\right)^{\sigma-1} S \tag{38}$$

Firms maximize profits by choosing the optimal domestic share sD

$$\pi_i = \max_{sD_i \in [0,1]} \left\{ u(sD_i)^{(1-\sigma)} B - w(n(sD_i)f + f_I I(n > 0)) \right\} \tag{39}$$

with

$$u(sD) = \left(\frac{1}{\phi_i}\left(\frac{w}{1-\gamma}\right)^{1-\gamma}\left(\frac{1}{\gamma}\right)^{\gamma}\right)^{1-\sigma} \left(\beta_i^\theta s_D(n)^{\frac{1-\theta}{\epsilon_X - 1}} (p_D/q_D)^{1-\theta} + (1-\beta_i)^\theta p_E^{1-\theta}\right)^{\frac{\gamma(1-\sigma)}{1-\theta}} B \tag{40}$$

$$B = \frac{1}{\sigma} \frac{\sigma}{\sigma - 1}^{1-\sigma} P^{\sigma-1} S \tag{41}$$

$$n(sD_i) = \left(\frac{1 - sD_i}{sD_i}\right)^{\frac{1}{\eta(\epsilon-1)}} \left(\frac{zq_D}{p_D}^{\frac{1}{\eta}}\right) \tag{42}$$

The derivative of the profit function wrt to sD is given by

$$\begin{aligned}\frac{\partial \pi_i}{\partial sD_i} = &\left(\frac{1}{\phi_i}\left(\frac{w}{1-\gamma}\right)^{1-\gamma}\left(\frac{1}{\gamma}\right)^{\gamma}\right)^{1-\sigma} B\frac{(1-\gamma)}{\epsilon - 1}\beta_i^\theta (p_D/q_D)^{1-\theta} \\ &\left(\beta_i^\theta s_D(n)^{\frac{1-\theta}{\epsilon_X - 1}} (p_D/q_D)^{1-\theta} + (1-\beta_i)^\theta p_E^{1-\theta}\right)^{\frac{\gamma(1-\sigma)}{1-\theta}-1} \\ &- (1 - sD_i)^{\frac{1-\eta(\epsilon-1)}{\eta(\epsilon-1)}} sD_i^{\frac{1-\theta}{\eta}} f = 0\end{aligned} \tag{43}$$

C.2 Optimal Domestic Share of a Firm

For the calibration exercise, to achieve consistency across models, I assume that all firms are importers and that fixed costs and fixed costs of importing are zero. To introduce variation in the domestic share, I assume that firms have a home bias α.

$$X_i = \left[\alpha_i q_D z_D^{\frac{\epsilon_X - 1}{\epsilon_X}} + (1-\alpha) X_F^{\frac{\epsilon_X - 1}{\epsilon_X}}\right]^{\frac{\epsilon_X}{\epsilon_X - 1}} \tag{44}$$

With the home bias, the price index of intermediates is given by

$$Q(\Sigma) = \left(\alpha_i^{\epsilon_X} (p_D/q_D)^{1-\epsilon_X} + (1-\alpha_i)^{\epsilon_X} P_F(\Sigma)^{1-\epsilon_X}\right)^{\frac{1}{1-\epsilon_X}} \tag{45}$$

Solving for the domestic share and plugging in the import price index, we get that the domestic share is given by

$$sD_i = \left(1 + \left(\frac{1-\alpha_i}{\alpha_i}\right)^{\epsilon_X} \left(\frac{p_D}{q_D z}\right)^{\epsilon_X - 1} n^{\eta(\epsilon_X - 1)}\right)^{-1} \tag{46}$$

Setting $n = 1$, I can find the domestic share of a firm given its home bias α_i.

C.3 Import Status of a Firm

A firm imports if the net gains from importing are larger than zero, with the net gains being defined as the difference between profits if the firm is an importer π^I and profits if the firm is a non-importer π^D.

$$\pi^I - \pi^D > 0 \tag{47}$$

with π^I and π^D given by

$$\begin{aligned} \pi^I = & \left(\frac{1}{\phi_i}\left(\frac{w}{1-\gamma}\right)^{1-\gamma}\left(\frac{1}{\gamma}\right)^{\gamma}\left((1-\beta_i)^{\theta} s_D(n)^{\frac{1-\theta}{\epsilon_X - 1}} (p_D/q_D)^{1-\theta} + \beta_i^{\theta} p_E^{1-\theta}\right)^{\frac{\gamma}{1-\theta}}\right)^{1-\sigma} B \\ & - n(sD)f - f_I \end{aligned} \tag{48}$$

$$\pi^D = \left(\frac{1}{\phi_i}\left(\frac{w}{1-\gamma}\right)^{1-\gamma}\left(\frac{1}{\gamma}\right)^{\gamma}\left((1-\beta_i)^{\theta} (p_D/q_D)^{1-\theta} + \beta_i^{\theta} p_E^{1-\theta}\right)^{\frac{\gamma}{1-\theta}}\right)^{1-\sigma} B \tag{49}$$

C.4 Emission Intensity

From the firm's cost minimization problem, it follows that the emissions of a firm are given by

$$E_i = \frac{sE}{p_E}\frac{1}{\phi_i}\left(\frac{\gamma}{1-\gamma}\right)^{\gamma}\left(\frac{1}{pM_i}\right)^{1-\gamma} u_i^{-\sigma} P^{\sigma-1} S = \gamma\left(\frac{\sigma-1}{\sigma}\right)\frac{sE}{p_E}\left(\frac{p_i}{P}\right)^{1-\sigma} S \tag{50}$$

where s_E is the emission share

$$s_E = \frac{\beta_i^{\theta} p_E^{1-\theta}}{\beta_i^{\theta} p_E^{1-\theta} + (1-\beta_i)^{\theta} Q(\Sigma_i)^{1-\theta}} = \beta^{\theta} p_E^{1-\theta} p_M^{\theta-1} \tag{51}$$

Dividing by value-added $va = (1-\gamma)\left(\frac{p_i}{P}\right)^{1-\sigma} S$ gives us the emission intensity of firm i

$$zi = \left(\frac{\sigma-1}{\sigma}\right)\frac{\gamma}{1-\gamma}\beta_i^{\theta} p_E^{-\theta}\left((1-\beta_i)^{\theta} Q(\Sigma)^{1-\theta} + \beta_i^{\theta} p_E^{1-\theta}\right)^{-1} \tag{52}$$

C.5 General equilibrium variables

Total spending S consists of consumer income S^C, firms' expenditure for domestic intermediate inputs S^{DOM}, and exports S^{ROW}.

$$S = S^C + S^{DOM} + S^{ROW} \tag{53}$$

Consumer income is the sum of labor income and profits. I assume that revenue from the carbon pricing scheme and carbon tariffs are lost due to rent-seeking.

$$S^C = \int l_i di + \frac{1}{\sigma} S \tag{54}$$

Standard calculations for the Cobb-Douglas production function imply that the labor expenditure of a firm is

$$l_i = \left(\frac{\sigma-1}{\sigma}\right)(1-\gamma)\left(\frac{p_i}{P}\right)^{1-\sigma} S \tag{55}$$

Domestic intermediate expenditure and total import spending are given by

$$\begin{aligned} S^{DOM} &= \int sX_i sD_i m_i di = \int sX_i sD_i \gamma s_i di = \int sX_i sD_i m_i \gamma \frac{\sigma-1}{\sigma} p_i y_i di \\ &= \gamma \frac{\sigma-1}{\sigma} S \int sX_i sD_i \left(\frac{p_i}{P}\right)^{1-\sigma} di \end{aligned} \tag{56}$$

$$\begin{aligned} S^{ROW} &= \int sX_i(1-sD_i) m_i di = \int sX_i(1-sD_i)\gamma s_i di = \int sX_i(1-sD_i) m_i \gamma \frac{\sigma-1}{\sigma} p_i y_i di \\ &= \gamma \frac{\sigma-1}{\sigma} S \int sX_i(1-sD_i)\left(\frac{p_i}{P}\right)^{1-\sigma} di \end{aligned} \tag{57}$$

Combining these equations, total spending is given by

$$S = \left(\frac{\sigma-1}{\sigma}\right)(1-\gamma) S \int \left(\frac{p_i}{P}\right)^{1-\sigma} di + \frac{1}{\sigma} S + \gamma \frac{\sigma-1}{\sigma} S \left(\int sX_i sD_i \omega_i di + \int sX_i(1-sD_i)\omega_i di\right) \tag{58}$$

The price index, the second general equilibrium variable, can be expressed as

$$P = \frac{\sigma}{\sigma-1}\left(\int u_i^{1-\sigma}\,di\right)^{\frac{1}{1-\sigma}}$$
$$= \frac{\sigma}{\sigma-1}\left(\int \left(\frac{1}{\phi_i}\left(\frac{w}{1-\gamma}\right)^{1-\gamma}\left(\frac{1}{\gamma}\right)^{\gamma}\left(\beta_i^{\theta} s_D(n)^{\frac{1-\theta}{\epsilon_X-1}}\left(p_D/q_D\right)^{1-\theta}+(1-\beta_i)^{\theta} p_E^{1-\theta}\right)^{\frac{\gamma}{1-\theta}}\right)^{(1-\sigma)} di\right)^{\frac{1}{1-\sigma}} \tag{59}$$

C.6 Equilibrium

The equilibrium is defined as a set of prices $[p_i]$ and allocations such that:

1. Firms maximize profits

$$\pi_i = \max_{sD}\left\{u(sD)^{(1-\sigma)}B - w(n(sD)f + f_I I(sD>0))\right\} \tag{60}$$

2. Consumers maximize their utility given by subject to their budget constraint

$$\int p_i c_i\,di = wL + \int \pi_i\,di \tag{61}$$

3. Good markets clear

$$y_i = c_i + y_i^{ROW} + \int y_v\,dv \tag{62}$$

4. Labor markets clear

$$L = \int \left(l_i + l_i^F\right) di \tag{63}$$

5. Trade is balanced

$$y_i^{ROW} = \int sD_i m_i\,di \tag{64}$$

D Model Extensions

Under construction

E Calibration

E.1 Simulated Method of Moments Algorithm

As preparation, set the number of firms to 31,529 and draw shocks for productivity, fixed costs of sourcing, and emission bias from a standard normal for each firm.

1. Guess a value for each internal model parameter. Set the weighting matrix equal to the identity matrix.

2. Draw productivity, fixed costs of sourcing, and emission bias for given parameters and shocks.

3. Given parameters, find the fixed point where general equilibrium objects S and P no longer change. For this, guess initial S and P.

4. Given S and P, solve the model and compute each moment.

5. Compute Euclidean distance between data and model moments.

6. Iterate until the distance between data and model moments is small enough. Otherwise, go back to step 1.

F Quantitative Exercise - Additional Results

Table 26: Carbon tariffs in % for different carbon prices and models

Carbon Price	14	50	100	150	200	500
Industry Carbon Tariff						
Aggregate, Het. emission bias	1.18	4.23	8.46	12.70	16.93	42.32
Het. Sourcing	1.18	4.23	8.46	12.69	16.92	42.29
Baseline	1.19	4.23	8.47	12.70	16.94	42.34
CBAM						
Aggregate, Het. emission bias	1.18	4.23	8.46	12.70	16.93	42.32
Het. Sourcing	0.90	3.21	6.42	9.64	12.85	32.12
Baseline	0.95	3.38	6.75	10.13	13.51	33.77

F.1 Increase in the Domestic Carbon Price

Table 27: Counterfactual percentage change in domestic, foreign, and global emissions of a domestic carbon price increase

	Domestic (%)	**Foreign (%)**	**Global (%)**	**Leakage Rate**
		Panel A: t = 14		
Baseline	-1.36	0.42	-0.60	0.23
Aggregate	-1.18	0.34	-0.53	0.21
Het. sourcing	-1.21	0.46	-0.49	0.29
Het. emission bias	-1.33	0.36	-0.60	0.21
		Panel B: t = 50		
Baseline	-12.44	3.92	-5.40	0.24
Aggregate	-10.77	3.22	-4.75	0.23
Het. sourcing	-11.05	4.43	-4.39	0.30
Het. emission bias	-12.05	3.47	-5.37	0.22
		Panel C: t = 100		
Baseline	-24.88	8.13	-10.68	0.25
Aggregate	-21.62	6.89	-9.35	0.24
Het. sourcing	-22.16	9.55	-8.51	0.33
Het. emission bias	-23.99	7.42	-10.48	0.23
		Panel D: t = 150		
Baseline	-34.78	11.72	-14.77	0.25
Aggregate	-30.32	10.23	-12.87	0.25
Het. sourcing	-31.05	14.24	-11.56	0.35
Het. emission bias	-33.43	11.01	-14.31	0.25
		Panel E: t = 200		
Baseline	-42.78	14.79	-18.01	0.26
Aggregate	-37.44	13.29	-15.61	0.27
Het. sourcing	-38.31	18.59	-13.82	0.37
Het. emission bias	-41.05	14.29	-17.24	0.26
		Panel F: t = 500		
Baseline	-69.58	26.44	-28.27	0.29
Aggregate	-62.36	27.60	-23.65	0.33
Het. sourcing	-63.54	39.32	-19.27	0.47
Het. emission bias	-66.70	29.53	-25.29	0.33

Table 28: Comparing welfare effects of the baseline and aggregate models without a carbon tariff

	Real Income (€)	**Emissions (€)**	**Change Welfare (€)**
	Panel A: t = 14		
Baseline	-3.49	0.51	-2.98
Aggregate	-4.47	0.45	-4.02
Het. sourcing	-4.50	0.42	-4.08
Het. emission bias	-4.47	0.51	-3.96
	Panel B: t = 50		
Baseline	-32.10	4.58	-27.52
Aggregate	-42.04	4.03	-38.01
Het. sourcing	-42.23	3.72	-38.50
Het. emission bias	-41.96	4.56	-37.41
	Panel C: t = 100		
Baseline	-65.00	9.06	-55.94
Aggregate	-87.50	7.93	-79.57
Het. sourcing	-87.65	7.22	-80.42
Het. emission bias	-87.18	8.89	-78.29
	Panel D: t = 150		
Baseline	-91.89	12.54	-79.35
Aggregate	-126.79	10.92	-115.86
Het. sourcing	-126.67	9.81	-116.86
Het. emission bias	-126.10	12.14	-113.96
	Panel E: t = 200		
Baseline	-114.26	15.29	-98.97
Aggregate	-161.19	13.25	-147.94
Het. sourcing	-160.65	11.73	-148.92
Het. emission bias	-160.06	14.63	-145.44
	Panel F: t = 500		
Baseline	-195.79	23.99	-171.80
Aggregate	-304.53	20.07	-284.46
Het. sourcing	-300.25	16.35	-283.90
Het. emission bias	-300.33	21.46	-278.87

Table 29: Decomposing the change in emissions (million t CO_2)

	Emission Intensity	**Output**	**Offshoring**	**EI Imports**	**Total**
		Panel A: t = 14			
Baseline	-3.46	-0.62	0.94	0.00	-3.14
Aggregate	-3.70	0.18	0.76	0.00	-2.77
Het. sourcing	-3.64	0.02	1.03	0.00	-2.59
Het. emission bias	-3.49	-0.48	0.82	0.00	-3.16
		Panel B: t = 50			
Baseline	-31.65	-6.17	8.82	0.03	-28.35
Aggregate	-33.74	1.71	7.28	0.00	-24.95
Het. sourcing	-33.21	0.20	10.00	0.02	-23.04
Het. emission bias	-31.92	-4.59	7.84	0.00	-28.20
		Panel C: t = 100			
Baseline	-63.59	-13.60	18.31	0.05	-56.06
Aggregate	-67.47	3.64	15.57	0.00	-49.08
Het. sourcing	-66.49	0.39	21.52	0.05	-44.69
Het. emission bias	-64.09	-9.69	16.76	0.00	-55.00
		Panel D: t = 150			
Baseline	-89.29	-20.65	26.38	0.08	-77.56
Aggregate	-94.38	5.39	23.11	0.00	-67.58
Het. sourcing	-93.08	0.53	32.11	0.07	-60.67
Het. emission bias	-89.93	-14.21	24.87	0.00	-75.12
		Panel E: t = 200			
Baseline	-110.38	-27.30	33.30	0.10	-94.57
Aggregate	-116.27	6.99	30.03	0.00	-81.97
Het. sourcing	-114.75	0.63	41.91	0.08	-72.57
Het. emission bias	-111.11	-18.27	32.28	0.00	-90.49
		Panel F: t = 500			
Baseline	-184.52	-59.47	59.52	0.17	-148.42
Aggregate	-191.66	14.33	62.35	0.00	-124.16
Het. sourcing	-189.78	0.82	88.64	0.16	-101.16
Het. emission bias	-185.36	-36.10	66.71	0.00	-132.79

F.2 Increase in Import Price

Table 30: Counterfactual percentage change in domestic, foreign, and global emissions of a foreign price increase

	Domestic (%)	**Foreign (%)**	**Global (%)**	**Leakage Rate**
		Panel A: t = 14		
Baseline	0.68	-0.54	0.15	0.60
Aggregate	0.13	-1.00	-0.35	5.60
Het. sourcing	0.23	-1.07	-0.33	3.57
Het. emission bias	0.23	-1.01	-0.31	3.36
		Panel B: t = 50		
Baseline	2.39	-1.92	0.54	0.61
Aggregate	0.47	-3.49	-1.23	5.62
Het. sourcing	0.79	-3.72	-1.16	3.58
Het. emission bias	0.80	-3.54	-1.07	3.37
		Panel C: t = 100		
Baseline	4.69	-3.79	1.04	0.61
Aggregate	0.91	-6.78	-2.40	5.64
Het. sourcing	1.52	-7.21	-2.24	3.58
Het. emission bias	1.54	-6.88	-2.08	3.37
		Panel D: t = 150		
Baseline	6.89	-5.62	1.51	0.62
Aggregate	1.32	-9.88	-3.50	5.66
Het. sourcing	2.21	-10.48	-3.25	3.59
Het. emission bias	2.24	-10.03	-3.04	3.37
		Panel E: t = 200		
Baseline	9.01	-7.39	1.96	0.62
Aggregate	1.70	-12.82	-4.54	5.68
Het. sourcing	2.85	-13.56	-4.21	3.59
Het. emission bias	2.91	-13.00	-3.94	3.38
		Panel F: t = 500		
Baseline	20.13	-17.07	4.13	0.64
Aggregate	3.59	-27.51	-9.79	5.79
Het. sourcing	5.97	-28.65	-8.93	3.62
Het. emission bias	6.18	-27.85	-8.46	3.40

Table 31: Comparing welfare effects of the baseline and aggregate models for a foreign price increase

	Real Income (€)	**Emissions (€)**	**Change Welfare (€)**
	Panel A: t = 14		
Baseline	-9.81	-0.13	-9.94
Aggregate	-4.52	0.30	-4.22
Het. sourcing	-4.52	0.28	-4.24
Het. emission bias	-4.52	0.26	-4.26
	Panel B: t = 50		
Baseline	-34.17	-0.45	-34.62
Aggregate	-15.69	1.05	-14.64
Het. sourcing	-15.68	0.98	-14.69
Het. emission bias	-15.69	0.91	-14.78
	Panel C: t = 100		
Baseline	-66.04	-0.88	-66.92
Aggregate	-30.22	2.04	-28.19
Het. sourcing	-30.17	1.90	-28.27
Het. emission bias	-30.21	1.77	-28.44
	Panel D: t = 150		
Baseline	-95.83	-1.28	-97.12
Aggregate	-43.72	2.97	-40.75
Het. sourcing	-43.61	2.76	-40.85
Het. emission bias	-43.69	2.58	-41.11
	Panel E: t = 200		
Baseline	-123.75	-1.66	-125.41
Aggregate	-56.29	3.86	-52.43
Het. sourcing	-56.10	3.57	-52.52
Het. emission bias	-56.23	3.34	-52.89
	Panel F: t = 500		
Baseline	-260.20	-3.50	-263.71
Aggregate	-116.43	8.31	-108.13
Het. sourcing	-115.68	7.58	-108.11
Het. emission bias	-116.21	7.18	-109.03

Table 32: Decomposing the change in emissions (million t CO_2)

	Emission Intensity	**Output**	**Offshoring**	**EI Imports**	**Total**
		Panel A: t = 14			
Baseline	0.43	1.61	-1.21	-0.02	0.81
Aggregate	0.51	-0.11	-2.25	0.00	-1.85
Het. sourcing	0.36	0.32	-2.40	-0.01	-1.74
Het. emission bias	0.38	0.30	-2.29	0.00	-1.61
		Panel B: t = 50			
Baseline	1.50	5.65	-4.28	-0.06	2.81
Aggregate	1.79	-0.39	-7.88	0.00	-6.48
Het. sourcing	1.25	1.12	-8.37	-0.05	-6.06
Het. emission bias	1.33	1.05	-8.00	0.00	-5.63
		Panel C: t = 100			
Baseline	2.93	11.05	-8.45	-0.12	5.46
Aggregate	3.47	-0.75	-15.31	0.00	-12.59
Het. sourcing	2.45	2.17	-16.21	-0.09	-11.75
Het. emission bias	2.57	2.03	-15.54	0.00	-10.93
		Panel D: t = 150			
Baseline	4.29	16.23	-12.52	-0.18	7.94
Aggregate	5.04	-1.08	-22.32	0.00	-18.38
Het. sourcing	3.59	3.16	-23.56	-0.14	-17.09
Het. emission bias	3.73	2.95	-22.66	0.00	-15.94
		Panel E: t = 200			
Baseline	5.60	21.18	-16.47	-0.23	10.27
Aggregate	6.53	-1.40	-28.95	0.00	-23.86
Het. sourcing	4.69	4.09	-30.47	-0.18	-22.11
Het. emission bias	4.82	3.82	-29.37	0.00	-20.68
		Panel F: t = 500			
Baseline	12.44	46.99	-38.07	-0.56	21.68
Aggregate	13.83	-2.95	-62.15	0.00	-51.40
Het. sourcing	10.42	8.76	-64.41	-0.44	-46.87
Het. emission bias	10.17	8.11	-62.90	0.00	-44.40

F.3 Industry Carbon Tariff

Table 33: Counterfactual percentage change in domestic, foreign, and global emissions of a domestic carbon price increase combined with an industry carbon tariff

	Domestic (%)	**Foreign (%)**	**Global (%)**	**Leakage Rate**
		Panel A: t = 14		
Baseline	-0.69	-0.12	-0.45	-0.14
Aggregate	-1.05	-0.66	-0.88	-0.48
Het. sourcing	-0.99	-0.61	-0.83	-0.47
Het. emission bias	-1.10	-0.66	-0.91	-0.45
		Panel B: t = 50		
Baseline	-10.23	2.07	-4.94	0.15
Aggregate	-10.34	-0.34	-6.04	-0.02
Het. sourcing	-10.32	0.59	-5.63	0.04
Het. emission bias	-11.33	-0.15	-6.52	-0.01
		Panel C: t = 100		
Baseline	-20.96	4.65	-9.94	0.17
Aggregate	-20.85	-0.17	-11.96	-0.01
Het. sourcing	-20.86	1.84	-11.09	0.07
Het. emission bias	-22.75	0.22	-12.87	0.01
		Panel D: t = 150		
Baseline	-29.52	6.80	-13.90	0.17
Aggregate	-29.30	-0.28	-16.81	-0.01
Het. sourcing	-29.30	2.71	-15.53	0.07
Het. emission bias	-31.81	0.29	-18.00	0.01
		Panel E: t = 200		
Baseline	-36.48	8.61	-17.08	0.18
Aggregate	-36.23	-0.59	-20.89	-0.01
Het. sourcing	-36.21	3.26	-19.23	0.07
Het. emission bias	-39.14	0.13	-22.25	0.00
		Panel F: t = 500		
Baseline	-60.45	15.26	-27.88	0.19
Aggregate	-60.59	-4.77	-36.57	-0.06
Het. sourcing	-60.41	2.73	-33.24	0.03
Het. emission bias	-64.16	-3.57	-38.09	-0.04

Table 34: Comparing welfare effects of the baseline and aggregate models with an industry carbon tariff

Model	**Real Income (€)**	**Emissions (€)**	**Change in Welfare (€)**
	Panel A: t = 14		
Baseline	-13.32	0.38	-12.94
Aggregate	-8.99	0.75	-8.24
Het. sourcing	-9.02	0.70	-8.32
Het. emission bias	-8.99	0.77	-8.22
	Panel B: t = 50		
Baseline	-66.96	4.19	-62.77
Aggregate	-57.89	5.12	-52.77
Het. sourcing	-58.21	4.77	-53.44
Het. emission bias	-57.84	5.53	-52.31
	Panel C: t = 100		
Baseline	-133.83	8.44	-125.39
Aggregate	-118.39	10.14	-108.24
Het. sourcing	-119.11	9.41	-109.70
Het. emission bias	-118.19	10.92	-107.27
	Panel D: t = 150		
Baseline	-193.61	11.79	-181.82
Aggregate	-171.93	14.27	-157.66
Het. sourcing	-173.04	13.18	-159.87
Het. emission bias	-171.50	15.27	-156.23
	Panel E: t = 200		
Baseline	-247.72	14.50	-233.22
Aggregate	-219.84	17.73	-202.11
Het. sourcing	-221.37	16.31	-205.06
Het. emission bias	-219.14	18.88	-200.26
	Panel F: t = 500		
Baseline	-495.66	23.66	-472.00
Aggregate	-431.29	31.03	-400.26
Het. sourcing	-435.79	28.20	-407.58
Het. emission bias	-428.75	32.32	-396.42

Table 35: Decomposing the change in emissions (million t CO_2)

	Emission Intensity	**Output**	**Offshoring**	**EI Imports**	**Total**
		Panel A: t = 14			
Baseline	-3.04	0.99	-0.27	-0.01	-2.35
Aggregate	-3.20	0.07	-1.50	0.00	-4.63
Het. sourcing	-3.29	0.34	-1.37	-0.01	-4.34
Het. emission bias	-3.12	-0.18	-1.48	0.00	-4.78
		Panel B: t = 50			
Baseline	-30.28	-0.36	4.70	-0.03	-25.94
Aggregate	-32.10	1.32	-0.76	0.00	-31.69
Het. sourcing	-32.08	1.35	1.36	-0.02	-29.53
Het. emission bias	-30.70	-3.55	-0.34	0.00	-34.23
		Panel C: t = 100			
Baseline	-61.15	-1.90	10.56	-0.06	-52.21
Aggregate	-64.63	2.88	-0.39	0.00	-62.77
Het. sourcing	-64.50	2.72	4.21	-0.04	-58.20
Het. emission bias	-61.92	-7.69	0.50	0.00	-67.55
		Panel D: t = 150			
Baseline	-86.01	-3.10	15.44	-0.09	-72.95
Aggregate	-90.62	4.27	-0.63	0.00	-88.27
Het. sourcing	-90.45	4.04	6.18	-0.06	-81.52
Het. emission bias	-87.04	-11.32	0.66	0.00	-94.48
		Panel E: t = 200			
Baseline	-106.44	-3.99	19.57	-0.11	-89.69
Aggregate	-111.82	5.52	-1.33	0.00	-109.69
Het. sourcing	-111.63	5.32	7.45	-0.09	-100.93
Het. emission bias	-107.66	-14.55	0.28	0.00	-116.79
		Panel F: t = 500			
Baseline	-178.57	-4.84	34.78	-0.30	-146.37
Aggregate	-185.44	11.13	-10.78	0.00	-191.99
Het. sourcing	-185.33	12.36	6.38	-0.22	-174.49
Het. emission bias	-180.30	-28.52	-8.07	0.00	-199.97

F.4 CBAM

Table 36: Counterfactual percentage change in domestic, foreign, and global emissions of a domestic carbon price increase combined with CBAM

	Domestic (%)	**Foreign (%)**	**Global (%)**	**Leakage Rate**
		Panel A: t = 14		
Baseline	-0.68	-0.12	-0.44	-0.13
Aggregate	-1.05	-0.66	-0.88	-0.48
Het. sourcing	-0.99	-0.61	-0.83	-0.47
Het. emission bias	-1.10	-0.66	-0.91	-0.45
		Panel B: t = 50		
Baseline	-10.21	2.09	-4.92	0.15
Aggregate	-10.34	-0.34	-6.04	-0.02
Het. sourcing	-10.32	0.59	-5.62	0.04
Het. emission bias	-11.33	-0.15	-6.52	-0.01
		Panel C: t = 100		
Baseline	-20.92	4.70	-9.90	0.17
Aggregate	-20.85	-0.17	-11.96	-0.01
Het. sourcing	-20.85	1.84	-11.09	0.07
Het. emission bias	-22.75	0.22	-12.87	0.01
		Panel D: t = 150		
Baseline	-29.46	6.87	-13.83	0.18
Aggregate	-29.30	-0.28	-16.81	-0.01
Het. sourcing	-29.30	2.70	-15.53	0.07
Het. emission bias	-31.81	0.29	-18.00	0.01
		Panel E: t = 200		
Baseline	-36.41	8.71	-17.00	0.18
Aggregate	-36.23	-0.59	-20.89	-0.01
Het. sourcing	-36.21	3.25	-19.22	0.07
Het. emission bias	-39.14	0.13	-22.25	0.00
		Panel F: t = 500		
Baseline	-60.35	15.50	-27.72	0.19
Aggregate	-60.59	-4.77	-36.57	-0.06
Het. sourcing	-60.40	2.71	-33.24	0.03
Het. emission bias	-64.16	-3.57	-38.09	-0.04

Table 37: Comparing welfare effects of the baseline and aggregate models with CBAM

Model	**Real Income (€)**	**Emissions (€)**	**Change in Welfare (€)**
	Panel A: t = 14		
Baseline	-13.41	0.37	-13.04
Aggregate	-8.99	0.75	-8.24
Het. sourcing	-9.02	0.70	-8.32
Het. emission bias	-8.99	0.77	-8.22
	Panel B: t = 50		
Baseline	-67.27	4.17	-63.10
Aggregate	-57.89	5.12	-52.77
Het. sourcing	-58.20	4.77	-53.43
Het. emission bias	-57.84	5.53	-52.31
	Panel C: t = 100		
Baseline	-134.44	8.40	-126.04
Aggregate	-118.39	10.14	-108.24
Het. sourcing	-119.09	9.41	-109.68
Het. emission bias	-118.19	10.92	-107.27
	Panel D: t = 150		
Baseline	-194.49	11.73	-182.75
Aggregate	-171.93	14.27	-157.66
Het. sourcing	-173.02	13.17	-159.84
Het. emission bias	-171.50	15.27	-156.23
	Panel E: t = 200		
Baseline	-248.84	14.42	-234.42
Aggregate	-219.84	17.73	-202.11
Het. sourcing	-221.34	16.31	-205.03
Het. emission bias	-219.14	18.88	-200.26
	Panel F: t = 500		
Baseline	-497.88	23.52	-474.36
Aggregate	-431.29	31.03	-400.26
Het. sourcing	-435.74	28.20	-407.54
Het. emission bias	-428.75	32.32	-396.42

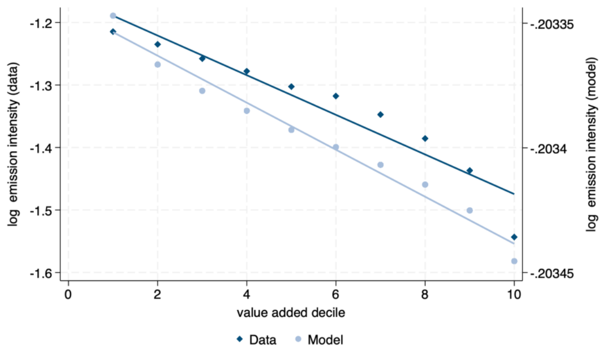
Table 38: Decomposing the change in emissions (million t CO_2)

	Emission Intensity	**Output**	**Offshoring**	**EI Imports**	**Total**
		Panel A: t = 14			
Baseline	-3.04	1.01	-0.25	-0.01	-2.31
Aggregate	-3.20	0.07	-1.50	0.00	-4.63
Het. sourcing	-3.29	0.35	-1.38	-0.01	-4.34
Het. emission bias	-3.12	-0.18	-1.48	0.00	-4.78
		Panel B: t = 50			
Baseline	-30.28	-0.28	4.75	-0.03	-25.81
Aggregate	-32.10	1.32	-0.76	0.00	-31.69
Het. sourcing	-32.08	1.37	1.36	-0.02	-29.53
Het. emission bias	-30.70	-3.55	-0.34	0.00	-34.23
		Panel C: t = 100			
Baseline	-61.15	-1.73	10.66	-0.05	-51.96
Aggregate	-64.63	2.88	-0.39	0.00	-62.77
Het. sourcing	-64.51	2.74	4.20	-0.04	-58.20
Het. emission bias	-61.92	-7.69	0.50	0.00	-67.55
		Panel D: t = 150			
Baseline	-86.01	-2.85	15.60	-0.07	-72.60
Aggregate	-90.62	4.27	-0.63	0.00	-88.27
Het. sourcing	-90.46	4.07	6.16	-0.06	-81.51
Het. emission bias	-87.04	-11.32	0.66	0.00	-94.48
		Panel E: t = 200			
Baseline	-106.43	-3.66	19.78	-0.10	-89.24
Aggregate	-111.82	5.52	-1.33	0.00	-109.69
Het. sourcing	-111.64	5.37	7.43	-0.08	-100.93
Het. emission bias	-107.66	-14.55	0.28	0.00	-116.79
		Panel F: t = 500			
Baseline	-178.56	-4.10	35.30	-0.26	-145.52
Aggregate	-185.44	11.13	-10.78	0.00	-191.99
Het. sourcing	-185.34	12.45	6.33	-0.20	-174.50
Het. emission bias	-180.30	-28.52	-8.07	0.00	-199.97

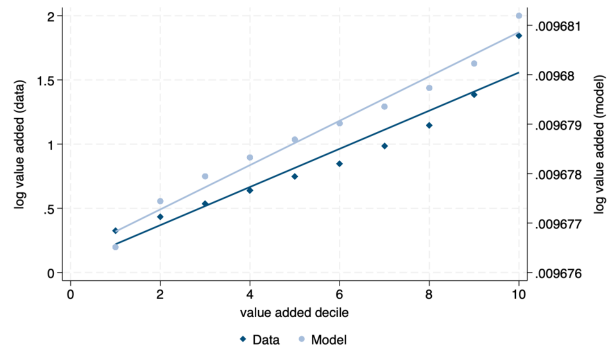
F.5 Model Validation

F.5.1 Aggregate Model

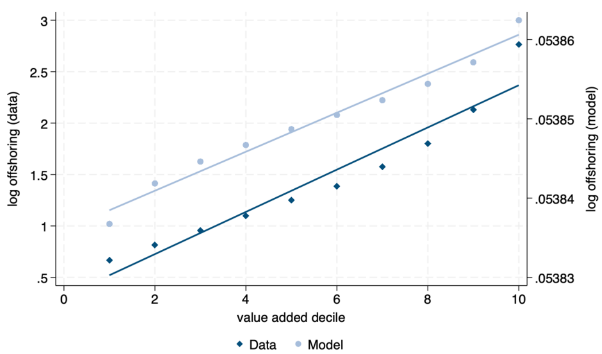
Figure 20: Firm responses: model vs data



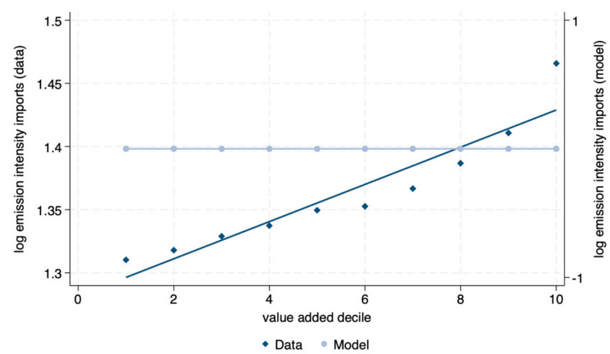
(a) Emission intensity



(b) Output

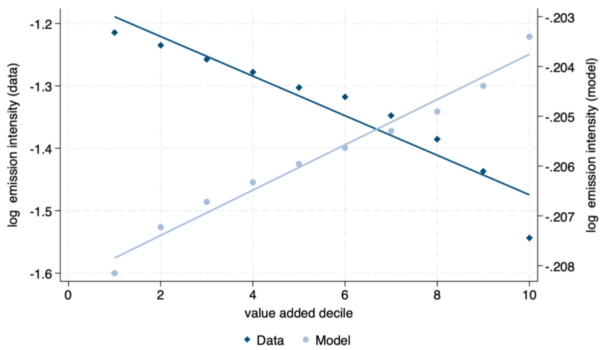


(c) Offshoring

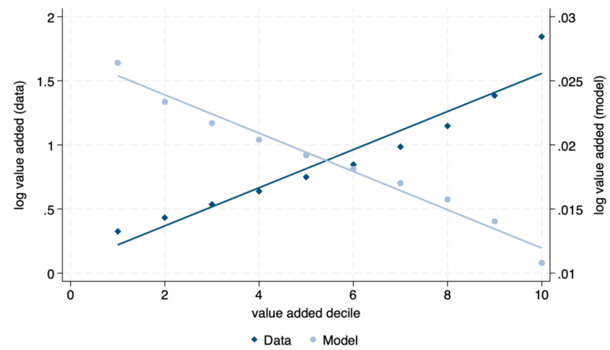


(d) Emission Intensity of Imports

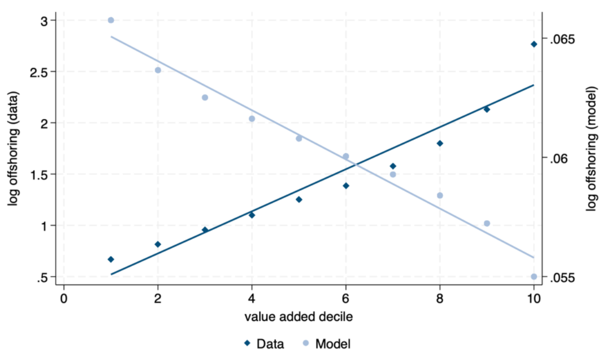
F.5.2 Heterogeneous Emission Bias Model



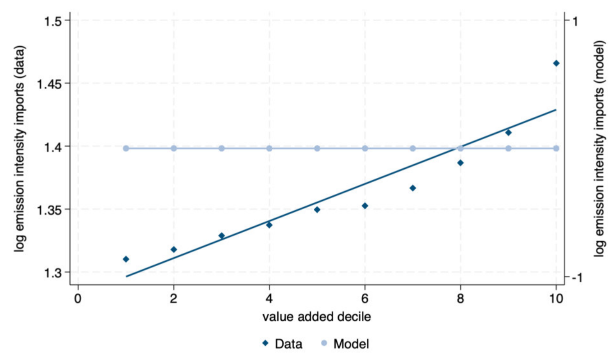
(a) Emission intensity



(b) Output



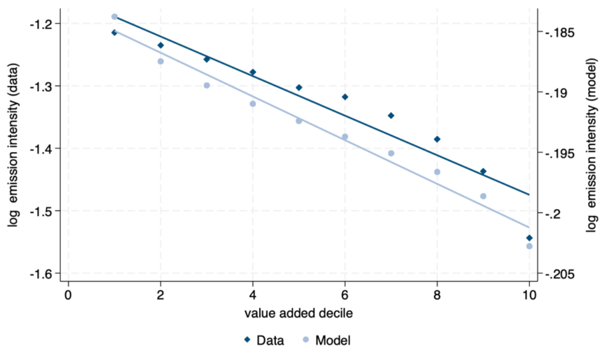
(c) Offshoring



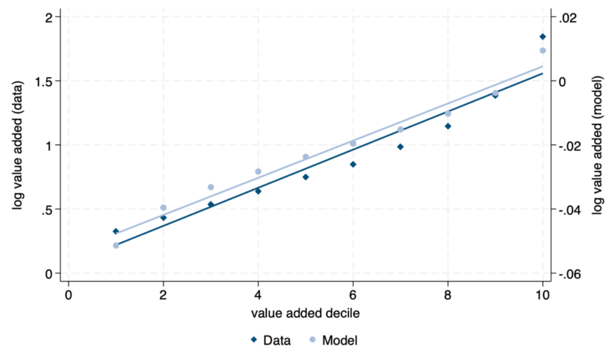
(d) Emission Intensity of Imports

Figure 21: Firm responses: model vs data

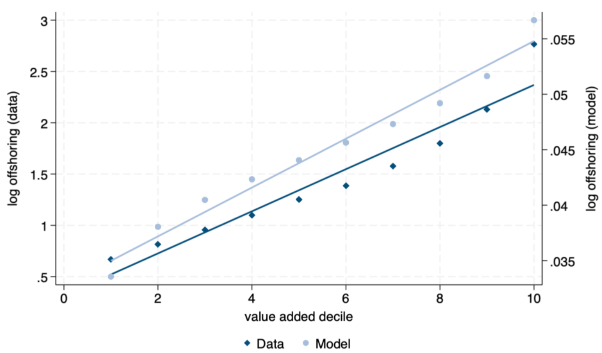
F.5.3 Heterogeneous Fixed Costs Model



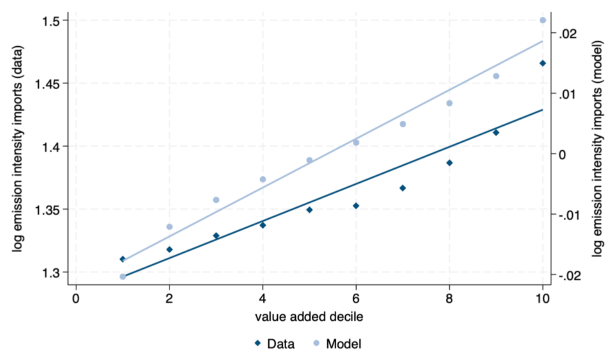
(a) Emission intensity



(b) Output



(c) Offshoring



(d) Emission Intensity of Imports

Figure 22: Firm responses: model vs data