# Firms' Supply Chain Adaptation to Carbon Taxes*

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**Abstract**

This paper studies how firms adjust input sourcing in response to climate policy. Using the EU Emissions Trading System (ETS) as a natural experiment and French product-level import and production data, we show that firms increasingly shifted imports of ETS-regulated inputs to non-EU countries over the 2010s as the policy became more stringent, indicating carbon leakage. This leakage is economically significant: the share of ETS-regulated products sourced from outside the EU rose by 4.3 percentage points after the ETS was implemented. Motivated by these empirical findings, we estimate a heterogeneous firm model using pre-ETS data. Simulating the model under a €100 carbon tax reproduces observed leakage, raises domestic prices and modestly reduces French emissions. Adding a carbon tariff similar to the EU's Carbon Border Adjustment Mechanism (CBAM) reverses the leakage but further increases prices. The combined ETS+CBAM regime is seven times more effective than the ETS alone in reducing emissions.

*JEL Classifications*: F14, F18, F64, H23, Q56

*Keywords*: Firm sourcing, supply chain adaptation, carbon tax, carbon tariffs, carbon leakage

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# 1 Introduction

The implementation of national carbon policies has become a common approach to raising carbon prices in order to combat climate change. However, the effectiveness of unilateral policies in reducing global emissions remains questionable, primarily due to firms' ability to shift production – and consequently emissions – across borders to avoid taxation, a phenomenon referred to as *carbon leakage*.[1] One proposed solution to mitigate leakage is the implementation of a carbon border adjustment mechanism (CBAM), which taxes the carbon content of imported goods (a 'carbon tariff'). Firms' ability to adapt to carbon policies in an open economy is therefore crucial for assessing their impact on both emissions and economic efficiency.

To address this issue, we use the EU's experience with climate policy as a natural laboratory for analysis. This setting is ideal for studying how firms respond to carbon policy in an open-economy context, as the EU's cap-and-trade system – the Emissions Trading System (ETS) – has been in place since 2005, and a CBAM framework was introduced in 2023 and is set to take effect in 2026. Using a novel data set, we show that French firms adapted their foreign sourcing of inputs in response to the ETS over 2005–19, which led to carbon leakage. Motivated by this finding, we then build a heterogeneous firm model of input sourcing and estimate it using pre-ETS data. Finally, we use the estimated model to quantify how firms' adaptation to climate policies, such as the ETS and CBAM, impacts carbon leakage and affects the aggregate efficiency of these policies.

We begin by providing new evidence on how firms adapted their sourcing of intermediate inputs after the EU adopted its ETS. A necessary step to achieve this goal is the construction of a new product-level data set that distinguishes regulated goods from unregulated goods. Unlike common approaches that rely on emissions data to assess firms' or sectors' exposure to environmental policies, we define regulation at the product level based on whether a good is subject to an environmental policy rather than its emissions during production. This approach leverages the scope of European policies, particularly the EU ETS, which is applied to selected high-emission sectors in member states of the EU and European Free Trade Association (Iceland, Liechtenstein, and Norway). The sectoral coverage informs our definition of regulated inputs.[2] We compare the geographic sourcing of these regulated inputs

[1]In the literature, carbon leakage refers to two distinct consequences of unilateral carbon policies: i) the impact on production costs, leading firms to shift production away from countries with stringent climate policies (the *trade channel*), and ii) the effect on global fossil fuel prices due to a decline in domestic demand (the *international energy price channel*). This paper focuses on the former, the trade channel.

[2]While the ETS scope has evolved, it primarily covers electricity, heat generation, and energy-intensive manufacturing sectors such as oil refineries, steel, aluminum, cement, glass, ceramics, and chemicals. Our focus is on tradable regulated inputs that are exposed to potential carbon leakage. For this reason, we do not

to a control group of unregulated inputs, before and after the implementation of ETS. This comparison captures how the policy indirectly affects downstream firms – those not directly covered by ETS but dependent on ETS-regulated inputs. A key advantage of our approach is its ability to track firms' input mix across different goods, offering a novel perspective on the policy's impact.

The first empirical fact that we document is that, relative to unregulated products, the import share of regulated products that a French manufacturing firm sources from outside of the EU increased after the implementation of the ETS. In 2019, the relative share of these imports had increased by 14% relative to the 2004 share.[3] The magnitude of this change is economically meaningful and accumulates over time as the impact of the ETS becomes more binding. Specifically, these estimates imply that, for the average French manufacturer, the import share of ETS-regulated products sourced from outside the EU increased by 4.3 percentage points (p.p.s) after the implementation of the ETS, from 29.7% to 34%. Second, we show that the reshuffling of the import portfolios is partially driven by the extensive margin, i.e., by French firms starting to import regulated products from new suppliers outside of the ETS zone. Our estimates imply that the probability that a regulated product is imported from a country located outside the ETS increases from 10.5% to 14.0%, a 3.6 p.p. increase over 2004–19.

Our quantitative analysis takes into account this extensive margin of sourcing using a model based on the seminal contribution of Antràs, Fort and Tintelnot (2017). We extend their framework to include the following additional ingredients that are necessary for the policy analysis we wish to examine: (i) multiple types of intermediate goods, so that firms source both regulated and unregulated inputs, and (ii) country- and input-specific carbon taxes. We also follow the climate-trade literature and incorporate carbon damages into households' utility (e.g., Shapiro, 2021). This framework allows us to quantify the trade and welfare consequences of environmental policies. Importantly, the model captures adjustments in firm-level sourcing decisions, both at the intensive and extensive margins.

Following Antràs et al. (2017), we first estimate the strength of comparative advantages, by country and input type, using firm-level data on the geography of input sourcing. We then calibrate a number of elasticity parameters using insights from the literature. Finally,

explicitly model the taxation of energy producers and instead focus on how the taxation of energy-intensive tradable inputs affects sourcing decisions.

[3]The increased import share is observed when focusing on French firms' sourcing from outside of the ETS zone using the sourcing of unregulated inputs from the same countries as controls. We also confirm that these results hold qualitatively in a difference-in-differences model that compares regulated inputs sourced from outside versus within the ETS zone. The former regression is our preferred specification because changes in the declaration threshold for intra-EU imports blur the comparison of intra- and extra-ETS sourcing strategies during the period under study, as EU and ETS countries largely overlap.

the remaining structural parameters, most notably those affecting the fixed cost of sourcing from any given foreign country, are estimated using simulated method of moments (SMM). The quantified model matches the trading patterns observed in the data well.

We next run policy experiments that allow for the imposition of a carbon tax on regulated inputs sourced from within the EU ETS, including domestically produced goods. We then apply an equally-sized carbon tax to regulated inputs from non-ETS source countries, as detailed in the CBAM legislation. In order to mimic the actual incidence of taxation, we compute carbon tax rates that incorporate both domestic and foreign input-output linkages in the production of the input that is used in domestic final goods production.[4] Furthermore, we also use data on sector$\times$country-level of emissions to calculate tax rates, recognizing that sectors and countries are not taxed uniformly due to varying emissions intensities in the production of one unit of output.

The baseline quantitative exercise, which applies a tax level of €100 per ton of $CO_2$, yields several interesting results.[5] The ETS-only simulation produces carbon leakage due to firms' adaptation at the intensive and extensive margins that are comparable to those estimated in the data. Specifically, we match our empirical regression estimates of firms' sourcing choices using simulated firm-level data. The reshuffling of import portfolios towards regulated producers outside of the ETS zone is comparable in the model and in the data, but the model underestimates adjustments at the extensive margin. The model-based regressions also explore the role of firm heterogeneity in driving leakage. Carbon leakage is entirely concentrated in the top quartile of the firm-size distribution. In relative terms, the most affected firms are those displaying intermediate productivity, as these firms lie close to the productivity cutoff for imports in the baseline model without carbon taxes.

Holding total French expenditures constant, the ETS-system simulation leads to a relatively small fall in the aggregate emissions-content of inputs sourced by French firms: $-0.67$M tons of carbon relative to a no-tax equilibrium, a 0.42% reduction. This result is driven by supply chain reallocation across two margins: while the economy experiences carbon leakage as French firms substitute to non-ETS regulated producers, the tax also leads domestic firms to substitute towards unregulated inputs. This fall in emissions coincides with a rise in input costs and thus the price level of the composite manufactured final good. The price

[4] An alternative would have been to formally model firm or sectoral input-output linkages, but this would have substantially increased the degree of complexity in solving the model.

[5] The €100 tax aligns with recent EU climate policy studies (e.g., Coenen, Lozej and Priftis, 2024) and the estimates of the International Energy Agency that industrialized nations must reach a \$140 per ton $CO_2$ price by 2030 to meet net-zero pledges. With respect to our study, this value is arguably conservative, as it may understate the effective tax that firms internalize given their expectations of higher carbon prices and the system becoming more stringent over time. However, the ETS's carbon price has hit such high levels infrequently historically, averaging closer to €65 per ton of $CO_2$.

increase is modest, at 0.87% relative to a no-tax equilibrium. Applying the utility function of Shapiro (2021), which considers emissions damages, we find that welfare decreases slightly, −0.201% relative to a no-tax equilibrium, as the price rise dominates the utility gain from lower emissions. Rebating the revenues from the tax to households reduces the adverse effect on welfare about twofold.

Next, turning to the baseline ETS+CBAM simulation, implementing a €100 border tax in addition to the ETS tax allows us to conduct several exercises. We first use the simulated firm data to run the reduced-form regressions. The estimated coefficients for the import share and import probability specifications flip signs relative to the ETS-only regressions, indicating that leakage is reversed. Looking at the geographical distribution driving this change in leakage, we see that the bulk of the fall in imports induced by the CBAM is driven by French firms decreasing their imports from Russia and China, while also increasing domestic sourcing of regulated inputs.[6] This result is in contrast with the ETS-only scenario, which mostly induces a reallocation of demand away from European high-emitting countries, such as Bulgaria and Romania, towards non-ETS sources. These adjustments are entirely concentrated in the upper half of the distribution of firms' productivity. The most affected firms are in the top 1% of the productivity distribution, as these firms are already more likely to source inputs from non-ETS countries prior to the implementation of ETS, and are thus more exposed to input-related carbon taxes.

On aggregate, the addition of the CBAM to the ETS decreases the emission content of inputs sourced by French firms to −4.97M tons (−3.07%) relative to the no-tax equilibrium, which is seven times larger than the decline in the ETS-only simulation. This fall reflects a large decrease in the use of regulated inputs as carbon leakage is more than reversed. However, the reduction in emissions comes at a cost, as the price index now increases by 1.42%. Again, the effect on real consumption dominates the utility gains associated with lower global emissions and welfare decreases (−0.33%). Rebating tax revenues to households or considering a higher social cost of carbon only tempers the negative welfare effect.

**Related literature.** We contribute to several strands of the literature. First, our results complement the literature that studies the impact of the EU ETS on firms, such as Joltreau and Sommerfeld (2019), Borghesi et al. (2020), Dechezleprêtre, Gennaioli, Martin, Muûls and Stoerk (2022), Barrows, Calel, Jégard and Ollivier (2024), Colmer, Martin, Muûls and Wagner (2024), Känzig, Marenz and Olbert (2024). We differ from these studies by focusing on manufacturing firms' sourcing of intermediate goods, rather than just ETS-regulated

[6] Note that in our quantitative exercises, total sales and hence total input purchases remains fixed across simulations. Therefore, a decrease in imports from a country in a given counterfactual is equivalent to a lower share of imports sourced from this country.

firms or multinationals, and by drilling down to the product level to study the potential for leakage. In doing so, we contribute to the literature examining the trade effects of climate policies.[7] Naegele and Zaklan (2019) also study the trade impact of the EU-ETS using product-level trade flows. They do not find any significant carbon leakage over 2004–11, which is not necessarily surprising as the system was not binding before the 2010s. In our data, carbon leakage is found significant from 2013 onward.

Our results complement Colmer et al. (2024), who find that French ETS-regulated firms were unaffected by the ETS due to their innovation capacity and show no change in imports relative to non-regulated firms. Our analysis differs in three key ways. First, we focus specifically on carbon leakage rather than innovation, examining how ETS regulation affects not only regulated firms but also firms in downstream industries through price spillovers across the value chain.[8] Second, our treatment group includes all manufacturing firms using regulated inputs, not just ETS firms themselves. Third, we employ a novel empirical strategy using product-level data to compare firms' geographic sourcing patterns for regulated versus unregulated inputs, rather than analyzing total imports. This approach provides complementary evidence on manufacturing firms' adaptation to carbon policy beyond the innovation channel.

Our modeling approach is in the spirit of recent contributions to the quantitative trade and environmental literature, such as Shapiro (2016, 2021), Larch and Wanner (2017), Bellora and Fontagné (2023), Caliendo, Dolabella, Moreira, Murillo and Parro (2024), or Garcia-Lembergman, Ramondo, Rodríguez-Clare and Shapiro (2025). See Copeland, Shapiro and Taylor (2022) for a review.[9] However, a notable difference in our approach is the focus on the firm and product levels rather than the sector-level, which is the most common level of aggregation analyzed in the literature. This difference in methodology has pros and cons. On the one hand, given data and computation limitations, we are constrained to performing the analysis for only one country, and thus cannot take into account the full global general equilibrium adjustment of trade and production. Therefore, our analysis is only partial equilibrium in this sense and cannot be used to make any inference of the impact of policy on global emissions. Moreover, we cannot consider the impact of CBAM on other countries' incentives to implement carbon taxes (e.g., Clausing and Wolfram, 2023; Clausing, Colmer, Hsiao and Wolfram, 2025). On the other hand, by focusing on the firm and product levels,

[7]See Dechezleprêtre and Sato (2017) for a survey. There is also a literature that examines leakage within a domestic context for the U.S. (e.g., Greenstone, 2002; Bushnell, Peterman and Wolfram, 2008; Fowlie, 2009; Fowlie, Reguant and Ryan, 2016; Fowlie, Petersen and Reguant, 2021).

[8]Känzig (2023) provides evidence that ETS regulatory shocks have an inflationary impact in the EU.

[9]See also Branger and Quirion (2014) and Carbone and Rivers (2017), who survey results recovered from a wide range of ex-ante analyses using computable general equilibrium models.

we analyze potentially important mechanisms that firms can use to adapt to climate policy. Furthermore, the analysis gauges the importance of extensive margin adjustments in carbon leakage, which would not be possible using sector-level data.

Finally, we also provide evidence of carbon leakage that is relevant to the literature on the design of optimal environmental policy in an open economy, such as the recent contributions of Bohringer, Carbone and Rutherford (2016), Weisbach, Kortum, Wang and Yao (2023), Kortum and Weisbach (2024), and Farrokhi and Lashkaripour (2025) – see Farrokhi, Kortum and Nath (2025) for a recent survey on climate policy and international trade. The evidence we present on leakage speaks directly to how increases in foreign emissions can undermine the effectiveness of domestic climate policies and the impact of a carbon tariff on domestic firms.

Section 2 describes the construction of the new data set. Section 3 provides evidence on firms' sourcing choices of regulated and unregulated products from within and outside of the EU ETS. Section 4 presents the theoretical framework that is used to model firms' sourcing of domestic and foreign intermediate goods. Section 5 estimates the model, and Section 6 provides quantitative evidence on the impact of implementing the ETS and then the CBAM on firms' sourcing decisions, emissions and welfare. Section 7 concludes.

# 2 Data

A key aspect of our analysis is the identification of firms' sourcing of regulated and unregulated inputs from home and abroad. Rather than relying on the emissions content of goods for this identification, we use information from the ETS and CBAM to define regulated goods by the actual coverage of these policies. This methodology follows several steps and relies on information at the product, firm and sector levels.[10] In this section, we sketch the main approaches taken in the construction of this new data set, with details relegated to Appendix A and summarized in Table A.1.

## 2.1 Defining regulated and unregulated products

We use information from the EU Transaction Log (EUTL) to recover a list of regulated sectors under the ETS.[11] We complement these data with information from the European Commission on the list of products that will be covered by the CBAM.[12] We use these two

[10] We will use the words "product" and "good" interchangeably in what follows. The use of product follows from the classification of goods in the import data that we use.

[11] See https://www.euets.info/ for a link to the underlying data set.

[12] See Regulation (EU) 2023/956 of the European Parliament and of the Council of 10 May 2023 establishing a carbon border adjustment mechanism. The products are defined at the Combined Nomenclature (CN)

data sets to create a list of regulated products as follows.

First, we use the list of activities covered by the ETS scheme and manually map it to a list of HS-classified products. To be precise, an "activity," such as the production of glassware, can be thought of as a "sector" of production. While the classification of activities is internal to the ETS system, the mapping between ETS sectors and HS products is relatively straightforward (see Table A.2). For example, the ETS covers firms that refine mineral oil (activity 21 in the ETS classification), so we categorize as regulated all products starting with 27 in the HS categorization (Mineral fuels, mineral oils and products of their distillation). Second, we utilize the CBAM product list to directly identify regulated products and then use these data to supplement the ETS list of regulated products (see Table A.3).

A typical approach to classify variables in the climate change literature focuses on emissions-based measures. However, our classification approach allows us to directly measure that scope of regulation and its impact on input prices, which create the economic incentives for firms to adapt via the geography of their input sourcing. Indeed, using PPI data, Figure 1 shows that the relative price of regulated products rose vis-à-vis unregulated products over the ETS period.[13] An additional benefit of our approach is that defining regulated products based on policies rather than based on their emissions content avoids erroneously classifying products as regulated when they are not actually taxed by either ETS or CBAM.[14]

## 2.2 Firm-level variables

We combine the above categorization of HS products with firm-level import data to use in our regression analysis below. To create this merged data set, we use customs data, which contains import flows by firm, origin country and product category, from 2000 to 2019.[15] Import flows are aggregated at the annual level. We categorize origin countries into ETS and non-ETS countries and product categories into regulated and unregulated inputs, based on our new database described above. The list of ETS countries includes all EU member states plus Iceland, Liechtenstein, and Norway. The sample of firms is restricted to 44 regulated-intensive manufacturing sectors, using information recovered from the 2011 INSEE input-output (IO) table.[16] Finally, our empirical analysis focuses on a subset of

level, which is an 8-digit classification of goods in the European Union, whose first 6 digits align with the Harmonized System (HS) used internationally for categorizing products.

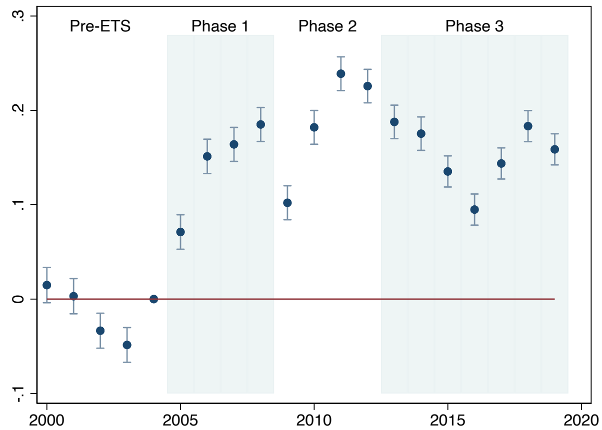
[13] The data are sourced from INSEE (https://www.insee.fr/en/statistiques/series/117384650). We use manufacturing production price indices defined at the 4-digit CPF level. We then classify industries as regulated or unregulated manually based industries' labels in the INSEE data set.

[14] Further details about the classification of regulated and unregulated goods can be found in Appendix A.1, which includes the prevalence of regulated goods across HS categories in Table A.4.

[15] See Bergounhon, Lenoir and Mejean (2018) for a thorough description of the data set.

[16] We first establish a mapping between the 138 sectors composing the French IO table and the list of ETS sectors listed in Table A.2 to recover a list of regulated-*producing* sectors. We then use the IO table to

**Figure 1.** Evolution of relative prices of regulated versus unregulated products: Evidence from French PPI data




**Notes:** This figure illustrates the evolution of the relative price of regulated products compared to unregulated products over the period 2000–20. The price data are sourced from INSEE (PPI data at the industry level). The statistical model used to recover the relative price dynamics uses:

$$p_{st} = \sum_{\tau=-4}^{15} \beta_\tau \mathbb{1}\left(s \in regulated\right) + \mathbf{X'}_{st}\boldsymbol{\theta} + \varepsilon_{st},$$

where $p_{st}$ is the log of the price in sector $s$ at time $t$, $\mathbb{1}\left(s \in regulated\right)$ is a dummy that is equal to one if sector $s$ falls within the set of regulated sectors and the set of controls $\mathbf{X'}_{st}$ includes sector×month and year fixed effects, with the former controlling for sector-specific seasonality. The blue areas correspond to Phases 1 and 3 of ETS.

firms' core inputs. The purpose of the restriction is to avoid including product categories that are either marginal in a firm's intermediate usage, or purchased occasionally.[17] To this end, we first remove imports of capital goods. We then use the IO table to identify the list of the most important upstream sectors for each downstream industry, using a 10% intermediate consumption threshold. Then using a mapping between products and NAF sectors, we identify the set of core inputs for each sector, and thus each firm in these sectors. See Appendix A.3 for further details.

The quantitative model requires additional information on firms. We use 2004 (pre-ETS) information from the administrative firm-level balance sheet and income statement data set from INSEE-FICUS, which provides information on firms' total use of intermediate goods

categorize regulated-*intensive* input-use sectors. The analysis is restricted to manufacturing sectors relying on regulated-producing sectors for at least 10% of their inputs. See details in Appendix A.2.

[17]The restriction is especially useful once we balance the panel in the firm×product×country dimension. In doing so, we expand the data set significantly, since every product×country pair that is observed once in a firm's portfolio is considered a sourcing option in every other year. Restricting the data set to the firm's core products avoids inflating the sample with too many zeros.

and production. The model requires information on the intensity of firms' input purchases of regulated and unregulated inputs. In the absence of firm-level information, we match the data with the detailed sector-level IO data set described in the previous paragraph, and apply the sector-specific share to firm-level input purchases. We can then use the customs import data for 2004 to determine the mix of domestic and foreign inputs used by French firms, for each input type (see Appendix A.4). This methodology yields a 2004 data set that is used to calibrate the model, in which we have, at the firm level, the share of input purchases by input type and by origin country, including domestic products, as well as total sales.

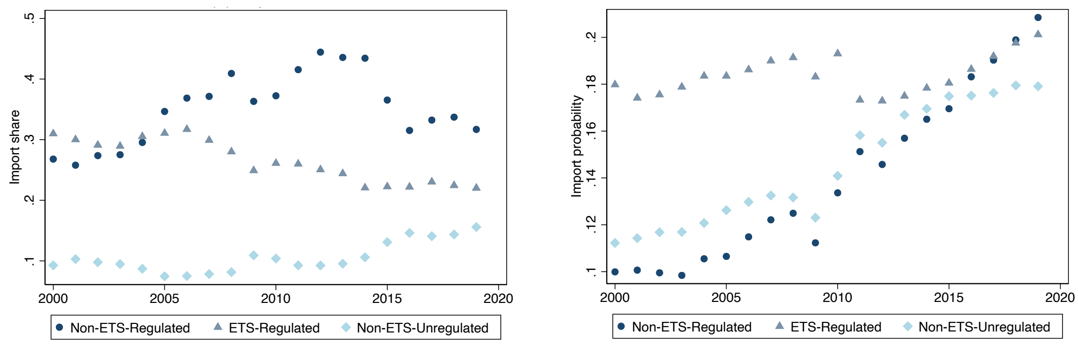
Table A.8 reports summary statistics on the population of firms for 2004. The sample covers 62,525 manufacturing firms, among which 18,929 import some of their inputs. On average, importers source 3,385 thousand euros from abroad, or 16.2% of their inputs, from 5.4 different countries. Our population is selected from large manufacturers but a very small share of these are directly covered by ETS regulations (only 268 firms). The reason for this small share is that we have selected firms from sectors that lie downstream of ETS-regulated sectors, based on the prevalence of ETS-regulated products in the firms' aggregate input purchases.

# 3 Motivating Facts

This section documents the evolution of French firms' sourcing of foreign regulated and unregulated products after the introduction of the ETS. To be precise, we explore the time variation of potential carbon leakage via intermediate inputs, since adjustments to the ETS were made over three phases (Phase 1: 2005–08, Phase 2: 2009–12, Phase 3: 2013–20) after its announcement in 2003.[18] The system has not been binding throughout its history given different institutional features of the ETS. In particular, the total amount of allowances issued exceeded emissions during Phase 1, and the price of allowances actually fell to zero in 2007. Phase 2 coincided with the first commitment period of the Kyoto Protocol, where the countries in the EU ETS had concrete emissions' reduction targets to meet. The cap on allowances was reduced, based on actual emissions, and the penalty for non-compliance increased. However, the proportion of free allowances was still high, at approximately 90%. This changed during Phase 3, when auctioning became the default method for allocating allowances. Given that the change in protocol over the phases was public knowledge, our estimates arguably pick up the forward-looking behavior of firms' sourcing decisions.

[18]The first ideas on the design of the EU ETS were presented in a green paper from the European Commission in March 2000.

**Figure 2.** Aggregate import shares and probability of sourcing from a new supplier market: control vs. treatment groups




**(a)** Import share

**(b)** Import probability

**Notes:** This figure presents aggregate import statistics based on the firm× product import data set that classifies products as either unregulated or regulated. Panel (a) presents import shares and panel (b) presents the probability of sourcing from a given sourcing country (extensive margin). Each panel plots the treated group, 'non-ETS regulated', vs. both control groups: (i) 'non-ETS unregulated' or (ii) 'ETS-regulated'.

## 3.1 Aggregate statistics

We first present aggregate evidence on French imports using our newly constructed data set. To foreshadow the micro regressions estimated below, we report aggregated import statistics based on various "treatment" and "control" groups. We aggregate the data into two separate dimensions to give some insight on patterns of leakage of French firms regulated inputs. Figure 2 presents these statistics for the share in overall imports in panel (a) and the probability of sourcing from a given supplier (i.e., the extensive margin) in panel (b).

The plots are constructed using the same data sample as used in our regressions below. The sample is first balanced in the firm×product×source country dimension, which amounts to assuming that an input sourced by a firm from a given country at some point between 2000 and 2019 could have been sourced from there at any other period. We then create a dummy variable equal to one in years when the product is actually sourced from the supplier country. Averaging across firms, products and countries within each product type (unregulated or regulated) × country group (ETS country or not) at the yearly level gives a time-series of the import probability. As for the import share variable, imports are summed across firms, products and countries within each product type (unregulated or regulated) × country group (ETS country or not) at the yearly level. Taking the ratio of these values over total imports yields the aggregate import share. In both panels, we begin plotting the data five years prior to the initiation of the ETS to check for potential pre-trends in the aggregate import data that might contaminate our regressions.

The regulated import share from non-ETS countries, the treated group,[19] is plotted in panel (a) and depicted by the dark blue circles. The share increases over time, but the series is volatile. The first control group, the unregulated import share from non-ETS countries (light blue diamonds) exhibits a less volatile upward trend. The share of non-ETS regulated imported goods is always larger than its unregulated counterpart, but this difference has fallen over time. The second control group, the regulated import share from ETS countries (grey triangles) appears to be falling over time relative to the treated group's share.

Panel (b) next plots the probability of importing from a particular source country for the treated and two control groups. The probability of a firm importing a product from a non-ETS source country has increased over time for both regulated and unregulated products, though the rate of increase has been stronger in recent years for regulated inputs. Turning to comparing the treated group to the second control group, we see a marked difference in the dynamics of the extensive margin. While the probability of sourcing a regulated product from ETS member countries has not changed greatly over time, we do see a substantial increase in the extensive margin of importing regulated products from non-ETS countries, where now a firm appears to be equally likely to source a regulated product from within or outside the ETS. However, it should be noted that these relative trends are somewhat biased by a change in the declaration threshold imposed on French firms on their intra-EU imports. In 2011, the declaration threshold increased from 150 to 460 thousands of euros.[20] We take into account this discontinuity in our regression strategy below.[21]

## 3.2 Regression evidence

We next test for how French firms' sourcing decisions changed over time by exploiting the granular data set we have constructed, which allows us to control for a host of potential confounding factors using a rich array of fixed effects. This estimation strategy allows us to drill down to within-firm variation over time at the product level, while controlling for potential trends such as those depicted in Figure 2.

Throughout the analysis, we remain flexible on the timing of firm-level adjustments. As sourcing decisions are associated with important investment flows, carbon leakage may be observed in periods in which the carbon price is not binding if firms anticipate that it

[19] We refer to non-ETS countries as being "treated" even though the ETS carbon policy is not applied to them. The reason that we do this is because our measure of the impact of the policy is carbon leakage via French imports from non-ETS countries. Thus, these countries should in theory benefit from this leakage.

[20] The declaration threshold is defined over annual imports across all EU member states, which constitute the majority of ETS countries. We also exclude new EU member states in constructing this plot to avoid additional discontinuities.

[21] The other discontinuity, observed in all series, corresponds to the trade collapse of 2009.

will become binding in the future. We use a difference-in-differences model estimated using Poisson Pseudo Maximum Likelihood (PPML), which can be generally written as:

$$y_{fpit} = \exp\left[\sum_{\tau=-4}^{15} \beta_\tau \mathbb{1}\left(i \notin ETS\right) \mathbb{1}\left(p \in regulated\right) + \mathbf{X}'_{fpit}\boldsymbol{\theta} + \varepsilon_{fpit}\right], \tag{1}$$

where $y_{fpit}$ is either the share of product $p$ sourced from country $i$ in firm $f$'s overall imports at time $t$ or a dummy variable for whether firm $f$ imports product $p$ from country $i$ in year $t$. While the import share is targeted in the model developed below, studying the probability of importing allows us to focus on sourcing adjustments at the extensive margin. The notation $\mathbb{1}()$ is used for dummy variables in (1), where $\mathbb{1}\left(i \notin ETS\right)$ is a dummy variable which equals one if $i$ is not an ETS member country, $\mathbb{1}\left(p \in regulated\right)$ identifies regulated products, and $\mathbf{X}_{fpit}$ controls for all necessary additional interaction terms as well as fixed effects. As explained in the previous section, the control group for this regression can be composed of either unregulated inputs sourced from non-ETS countries or regulated inputs sourced from ETS countries, with the former being our preferred control group due to changes in the declaration threshold for intra-EU imports in 2011.[22] Finally, note that regression (1) is run on a balanced panel in which any product×country pair that the firm eventually imports from is considered a potential sourcing option throughout the estimation period. An estimated $\beta_\tau > 0$ for $\tau > 0$ implies that there is some carbon leakage.

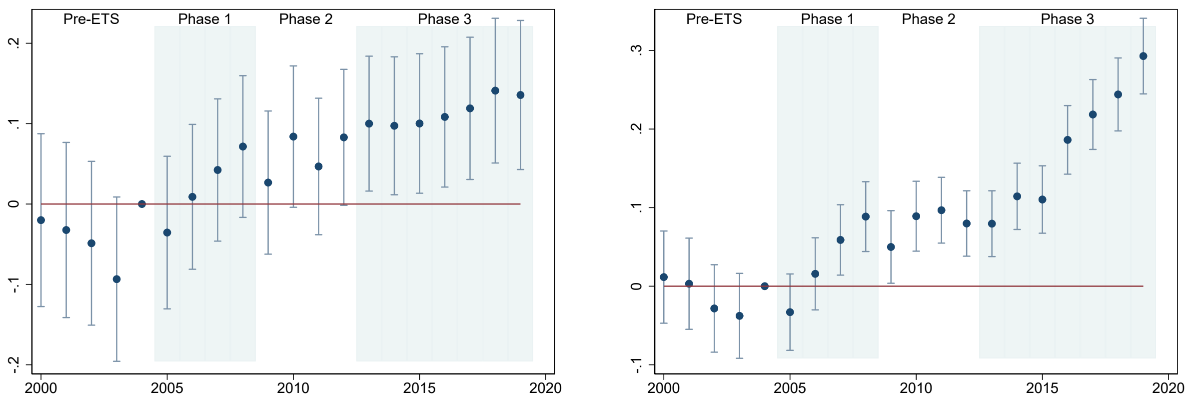
We start with a specification that solely controls for product×country and year fixed effects, thus identifying coefficients using variation within and between manufacturing firms. Results are summarized in Figure 3, in which we report the coefficients estimated on the interaction between the treatment and each year before and after 2004, i.e., before and after the introduction of the ETS.

Panel (a) first compares import shares across countries and products. Results point to an upward trend in the relative share of regulated inputs sourced from non-ETS countries. While the trend is slightly negative before the ETS, it then reverses, with coefficients being significantly different from zero from ETS Phase 2 onwards. In 2019, the import share of regulated inputs sourced from non-ETS countries had increased by 14% relative to the share of unregulated inputs sourced from the same area. Given a baseline regulated-goods import share of 0.297, this increase in the relative share corresponds to a 4.3 p.p. increase in the sourcing of regulated inputs from non-ETS countries during the sample period.[23]

[22] We also tried exploiting a triple interaction regression specification in which we compared the dynamics of regulated versus unregulated products in non-ETS versus ETS countries. The analysis was not fruitful since the data exhibit a severe pre-trend that is driven by the marked decline in imports of unregulated inputs sourced from ETS member countries in the early 2000s.

[23] The 0.297 is calculated as an import-weighted average across all firms. This value is comparable with

**Figure 3.** Evolution of firm-level imports from non-ETS countries: regulated vs. unregulated inputs




**(a)** Import share

**(b)** Import probability

**Notes:** This figure shows the point estimates recovered from the estimation of equation (1), using 2005 as the first "treatment" date. The treatment group is composed of import flows on regulated inputs sourced in non-ETS countries. The control group covers unregulated inputs imports from non-ETS countries. The equation controls for product×country and year fixed effects. Standard errors are clustered in the product×country×year dimension. The confidence intervals are defined at the 95% level. The blue areas correspond to Phases 1 and 3 of ETS.

Next, Panel (b) shows that changes in import shares are in part driven by extensive-margin adjustments, namely an increasing propensity for French firms to source their regulated inputs from non-ETS countries. Here, the post-ETS positive trend is even more pronounced and the difference is already significant during the first phase of the ETS.

Table 1 reports estimation results for regression (1) using various sets of fixed effects as controls. To simplify, coefficients on the treatment effects are constrained to equality within each phase of ETS, with 2000–04 used as reference. Panel (a) presents results for the import share, while panel (b) focuses on the extensive margin of imports. Moving from left to right, we increase the array of fixed effects included, first using product×country and year effects as in Figure 3 (column (1)). In column (2), we restrict our attention to within-firm variation by using firm×product×country fixed effects. In columns (3)-(5), we further control for time-varying confounding factors using country×year and/or sector×year fixed effects. The set of fixed effects that have the largest impact include the sectoral controls, which halve the coefficients of interest. Even in the most demanding specification of column (5), we recover significantly positive and increasing estimated coefficients, consistent with carbon leakage at the firm level.

the statistics in Figure 2, panel (a). If we instead take a simple average, the baseline share is lower (8.7%), and the corresponding increase in regulated inputs sourced from non-ETS countries is also lower (1.3 p.p.s).

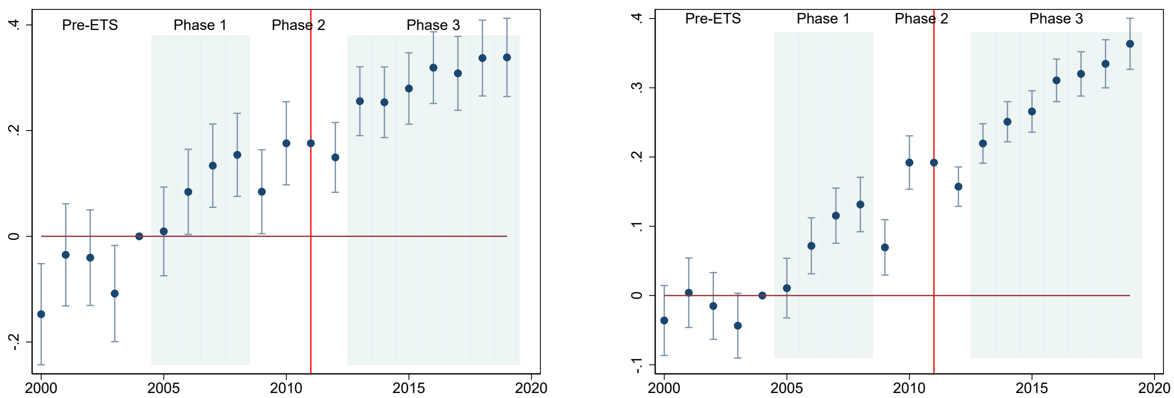
**Table 1.** Firm-product-level evidence on carbon leakage: Regulated vs. unregulated inputs imports from non-ETS countries

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Panel (a)** Import Share | | | | | |
| Regulated product × Non-ETS | | | | | | |
| × ETS Phase 1 | 0.043* | 0.072*** | 0.145*** | 0.074** | 0.074** | 0.071*** |
| | (0.025) | (0.024) | (0.024) | (0.035) | (0.035) | (0.024) |
| × ETS Phase 2 | 0.100*** | 0.159*** | 0.264*** | 0.110*** | 0.110*** | 0.164*** |
| | (0.021) | (0.021) | (0.021) | (0.030) | (0.030) | (0.021) |
| × ETS Phase 3 | 0.154*** | 0.260*** | 0.350*** | 0.121*** | 0.121*** | 0.268*** |
| | (0.020) | (0.021) | (0.020) | (0.029) | (0.029) | (0.021) |
| Pseudo $R^2$ | 0.160 | 0.381 | 0.385 | 0.387 | 0.387 | 0.381 |
| | **Panel (b)** Import Probability | | | | | |
| Regulated product × Non-ETS | | | | | | |
| × ETS Phase 1 | 0.026** | 0.019 | 0.045*** | 0.031* | 0.029 | 0.018 |
| | (0.013) | (0.013) | (0.012) | (0.018) | (0.018) | (0.013) |
| × ETS Phase 2 | 0.092*** | 0.089*** | 0.107*** | 0.085*** | 0.078*** | 0.102*** |
| | (0.011) | (0.011) | (0.010) | (0.015) | (0.015) | (0.011) |
| × ETS Phase 3 | 0.193*** | 0.192*** | 0.149*** | 0.074*** | 0.071*** | 0.214*** |
| | (0.011) | (0.011) | (0.010) | (0.015) | (0.015) | (0.011) |
| Pseudo $R^2$ | 0.044 | 0.157 | 0.165 | 0.161 | 0.168 | 0.157 |
| Observations | 7,474,109 | | | | | |
| # Firms | 27,240 | | | | | |
| Control group | Non-ETS Unregulated products | | | | | |
| Fixed effects | pc,t | fpc,t | fpc,ct | fpc,st | fpc,ct,st | fpc,ETSt |

**Notes:** This table presents the estimated $\beta$ for regression (1) using various sets of fixed effects. The treatment effects are constrained to equality within each phase of ETS. f, p, c, s and t respectively stand for a firm, the imported product, the sourcing country, the sector of the firm and the time period. The last column controls for yearly dummies, interacted with a variable identifying firms that are regulated under the ETS system and those that are not ("ETSt"). Standard errors are clustered in the product×source country×year dimension. (*,**,***) indicates significance at the (10%, 5%, 1%) level.

Column (6) further controls for dynamic adjustments that are differentiated across two groups of firms, namely ETS-regulated and ETS-non regulated firms. The results from this specification are interesting to contrast with others in the literature, such as Colmer et al. (2024) who focus on French firms that are regulated under ETS and who do not find evidence of leakage. The authors argue that their finding is driven by regulated firms adjusting to the ETS by innovating. The ETS×year fixed effects in column (6) absorbs the average

**Figure 4.** Evolution of firm-level imports of regulated inputs: Non-ETS vs. ETS origin countries




**(a)** Import share **(b)** Import probability

**Notes:** This figure shows the point estimates recovered from the estimation of equation (1), using 2005 as the first "treatment" date. The treatment group is composed of import flows on regulated inputs sourced in non-ETS countries, with sourcing of regulated inputs from ETS countries taken as control. The equation controls for product×country and year fixed effects, as well as a dummy that is equal to 1 from 2011 for intra-European flows. Because the latter control is collinear with the treatment effects after 2011, the point estimates recovered from 2012 to 2019 are defined in relative terms with respect to their 2011 counterpart. Standard errors are clustered in the product×country×year dimension. The confidence intervals are defined at the 95% level. The blue areas correspond to Phases 1 and 3 of ETS. The red line corresponds to the break in the customs data.

increase in innovation activities that ETS-regulated firms perform and these controls do not affect our main results. Perhaps more importantly, however, is that our estimation sample is quite different than Colmer et al.'s. As Table A.8 shows, the vast majority of firms in our estimation sample are *not* regulated under ETS. Our empirical strategy instead accounts for the possibility that carbon leakage may be indirect. Firms that are not directly exposed to the ETS but purchase inputs that are produced by regulated firms may switch to non-ETS sourcing countries as a consequence of the price of their regulated inputs increasing.[24]

As explained in Section 3.1, evidence of carbon leakage could in principle be recovered from the comparison of regulated input sourcing from non-ETS versus ETS source countries. Unfortunately, the change in the declaration threshold for intra-EU imports creates an additional difficulty, as this break in the data shifts all the treatment effects after 2011.[25] In

[24] Figure B.1 confirms that our evidence of carbon leakage is driven by firms that are not regulated under the ETS. If anything, the impact on ETS firms goes in the opposite direction. The import probability of regulated inputs sourced from non-ETS countries seems to decrease during Phase 3 of the ETS.

[25] See evidence for this shift in Figure B.2. The positive shift in import probabilities is mechanical as some firms that used to declare intra-EU imports under the low declaration threshold stop declaring these flows after 2011. Because the selection effect is concentrated on relatively small import flows, this also shifts relative import shares up.

Figure 4, we control for this break, and thus estimate the evolution of import shares and import probabilities, between 2005 and 2010, relative to 2004, and between 2012 and 2019, relative to 2011.[26] Results confirm the trends in Figure 3 despite the estimation sample and identification strategy being completely different. Both the import share and the import probabilities start increasing during the first phase of ETS, thus suggesting a form of leakage away from ETS countries. Carbon leakage accelerates during the third phase of ETS when the price of carbon permits starts increasing.

Appendix B presents a number of additional robustness checks. First, in Figure B.3, we show that our baseline results are robust to controlling for heterogeneous treatment effects following de Chaisemartin and D'Haultfœuille (2020).[27] Second, we check that the average treatment effects are not driven by a specific country. One particular concern is that the estimation period overlaps with important changes in the geography of world trade following the entry of China into the WTO. We conduct a "leave-one-out" exercise by running the regressions removing one (non-ETS) country at a time. The results presented in Figure B.4 confirm a significant increase in import shares and import probabilities of regulated products in twenty-five such sub-samples. Third, another possibility is that the average treatment effect is triggered by multinational firms, which arguably have more flexibility in reshaping their production process away from regulated markets. Although this phenomenon would not necessarily be inconsistent with our interpretation of the data, Figure B.5 shows that the average effect is driven mainly by firms that do not have foreign affiliates in the non-ETS countries under consideration.

Given these motivating empirical facts, we next provide a model of firms' sourcing decisions meant to explain the salient leakage that we observed in the data and which we can use to examine the impact of environmental taxes on both firm-level sourcing decisions and aggregate outcomes.

# 4 Model

This section sketches a quantitative multi-country sourcing model that provides a methodology to solve a firm's problem with interdependencies following the approach of Antràs et

[26] In practice, the break in the data only covers imports from EU member states, which is a slightly narrower country set than the ETS sample. However, since the vast majority of ETS imports is sourced from EU countries, exploiting this discrepancy is not possible. In Figure 4, we thus control for a break affecting all ETS countries from 2011 on, and estimate the treatment effects after 2011, in relative terms with respect to 2011.

[27] Note that their estimator uses a linear model, which means that the coefficients must be interpreted relative to the average outcome variable. In 2019, the average import share (resp. import probability) of unregulated inputs from the average non-ETS country is 1.6% (resp. 18%).

al. (2017), referred to as *AFT* henceforth.[28] We include the following additional ingredients to the baseline model to capture heterogeneous environmental taxes and their impact: (i) a production function combining regulated and unregulated inputs, and (ii) country- and input-specific carbon taxes. We also include carbon damages in households' utility. This framework allows us to think about the trade and welfare consequences of environmental policies and captures their impact both at the intensive and extensive margins of adjustments by firms in their sourcing decisions.

While the model is rich in terms of a firm's sourcing problem, we abstract from other production details to focus on matching the empirical facts we have documented. First, we do not include energy as a direct factor in either input or final goods production, as energy is not a tradable input from a firm's point of view. Instead, we capture how a firm may adapt via its use of both regulated and unregulated *tradable* inputs, which in turn will capture emissions that are generated via energy usage. Moreover, the use of input-output data to construct the tax rates we apply in our quantitative exercises captures the potential impact on a firm's energy usage, as the IO data include energy producing sectors. Second, we treat a firm's productivity level as given and thus do not allow for the possibility of an innovation channel, unlike Colmer et al. (2024) who focus on innovation responses to carbon policies. Third, as in *AFT*, the model focuses on the equilibrium of one industry – an aggregate of the 44 regulated-intensive manufacturing sectors analyzed in Section 3. This means that we neglect the general equilibrium consequences of carbon taxes. Finally, by assuming that final goods are not traded across countries, we neglect leakage through the trade of final goods. We however provide a back-of-the-envelope quantification of this effect later in the analysis.

## 4.1 Households

A representative household in country $i$ values the consumption of a CES aggregate of differentiated manufacturing varieties purchased from domestic final good producers, along with a homogeneous good that is included to pin down the equilibrium wage. The CES aggregator is written as:

$$C_i = \left[ \int_{\omega \in \Omega_i} q_i(\omega)^{\frac{\sigma-1}{\sigma}} \, d\omega \right]^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1, \tag{2}$$

where $\Omega_i$ denotes the set of manufacturing varieties available to a household and $\sigma$ measures the elasticity of substitution between varieties $\omega$.

It will be useful to summarize the demand side of the model later by a demand term $B_i$

[28] Appendix C provides details and proofs.

defined as:

$$B_i = \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} E_i P_i^{\sigma-1}, \tag{3}$$

where $E_i$ is (exogenous) nominal expenditures on manufacturing goods and the ideal price index is defined as $P_i \equiv \left[\int_{\omega\in\Omega_i} p(\omega)^{1-\sigma}\, d\omega\right]^{\frac{1}{1-\sigma}}$.

**Welfare and the cost of emissions.** We assume that consumption of manufactured goods, $C_i$, constitutes a share $\alpha$ of aggregate consumption, while the remaining share $1-\alpha$ is spent on a homogeneous outside good $H_i$ that is freely traded across countries and pins down wages. Following Shapiro (2021), we incorporate the disutility from pollution into the welfare formula. Utility in country $i$ is therefore modeled as:

$$U_i = H_i^{1-\alpha} C_i^{\alpha}\left[1+\mu_i(CO_2 - CO_2^0)\right]^{-1}. \tag{4}$$

This functional form has several useful properties. First, including pollution damages as multiplicative of aggregate consumption facilitates counterfactual analysis using ratios. Second, normalizing by baseline emissions, $CO_2^0$, allows us to abstract from the damages caused by these emissions and to focus instead on counterfactual damages in the quantitative exercises below. Third, the corresponding indirect utility function implies that damages are proportional to real income, allowing for the calibration of $\mu_i$ to match a specific carbon cost in real euro terms, as we discuss below. $CO_2$ emissions include all emissions from the production of inputs used by French firms, both domestically and abroad.

## 4.2 Production

**Final goods.** There is monopolistic competition in the final goods market, where each firm produces a single differentiated variety and sells it to domestic households at a price that is a constant markup, $\frac{\sigma}{\sigma-1}$, over marginal costs. Free entry ensures that there are no residual profits to be distributed to households.

Final goods production, $y_i$, is a combination of the firm's technology ($\omega$), and a bundle of intermediate goods, which are sourced from around the world to minimize costs. We depart from $AFT$ by introducing two categories of inputs, regulated and unregulated inputs. To this end, we introduce a nested-CES structure involving a firm-specific bundle of $U$nregulated inputs $y^U(\omega)$ and a bundle of $R$egulated inputs $y^R(\omega)$, which can be sourced domestically or imported:

$$y_i(\omega) = \omega \left[ \mathcal{A}^{1/\eta} \, y_i^R(\omega)^{\frac{\eta-1}{\eta}} + (1-\mathcal{A})^{1/\eta} \, y_i^U(\omega)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}},$$

with

$$y_i^R(\omega) = \left[ \int_0^1 y_i^R(\omega,\nu)^{\frac{\rho-1}{\rho}} \, d\nu \right]^{\frac{\rho}{\rho-1}}, \quad y_i^U(\omega) = \left[ \int_0^1 y_i^U(\omega,\nu)^{\frac{\rho-1}{\rho}} \, d\nu \right]^{\frac{\rho}{\rho-1}},$$

where $y_i(\omega)$ denotes the quantity produced of variety $\omega$, with $\omega$ also used to denote the productivity of the final good producer. Production is a CES aggregate of the quantity $y_i^U(\omega)$ of unregulated inputs and $y_i^R(\omega)$ of regulated inputs, with $\eta$ the elasticity of substitution between these bundles. We allow for heterogeneous technical coefficients over regulated and unregulated inputs, with $\mathcal{A} \in [0,1]$ scaling the share of regulated inputs in input purchases. All else being equal, an increase in $\mathcal{A}$ puts more weight on firms' cost of regulated inputs, making them more sensitive to the taxation of these inputs. Each bundle of inputs is itself a CES aggregate of a mass one of differentiated varieties, which are substituted at rate $\rho > 1$, assumed to be the same across regulated and unregulated inputs.

Firms discover their productivity, $\omega$, after incurring an entry cost $f_e$. Productivity is drawn from a country-specific distribution $g(\omega)$ with support $[\underline{\omega}, \infty)$ and with an associated continuous cumulative distribution $G(\omega)$. For estimation purposes, we assume that $G(\omega)$ is Pareto with shape parameter $\kappa$.

Cost minimization implies the following demand for inputs of type $t = U, R$:

$$\mathcal{A}^t c_i^t(\omega) y_i^t(\omega) = \mathcal{A}^t \left( \frac{c_i^t(\omega)}{c_i(\omega)} \right)^{1-\eta} \frac{c_i(\omega)}{\omega} y_i(\omega),$$

where

$$c_i(\omega) = \left[ \mathcal{A} \, c_i^R(\omega)^{1-\eta} + (1-\mathcal{A}) \, c_i^U(\omega)^{1-\eta} \right]^{\frac{1}{1-\eta}}$$

is the unit cost of the corresponding input bundles, given a vector of unit costs for individual inputs $\{c_i^t(\omega,\nu)\}$:

$$c_i^t(\omega) = \left[ \int_0^1 c_i^t(\omega,\nu)^{1-\rho} \, d\nu \right]^{\frac{1}{1-\rho}},$$

and $\mathcal{A}^R \equiv \mathcal{A}, \quad \mathcal{A}^U \equiv 1-\mathcal{A}$.

**Intermediate goods.** Intermediates can be sourced from any country $j \in I^t$ and we denote $a_j^t(\nu)$ the (constant) unit labor requirement of variety $\nu$ of input $t$ produced in country $j$. As is standard in the literature, we assume that there is some bilateral iceberg trade cost that must be paid to import a good, and which is normalized to one for goods sourced domestically. We further augment these trade costs with taxes that capture environmental policy. Specifically, we model bilateral trade costs between country $i$ and country $j$, denoted by $\{i, j\}$ for good type-$t$ as

$$\tau_{ij}^t = \underbrace{\tilde{\tau}_{ij}^t}_{\text{Iceberg trade cost}} \times \underbrace{tax_{ij}^t}_{\text{Bilateral carbon tax}},$$

with $tax_{ij}^t$ varying depending on the input type, the zone to which $i$ and $j$ belong, and the policy put into place. Note that $tax_{ij}^t = 1$ implies no carbon tax.

Following Eaton and Kortum (2002), we assume that the infinite-dimensional vectors of intermediate input efficiencies $1/a_j^t(\nu)$ are the realization of draws from a Fréchet distribution:

$$Pr\left(a_j^t(\nu) \leq a\right) = \exp\left(-T_j^t a^{\theta^t}\right), \quad \text{with} \quad T_j^t > 0.$$

These draws are independent across locations and inputs. $T_j^t$ governs the state of technology in country $j$ for type $t$ input while $\theta^t$ determines the variability of productivity draws across inputs of type $t$.

Although intermediaries are produced worldwide, a final-good producer in $i$ only acquires the capability to offshore in $j$ after incurring a fixed cost equal to $f_{ij}^t$ units of labor. In the following, we denote $\mathcal{I}^t(\omega)$ the set of countries for which firm $\omega$ has paid the associated fixed cost of offshoring type $t$ inputs, $\left\{w_i f_{ij}^t\right\}_{j \in \mathcal{I}^t(\omega)}$.Given its sourcing strategy, the price that firm $\omega$ pays for $t$-input $\nu$ is

$$c_i^t\left(\omega, \nu; \mathcal{I}^t(\omega)\right) = \min_{j \in \mathcal{I}^t(\omega)} \left\{\tau_{ji}^t a_j^t(\nu) w_j\right\}. \tag{5}$$

## 4.3 Solution to the sourcing problem

The firm's sourcing problem is solved in two stages. First, conditional on sourcing, the share of type-$t$ inputs sourced from country $j$, $\chi_{ij}^t$, is

$$\chi_{ji}^t(\omega; \mathcal{I}^t(\omega)) = \begin{cases} \frac{T_j^t\left(\tau_{ji}^t w_j\right)^{-\theta^t}}{\Theta_i^t(\omega; \mathcal{I}^t(\omega))} & \text{if} \quad j \in \mathcal{I}^t(\omega), \\ 0 & \text{if} \quad j \notin \mathcal{I}^t(\omega), \end{cases} \tag{6}$$

with

$$\Theta_i^t(\omega; \mathcal{I}^t(\omega)) \equiv \sum_{k \in \mathcal{I}^t(\omega)} T_k^t \left(\tau_{ki}^t w_k\right)^{-\theta^t}. \tag{7}$$

Therefore, more stringent and/or asymmetric carbon taxes increase bilateral trade costs, thus reducing the share of inputs from the regulating country in any firm's input bundle – this captures the *intensive margin* impact of climate policy in our model.

The firm's decision to source is solved to maximize profits, whereby the firm must decide whether or not to pay the fixed costs to source from a given country. Profits for a firm in country $i$ can then be written as a function of cost, market demand $B_i$, the wage $w_i$, and the fixed costs of importing both regulated and unregulated goods from potential source countries:

$$\pi_i(\omega; \mathcal{I}^R(\omega), \mathcal{I}^U(\omega)) = \left(\frac{c_i(\omega; \mathcal{I}^R(\omega), \mathcal{I}^U(\omega))}{\omega}\right)^{1-\sigma} B_i - w_i \sum_{j \in \mathcal{I}^R(\omega)} f_{ij}^R(\omega) - w_i \sum_{j \in \mathcal{I}^U(\omega)} f_{ij}^U(\omega), \tag{8}$$

with

$$\begin{aligned} c_i(\omega) &= \left[\mathcal{A}\, c_i^R(\omega)^{1-\eta} + (1-\mathcal{A})\, c_i^U(\omega)^{1-\eta}\right]^{\frac{1}{1-\eta}}, \\ c_i^t(\omega; \mathcal{I}^t(\omega)) &= \left(\gamma^t \Theta^t(\omega; \mathcal{I}^t(\omega))\right)^{-1/\theta^t}, \\ \gamma^t &\equiv \left[\Gamma\left(\frac{\theta^t + 1 - \rho}{\theta^t}\right)\right]^{\theta^t/(1-\rho)}, \end{aligned}$$

where $\Gamma()$ is the gamma function, which is defined for $\rho < 1 + \theta^t$.

Firms trade off the reduction in costs associated with a larger sourcing strategy set and the payment of additional fixed costs, given demand ($B_i$) and productivity ($\omega$). The solution to this problem is complex given the convexity of the cost function and therefore involves solving a large combinatorial optimization problem. Following $AFT$, we solve the model with an algorithm in the spirit of Jia (2008) and Arkolakis, Eckert and Shi (2023). While our approach builds on this literature, implementation is non-trivial because our extended model implies that firms jointly choose two interdependent sourcing margins, namely regulated and unregulated inputs. Under our calibration, only a mixture of the Arkolakis et al. (2023) conditions holds. We therefore design a hybrid algorithm tailored to solve these mixed cases, which we detail in Appendix C.

## 4.4 Industry equilibrium

Given sourcing decisions, one solves for the equilibrium number of final good producers using a free entry condition, given wages:

$$\int_{\tilde{\omega}_i}^{\infty} \left[\left(\frac{c_i(\omega; \mathcal{I}_i^U(\omega), \mathcal{I}_i^R(\omega))}{\omega}\right)^{1-\sigma} B_i - w_i \sum_{j \in \mathcal{I}^U(\omega)} f_{ij}^U(\omega) - w_i \sum_{j \in \mathcal{I}^R(\omega)} f_{ij}^R(\omega)\right] dG(\omega) = w_i f_e. \tag{9}$$

where $\tilde{\omega}_i$ denotes the minimum productivity for profitable entry into the manufacturing sector in country $i$. It can be shown that this equation delivers a unique market demand level $B_i$ (Antràs et al., 2017).

# 5 Model Estimation

We need to estimate parameter values to conduct a quantitative analysis of the impact of environmental policies on firms' sourcing decisions. Our estimation approach is the following. First, we use French import data to estimate a supplier country's *sourcing potential* by goods type, i.e., $T_j^t \left(\tau_{ji}^t w_j\right)^{-\theta^t}$. Second, we use data on the relative share of regulated products in input purchases to pin down technical coefficients ($\mathcal{A}$). Third, we calibrate elasticities and productivity parameters using our firm-level data and values from the literature. Fourth, given the model structure, we apply simulated method of moments (SMM) to firm-level data to estimate the vector of average fixed costs, their variance across firms, and market demand. We estimate the model using pre-ETS data in order to avoid capturing the impact of policy. Further, evidence in Section 3.2 confirms that there are no pre-trends in import sourcing variables.

## 5.1 Estimation of sourcing potential

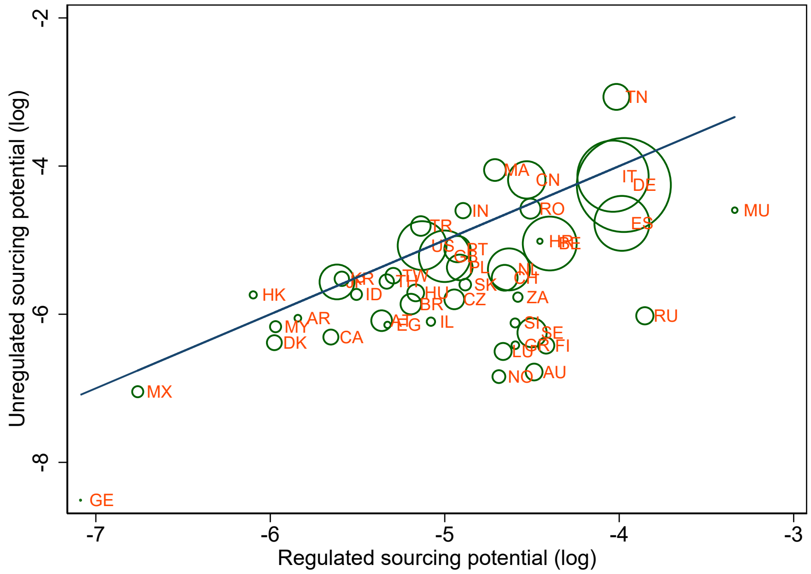
Given the model structure, we can use equations (6) and (7) to motivate the following fixed-effect regression to back out each country's sourcing potential for each type of good:

$$\log \chi_{fi,j}^t - \log \chi_{fi,i}^t = \log \alpha_{ij}^t + \varepsilon_{fi,j}^t, \tag{10}$$

where $\chi_{fi,j}^t$ is the ratio of firm $f$ in country $i$'s import of type-$t$ from country $j$ to the total type-$t$ inputs used by $f$, and $\chi_{fi,i}^t$ measures the consumption of domestic inputs relative to total inputs for each type $t$. In our data, all firms are located in country $i$ = France. The $\log \alpha_{ij}^t$ terms are estimated using source-country-type fixed effects. In the model, they are related to the country's sourcing potential, expressed in relative terms with respect to domestic sourcing: $\alpha_{ij}^t = \frac{T_j^t\left(\tau_{ji}^t w_j\right)^{-\theta^t}}{T_i^t\left(\tau_{ii}^t w_i\right)^{-\theta^t}}$. We estimate (10) separately for regulated and unregulated imports. Note that since equation (10) is in logs, the procedure relies on the subset of firms that source some of their inputs domestically and from abroad. We end up with 17,424 observations for unregulated inputs and 12,053 observations for regulated inputs.

Figure 5 plots the estimated sourcing potential for unregulated inputs on the y-axis vs. regulated inputs on the x-axis in log-log scale. We also include the 45-degree line so that countries below the line have a comparative advantage in the production of regulated inputs, compared to France. We represent origin countries with bubbles whose size reflect the importance of a source country in aggregate imports. Zooming in on the figure, we see that the majority of source countries are below the line, indicating that they have a comparative advantage over France on regulated inputs relative to unregulated inputs. These include non-ETS countries such as Russia (RU) and Australia (AU), and the ETS member Norway (NO),

**Figure 5.** Estimated sourcing potential for regulated and unregulated inputs




**Notes:** This figure plots the relative cost of sourcing regulated (x-axis) and unregulated (y-axis) products from each foreign country, estimated from equation (10). The size of the bubbles is proportional to the value of overall imports. The blue line is a 45-degree line. Countries positioned below the line have a comparative advantage over France in the production of regulated inputs.

which are major exporters of petroleum products and regulated raw materials. Interestingly, both China (CN) and India (IN) have slightly larger unregulated sourcing potentials than regulated ones compared to France. With the estimated sourcing potentials in hand, we can now proceed to back-out other necessary structural parameters.

## 5.2 Technical coefficients

The technical parameter scaling the share of regulated inputs in intermediate consumption ($\mathcal{A}$) cannot be estimated separately from the relative cost of producing regulated and unregulated inputs in the domestic economy $\left(\frac{T_i^R\left(\tau_{ii}^R w_i\right)^{-\theta^R}}{T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}}\right)$. Intuitively, a larger weight placed on regulated inputs and a higher average productivity of the domestic economy in the production of regulated inputs both increase the demand for regulated inputs. As the determinants of the demand for imported inputs are estimated relative to production costs in the domestic economy (see equation (10)), we are left with an identification problem. Appendix D.2 provides a strategy to jointly estimate the parameters, which we use as inputs for the SMM estimation.

## 5.3 Elasticities and productivity parameters

We follow di Giovanni, Levchenko and Ranciere (2011) and estimate the Pareto shape parameter of firms productivity using the distribution of domestic sales in the firm-level data. In particular $\kappa = \zeta(\sigma - 1)$ where $\zeta$ is the power law exponent in firm size. Using balance-sheet data for 2004, we obtain a value for $\zeta$ at 0.82. The elasticity of substitution between final good varieties is estimated by taking advantage of the CES form, which yields that firms' markups take the form $\frac{\sigma}{\sigma-1}$. We use our firm-level data to compute the median ratio of sales over total variable costs (input purchases plus salaries), which gives $\sigma = 3.48$. We set the value of the shape parameter of input efficiency, $\theta = 1.79$, to be the same for both $t = \{R, U\}$ and equal to the value estimated in $AFT$. We choose a value of $\eta = 1.25$ to govern the substitution between regulated and unregulated inputs. This value provides model-based firm-level regressions estimates that match those estimated in data in Section 3. Finally, we calibrate $\alpha$ to 0.24, matching the manufacturing share of total French output in the 2004 WIOD data.

## 5.4 Simulated method of moments

The remaining parameters are estimated using SMM. The first set of parameters that we must estimate relate to the fixed costs firms face in sourcing a type-$t$ good from a country $j$, $f^t_{ij}$. We follow $AFT$ by assuming that these fixed costs can be modeled parametrically using a gravity-style equation, and impose the following log-linear form on average bilateral fixed costs:

$$\begin{aligned} \log \bar{f}^t_{ij} = {} & \log \beta^t_0 + \sum_b \mathbb{1}(dist_{ij} \in Bin_b) \log \beta^t_b + \mathbb{1}(nonEU_{ij} = 1) \log \beta^t_{nonEU} + \\ & \beta^t_{TAB} \log TAB_j \ \left[+\beta^t_{Climate} \log Climate_j \text{ if } t = R\right], \end{aligned} \tag{11}$$

where $\mathbb{1}(dist_{ij} \in Bin_b)$ is a dummy variable if the distance between country $i$ (France) and country $j$ falls within bin $b$, $\mathbb{1}(nonEU_{ij} = 1)$ is a dummy variable identifying non-member states of the European Union, $TAB_j$ is $j$'s trading across borders score from the World Bank's Doing Business Index, a continuous variable $\in [0; 100]$ which is increasing in easiness to trade, and $Climate_j$ is $j$'s score in Yale's Environmental Protection sub-index on climate mitigation policy (continuous $\in [0; 100]$, higher is better).

The set of variables used to estimate (11) differ from $AFT$ given that we are examining French firms rather than US ones. Specifically, given the geographical closeness of Europe, we use distance bins to capture the non-linear fit of the distance variable for trade with other countries. We also exploit two institutional variables that better help us match the data. First, the $TAB_j$ variable helps to capture the fixed cost of overcoming barriers to

**Table 2.** Targeted moments in the data for SMM estimation

| Parameter | Moments matched |
|---|---|
| | Fixed cost of sourcing each type-$t$: $f_{ij}^t$ |
| $\boldsymbol{\beta}^t$ | Share of importers of $t$ goods as a fraction of all firms<br>Share of importers of $t$ goods from top 10 countries |
| $\delta^t$ | # firms importing $t$ goods from most popular country<br>over # of firms that import $t$ goods<br>Share of importers of $t$ goods among firms below the sales median |
| $B_i$ | Share of firms with sales below data median value |

**Notes:** $\boldsymbol{\beta}^t$ explain avg. source-country fixed costs; $\delta^t$ generates randomness in fixed costs across firms; $B_i$ is market demand.

entry in international trade for different countries. Second, given that we are also interested in differing sourcing behavior for regulated and unregulated products, we include a measure of source countries' climate mitigation policy ($Climate_j$), which may make it more costly to trade in some types of goods vs. others.

Further, following the methodology in *AFT* we also add some idiosyncratic randomness in fixed costs faced by firms in sourcing a given variety, where $\delta^t$ is an additional parameter to be estimated for each type of input:

$$f_{ij}^t(\omega) = \bar{f}_{ij}^t \times \exp\left(x^t\right), \ x^t \sim \mathcal{N}(0, {\delta^t}^2). \tag{12}$$

Table 2 presents the calibrated moments that we target to estimate the OLS coefficients of gravity equation (11) and the $\delta^t$ parameters for equation (12). The first set of moments are used to estimate the vector of $\boldsymbol{\beta}^t$ coefficients estimated in the gravity equation. Specifically, we exploit information on the share of importers along several dimensions to identify the different coefficients. First, the share of importers of $t$ goods as a fraction of all firms allows us to identify the average level of fixed costs $\beta_0^t$. Second, the share of importers of $t$ goods from each country allows us to identify parameters on country-specific variables in equation (11). Turning to the estimation of the variance parameters, $\delta^t$, we target (i) the number of firms importing $t$ goods from the most popular country over the number of firms that import $t$ goods, and (ii) the share of importers of $t$ goods with sales below median. The intuition for using (i) is that, as shown in proposition 1 in *AFT*, in the case of identical fixed costs across firms ($\delta^t = 0$), if a country is part of a firm's global set of sourcing countries, it is also necessarily part of the set of firms with higher productivity levels. With this in mind, in a world with $\delta^t = 0$, we would have that the number of firms importing $t$ goods from the most popular country is the same as the number of firms importing $t$ goods, yielding the ratio in (i) to equal one. Any deviation from one is indicative of the value of $\delta^t$.[29] The intuition behind using moment (ii), the share of importers of $t$ goods among firms below the sales median, is the following. With $\delta^t = 0$, the fixed costs would simply rely on country-specific data, and we would obtain a particular share of importers with sales below the median, not necessarily matching the data. Given the way random shocks and productivities are drawn, as explained in Appendix D.1, adjusting $\delta^t$ will allow us to match data moment (ii).[30]

The final parameter that needs to be estimated is market demand, $B_i$, which is estimated using the share of firms with sales below the median in the data as targeted moment. Note that $AFT$ target the distribution of costs, which is more complicated in our setting that involves two inputs. Finally, as discussed in Appendix C.2, $B_i$ cannot be identified separately from the average level of unregulated input costs in France, which is not a problem as we will directly estimate how the counterfactual experiments affect this variable using the free-entry condition.

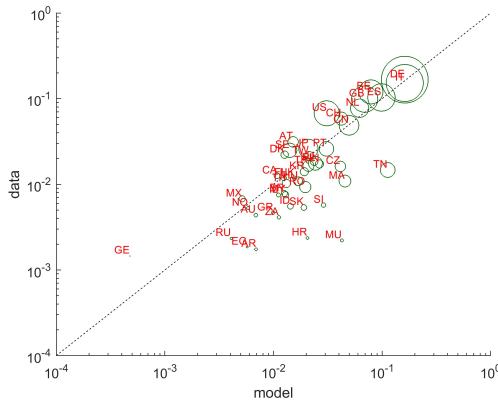
Figure 6 presents scatter plots to gauge the model fit of the SMM estimation, with the data on the y-axis and the model predictions on the x-axis. Panel I presents results for the extensive margin of imports. We plot the share of importers by country for regulated and unregulated inputs in sub-figures (a) and (b). The size of the bubble corresponds to the amount of total imports. Panel II next presents results for import shares, with unregulated in sub-figure (c) and regulated in sub-figure (d). None of the moments in Panel II are directly targeted in the estimation, while those from Panel I are. The overall fit of the model is good for both sectors, as many of the observation points fall close to the forty-five degrees line. This is especially true for large countries, while the model tends to overestimate trade probabilities and import shares for very small source countries. We further report the estimated parameters in Table D.2, the data and model moments in Table D.3, and the estimated fixed costs and sourcing potential for regulated and unregulated source countries

[29] Importantly, this moment is perfectly correlated with the value for the most popular country in the second moment used to estimate $\boldsymbol{\beta}^t$, i.e., the share of importers of $t$ goods from the top 10 countries. Hence, we do not need to add moment (i) in the estimation *per se*, as it is already captured in this other moment.

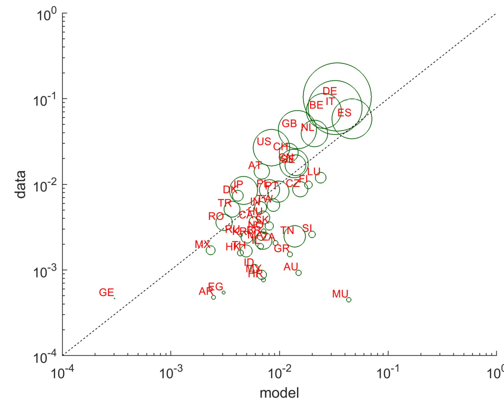
[30] As explained, in Appendix D.1, each productivity level $\omega$ is duplicated 100 times, such that each entry of this productivity level has a unique vector of fixed costs shocks. Also, each entry of each productivity level is applied to the same level of fixed costs shocks. This means that the first firm with productivity level $\omega_L$ has the same vector of shocks as the first firm with productivity level $\omega_H > \omega_L$. However, since in the model $\omega_H$ will be less sensitive to fixed costs changes, increasing or decreasing $\delta^t$ will change lower productivity firms' import strategies relatively more than higher productivity firms, helping us match moment (ii).

**Figure 6.** Model estimation and fit for France's manufacturing sector

**Panel I.** Share of importers by source country (*targeted*)

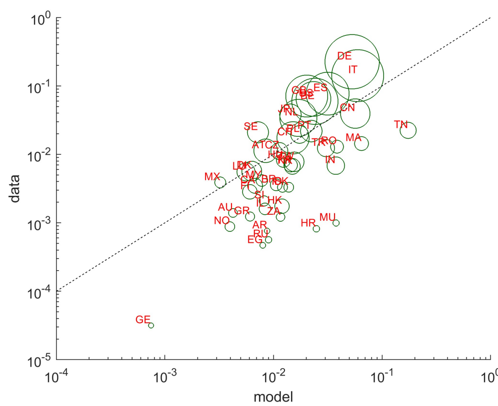



**(a)** Unregulated

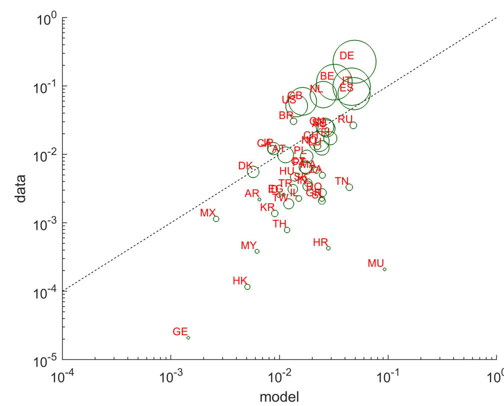



**(b)** Regulated

**Panel II.** Share of imports by source country (*untargeted*)




**(c)** Unregulated




**(d)** Regulated

**Notes:** This figure plots model-based trade statistics and their data counterparts. Panel I plots the share of manufacturing sector importers by source country for unregulated products in (a) and regulated products in (b). These statistics are targeted by the SMM algorithm. Panel II plots the share of manufacturing sector imports by source country for unregulated products in (c) and regulated products in (d). Those are untargeted moments. All data used in the model and for actual moments in the data are sourced for 2004.

in Figure D.2.

# 6 Quantitative Impact of Carbon Taxes

This section analyzes the impact of introducing a carbon tax, which is meant to mimic the ETS, followed by a carbon tariff to evaluate the potential impact of the CBAM. The model allows us to quantify how firms' sourcing choices are impacted by the taxes at different levels of granularity, as well as providing the welfare implications of the policies.

## 6.1 Carbon taxes and tariffs

To quantify the impacts of implementing a carbon tax and a carbon tariff, we run two experiments using the model, which follow current policies as closely as possible. In the first scenario, we apply a carbon tax of €100 per ton to all ETS sectors within ETS countries (as detailed in columns (1) and (4) of Table A.5). In a second scenario, we complement the first tax with a carbon tariff of €100 per ton to all imports in CBAM sectors from non-ETS countries (as detailed in columns (3) and (6) of Table A.5).

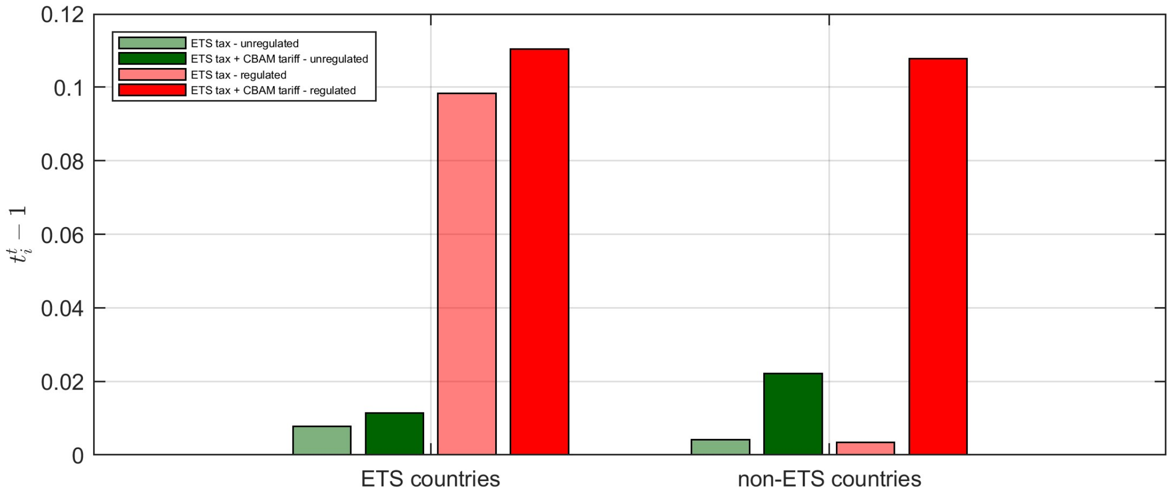
The first scenario is meant to capture the incidence of ETS regulations on production costs for regulated-intensive manufacturing sectors while the second scenario complements the unilateral carbon policy with a carbon border adjustment mechanism. In both cases, the product scope of the policy reproduces the actual coverage of the corresponding European scheme.Likewise, the geographical scope uses the actual borders of the ETS system while the ETS+CBAM scenario applies the tax to all products imported from outside of the ETS.[31] We calibrate the nominal tax rates using information on sectoral emissions intensities from WIOD for each country in our sample (Corsatea et al., 2019).[32] This amounts to computing the embodied direct carbon emissions using a sector-based approach in which all producers within a sector are taxed at the average emissions intensity of their direct production. Furthermore, we use global sectoral input-output linkages to compute the overall incidence of these taxes on manufacturing sectors' intermediate consumption. Doing so captures the pass-through of costs via roundabout production taking into account both domestic and foreign linkages, while only taxing direct emissions, thereby modeling actual policies as closely as possible. Moreover, incorporating input-output linkages implies that these taxes account for the regulation of electricity and heat generation in Europe, which affects the overall incidence of carbon taxes. While this analysis is not fully general equilibrium as we do not capture changes in trade and production abroad, the inclusion of input-output linkages in calculating the incidence of taxation maps into the actual impact of the tax on French firms.[33] Finally,

[31] As discussed in OECD (2020), the European Union should introduce exemptions for products that have already been taxed under national carbon policies. Moreover, it has been argued that exemptions for least-developed countries could be justified. In our stylized setting, we abstract from political economy concerns and apply the tax broadly. Whether the products are taxed under CBAM or under national carbon policies does not make a difference in our context as long as the level of the tax and the calculation of embodied carbon emissions is the same.

[32] The WIOD sectoral classification follows ISIC rev. 4. In Table A.6, similar to Table A.5 for NAF sectors, we present the classification of ETS and CBAM sectors according to ISIC rev. 4. Figure D.3 reproduces a heat graph of country-sector emissions.

[33] See Appendix D.4 for details.

**Figure 7.** Tax rates for regulated and unregulated inputs by country zone and policy scenario




**Notes**: This figure presents tax rates for each input type for ETS and non-ETS countries. Based on authors' calculations using data from WIOD's sector-level emissions + WIOD IO tables. Each bar is calculated as the average across the countries within that category. The model uses country×input level taxes depicted in Figure D.4.

our baseline calculations assume that tax revenues are not rebated to households and thus are a pure deadweight loss. For comparison, we further calculate aggregate welfare assuming that tax revenues are rebated to households.

Figure 7 presents the tax rates that we use for our quantification exercises, where we have aggregated up across countries that trade with France – see Figure D.4 for the underlying country-level tax rates. We present taxes for unregulated (green bars) and regulated (red bars) industries for the counterfactual mimicking the ETS regime ('ETS tax') and the counterfactual mimicking the ETS + CBAM regime ('ETS tax + CBAM tariff'). Unsurprisingly, the tax incidence is much larger for the regulated sectors, but taxes are not zero for unregulated sectors given the existence of roundabout production, which is captured by incorporating the IO linkages when calculating indirect taxes for each French sector. In addition, although non-ETS countries display higher pollution intensities on average, the average tariff rate is lower than the tax rate for ETS countries since tariffs cover less products than the ETS tax.[34]

With these tax rates in hand, we multiply the previously calculated sourcing potentials $T_j^t \left(\tilde{\tau}_{ij}^t w_j\right)^{-\theta^t}$ by the tax multiplier $\left(tax_{ij}^t\right)^{-\theta^t}$, with $tax_{ij}^t > 1$. Note that since the sourc-

[34] When taxing all regulated inputs with the same ETS coverage, tax rates are much higher for non-ETS countries, as seen in Figure D.5. In addition, when taxing all sectors, and not only the ETS sectors, this difference between ETS countries and non-ETS ones grows even larger, as seen in Figure D.6.

ing potentials estimated in Section 5.1 are normalized by France's, we need to adjust each post-tax sourcing potential by French sectors' exposure to the carbon tax. Last, any counterfactual requires the re-estimation of market demand $B_i$ in equation (3), from which we solve for the new mass of firms captured by $\Omega_i$.[35] It is important to note that nominal expenditure on manufacturing goods ($E_i$ in equation (3)) is held constant across simulations. As a result, aggregate input purchases also remain constant, implying that any geographical or input-type shift in imports reflects a change in the share of imports from specific countries or types of inputs. Similarly, any variation in aggregate emissions results from firms adjusting their input purchases toward unregulated inputs or countries while holding overall expenditures constant.

## 6.2 Policy experiments

### 6.2.1 Model-based carbon leakage under the ETS tax and CBAM tariff

We begin by analyzing the extent of carbon leakage generated by our model in the context of the ETS tax policy experiment, using a tax rate of €100 per ton of $CO_2$. We first calculate how firms adjust their import shares and extensive margin decisions when moving from the no-tax baseline scenario to the ETS tax counterfactual, and compare these results to our empirical estimates in Table 1. We then run a second experiment that adds the CBAM tariff to the ETS tax, which allows us to gauge the potential future impact of the EU's carbon tariff on French firms' carbon leakage.

**ETS tax scenario.** We use the model-generated firm-level data to run regressions similar to equation (1),[36] again using a control group composed of unregulated inputs sourced from ETS countries. Table 3 presents the regression estimates. Column (1) reproduces the results in Table 1, averaging across ETS phases, and using product×country and period fixed effects. Column (2) presents estimates based on the model-generated ETS scenario with a €100 per ton tax and the same structure of fixed effects. Results in panel (a), where the regressand is a firm's import share, show that the model generates an estimated coefficient that is not significantly different from the data regressions. Turning to the extensive margin adjustment in panel (b), we find that the model's generated data only reproduce a third of the estimated leakage in comparison to the estimate based on the data regressions.

[35] See details in Appendix C.

[36] Specifically, we simulate 5,625 firms and 47 source countries with two types of inputs, so that for each simulation we generate a matrix of import values with dimensions $5,625 \times 47 \times 2$. Since the model includes only two types of inputs, compared to the much larger number of products in the data set, the simulated data have a lower level of granularity. Nonetheless, we are able to run regressions with fixed effects that resemble those in the reduced-form analysis.

The model thus underestimates adjustments at the extensive margin when applying a €100 tax. One possible explanation for this result is that the model is static, thus neglecting the potential forward-looking dimension of import sourcing decisions that is captured in the empirical estimation. If firms anticipate that carbon policies will become more binding in the future, they may react more at the extensive margin, including in periods when ETS policies are not especially binding. Instead, import shares will remain relatively balanced between ETS and non-ETS countries, since they react more to the current level of the tax. Another possible explanation is that the carbon tax may affect both the fixed and the variable cost components of sourcing decisions in reality (e.g., by increasing paperwork), while our model assumes that the fixed cost of importing from non-ETS countries (compared to ETS countries) is left unaffected. Increasing the relative fixed cost of sourcing from ETS countries would indeed induce larger adjustments at the extensive margin in the simulated data.

**ETS tax + CBAM tariff scenario.** Having shown that our model accurately predicts carbon leakage under the ETS tax, at least qualitatively, we next study the potential impact of a carbon tariff in this environment. Column (3) in Table 3 replicates the firm-level regressions in the ETS+CBAM scenario. Compared to the ETS-only scenario, leakage is more than reversed, meaning that French firms *increase* their sourcing of regulated inputs from ETS countries compared to unregulated inputs. This happens despite the CBAM scheme having a lower sectoral coverage than the ETS. The reason is that non-ETS countries display relatively high emissions intensities compared to ETS countries. Once their production is taxed under the same carbon price as ETS production, French firms reallocate their intermediate consumption towards low-emitting countries in the EU.

### 6.2.2 Aggregate and welfare results

We next consider the two policy experiments' quantitative implications in Table 4. The first set of results presented in panel (a) of Table 4 show the change in millions of tons of emissions embedded in inputs sourced by French firms, both domestically and abroad. Panel (b) presents the change in the ideal price index along with the welfare changes, which are computed by taking the ratio of indirect utilities. We compute these changes for the baseline where taxes are treated as a deadweight loss as well as when they are rebated to households.[37] We consider two scenarios for the cost of carbon, one that sets the price at €200 and the other at €1500, aligning with recent estimates of the social cost of carbon from the literature (Rennert et al., 2022; Bilal and Känzig, 2024; Moore et al., 2024).

[37] In that case, $\Delta V_i$ is computed as $\Delta V_i = \left(\frac{P_i}{P_i'}\right)^{\alpha} \frac{I_i+T_i}{I_i} \left[1 + \mu_i \left(CO_2' - CO_{2,baseline}\right)\right]^{-1}$, where $I_i$ is total GDP.

**Table 3.** Carbon leakage regressions: Data and model-based policy experiments

| | Data (1) | ETS (2) | ETS + CBAM (3) |
|---|---|---|---|
| | **Panel (a)** Import Share | | |
| Regulated product × Non-ETS × $\mathbb{1}$ (Post) | 0.119*** | 0.134*** | -0.013 |
| | (0.019) | (0.006) | (0.044) |
| Pseudo $R^2$ | 0.161 | 0.370 | 0.371 |
| Observations | 7,514,923 | 341,412 | 341,412 |
| | **Panel (b)** Import Probability | | |
| Regulated product × Non-ETS × $\mathbb{1}$ (Post) | 0.136*** | 0.049*** | -0.035 |
| | (0.010) | (0.012) | (0.017) |
| Pseudo $R^2$ | 0.044 | 0.111 | 0.113 |
| Observations | 7,514,923 | 341,412 | 341,412 |
| # Importers | 27,345 | 3,711 | |
| Control group | Non-ETS Unregulated products | | |
| Fixed effects | pc,t | pc | |

**Notes:** This table presents the estimated $\beta$ from regression (1) using both the reduced form data set and two model-generated data sets (ETS and ETS+CBAM). In the data, we estimate a version of (1) that constrains all coefficients posterior to 2004 to equality. The model-based regressions compare the new equilibrium under ETS or ETS+CBAM to the baseline scenario without taxes. In the table, $f$, $p$, $c$, and $t$ represent: a firm, the imported product (2 types in the model regressions, all products in the reduced form), the source country, and either the tax level (0 or 100) in the model regression, or time in the reduced form. The model estimate runs a weighted least squares using sampling weights that corrects for over-sampling of large firms in the simulations. See Section D.1 for details. (*, **, ***) denote significance levels at 10%, 5%, and 1%, respectively.

**ETS tax scenario.** Implementing the ETS scenario in column (1) results in a 0.67 million tons reduction in emissions, a 0.42% reduction compared to the baseline equilibrium. The net reduction in emissions is driven by a fall in the use of regulated inputs ($-0.92$M tons). Meanwhile, firms substitute towards using unregulated inputs, so emissions embedded in the use of intermediate goods rises slightly (0.25M tons). The following three rows illustrate how firms' new sourcing decisions contribute to carbon leakage to non-ETS countries. Specifically, the reduction in sourcing from ETS countries results in a 2.19M tons decrease in emissions embedded in these countries' inputs, while emissions embedded in inputs from non-ETS countries rise by 1.83M tons. Overall, the net effect of increased emissions from sourcing

**Table 4.** Quantitative results: change from baseline

| Variable | ETS | ETS + CBAM |
|---|---|---|
| Panel (a): Impact on emissions ($\Delta$ Million tons emissions embedded in inputs) | | |
| Total | -0.67 | -4.97 |
| ... *from unregulated inputs only* | 0.25 | -0.67 |
| ... *from regulated inputs only* | -0.92 | -4.30 |
| ... *from FR inputs only* | -0.32 | 0.75 |
| ... *from ETS (ex. FR) inputs only* | -2.19 | -1.88 |
| ... *from non-ETS inputs only* | 1.83 | -3.83 |
| Panel (b): Impact on welfare | | |
| Manufacturing Price Index | | |
| $\% \Delta P_i$ | 0.868 | 1.421 |
| Indirect utility | | |
| Social Cost of Carbon: €200 | | |
| $\% \Delta V_i$ *without tax rebate* | -0.200 | -0.325 |
| $\% \Delta V_i$ *with tax rebate* | -0.123 | -0.197 |
| Social Cost of Carbon: €1500 | | |
| $\% \Delta V_i$ *without tax rebate* | -0.198 | -0.307 |
| $\% \Delta V_i$ *with tax rebate* | -0.120 | -0.178 |

**Notes:** $\Delta$ denotes changes. All simulations apply a carbon tax of €100 per ton of $CO_2$. Panel (a) describes the change in emissions embedded in input purchases. Note that the total value of input purchases is unchanged across simulations, as $E_i$ is fixed. The baseline level of emissions embedded in input purchases is equal to 161.8M tons of $CO_2$. The ETS policy (resp. ETS+CBAM policy) thus reduces emissions by 0.42% (resp. 3.07%). Panel (b) reports changes in welfare components, namely the price index of final goods in the manufacturing sector and overall indirect utility. Using equation (4), the change in indirect utility is defined as:

$$\Delta V_i = \left(\frac{P_i}{P_i'}\right)^{\alpha} \left[1 + \mu_i \left(CO_2' - CO_{2,baseline}\right)\right]^{-1},$$

where the primed variables represent counterfactual values. The $\mu_i$ coefficient is calibrated to match a social cost of carbon of either €200 or €1,500.

unregulated inputs and from leakage to non-ETS inputs is outweighed by the reduction in emissions from decreased sourcing of regulated inputs within the ETS zone, leading to the overall decrease in emissions. This happens despite our model assumption that total input purchases are constant as $E_i$ does not change. Hence, this emissions decrease is simply the result of a reshuffling of firms' input purchases.

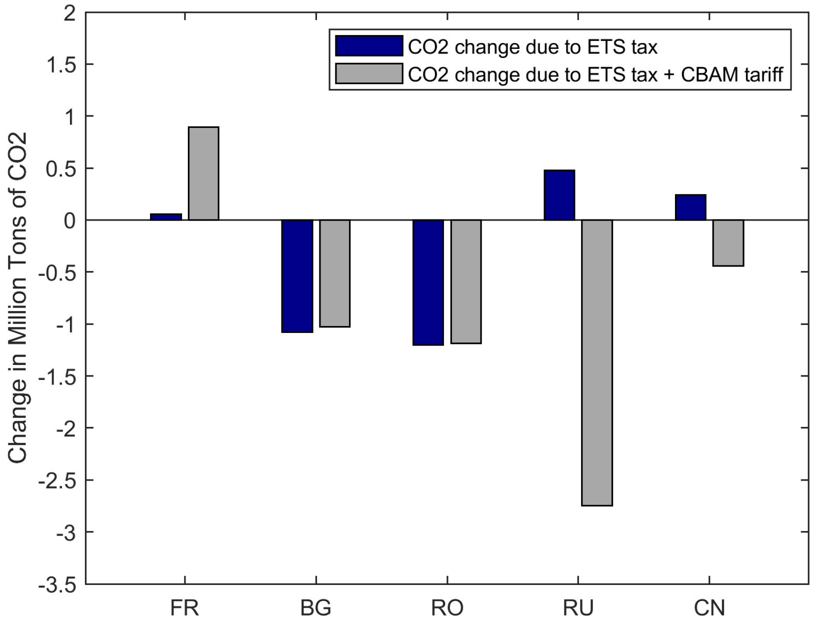
Panel (b) in Table 4 summarizes the welfare impact of the carbon tax. The carbon tax increases the price index of manufacturing goods, thus reducing real consumption. In the ETS scenario, the price impact is moderate, at 0.87%. This holds true despite tax rates reaching more than 20% for regulated inputs sourced from ETS countries (Figure 7). The reason for the low incidence is that firms adapt by substituting across supplier countries and input types. Still, the price increase is sufficiently high to generate a small fall in welfare, at −0.20%. This holds true even when we consider a social cost of carbon of €1500.[38] The benefit of a fall in emissions does not compensate the real consumption loss. This finding lines up with much of the quantitative literature, which shows that consumption losses tend to dominate the impact of changes in emissions in terms of aggregate welfare (e.g., see Copeland et al., 2022, for a review). One way of improving the welfare balance of this type of policies is to rebate tax revenues to households. In Table 4, we illustrate this point in an extreme scenario in which all tax revenues are rebated to domestic households. Welfare now only decreases by about 0.12%.

**ETS tax + CBAM tariff scenario.** While interesting in itself, the ETS scenario can also be compared with results recovered from a scenario combining a carbon tax and a carbon tariff as in column (2) of Table 4. Unsurprisingly, total emissions now fall substantially, as carbon leakage is no longer a profitable adaptation strategy. The overall efficiency of the policy is multiplied by seven, at −4.97M tons. In this scenario, both regulated and unregulated input sourcing contribute to the reduction in emissions. The result follows from French firms reshuffling their input portfolios towards less emitting countries. The geographical variation in the change in emissions is interesting. Results are summarized in Figure 8 for a subset of the most affected countries. Overall emissions from domestically-produced inputs increase slightly, together with domestic sourcing. The fall in emissions embedded in inputs sourced from other high-emission ETS-countries' inputs such as Bulgaria and Romania is large, although dominated by inputs sourced from non-ETS countries, most notably Russia. This result explains the reversal of leakage found in simulated data as shown in Table 3. The carbon tariff does come at a substantial cost, however. The ideal price index now rises by 1.42%, which leads to a further fall in utility. Again, the fall in emissions does not outweigh loss of purchasing power, and this holds for all the scenarios we consider.

**Carbon leakage for final manufacturing products.** Before concluding this section, it is important to keep in mind that the model – and thus the preceding quantification –

[38] See Appendix D.5 for further details on the calibration of $\mu_i$, and the utility trade-off between emission declines vs. price increases in these different scenarios.

**Figure 8.** The geography of leakage: ETS vs. ETS+CBAM scenarios




**Notes:** This figure plots the change in imports in emissions in millions of tons (panel (a)) and in millions of euros (panel (b)) when imposing either a carbon tax, or a carbon tax and a carbon tariff. Results are restricted to the 5 most impacted countries. Results for the rest of the sample are provided in Figure D.7.

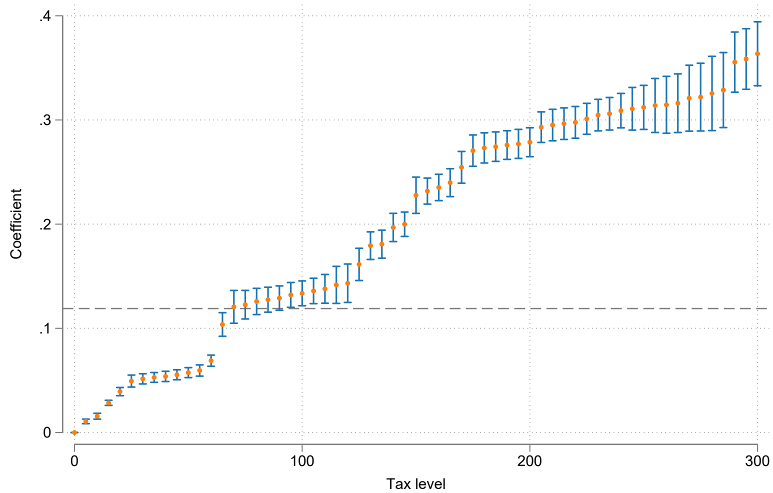
abstracts from trade in final goods. If producers in the manufacturing sector were instead exposed to international competition, the price effect of carbon taxes would generate carbon leakage further along the value chain, at the level of final products rather than just for regulated inputs. While modeling this effect is beyond the scope of the paper, we can quantify the magnitude of the associated leakage using a simple back-of-the-envelope calculation. To a first order, the change in demand for domestic final goods can be written as:

$$\Delta \log E_i = (1-\varepsilon)(\Delta \log P_i - \Delta \log P),$$

where $\varepsilon$ is the price elasticity of demand, $\Delta \log P_i$ denotes the change in the price index of domestic manufacturing products and $\Delta \log P$ is the change in the overall manufacturing price index. When manufacturing products are non-traded, $\Delta \log P_i = \Delta \log P$, and thus nominal demand remains unchanged. In practice, around 40% of French consumption of final manufacturing products is sourced from non-ETS countries. Under the (admittedly extreme) assumptions that all ETS products experience the same competitiveness loss as French firms, while all non-ETS producers remain unaffected,[39] the change in nominal demand can be expressed as $\Delta \log E_i = 0.4(1-\varepsilon)\Delta \log P_i$. Assuming an elasticity of $\varepsilon = 6$, this corresponds

[39] In general equilibrium, the incidence on non-ETS producers is not zero, as they also source some inputs from ETS countries.

**Figure 9.** Model leakage depending on the size of the tax




**Notes:** This figure plots model-based leakage values as a function of the tax level. The leakage coefficient is computed as in Column (2) of Panel (a) in Table 3, using simulated data obtained from a model calibrated with increasing carbon taxes. The blue lines correspond to confidence intervals at the 95% level. The dashed line is the data counterpart (column (1) in Table 3, panel (a)).

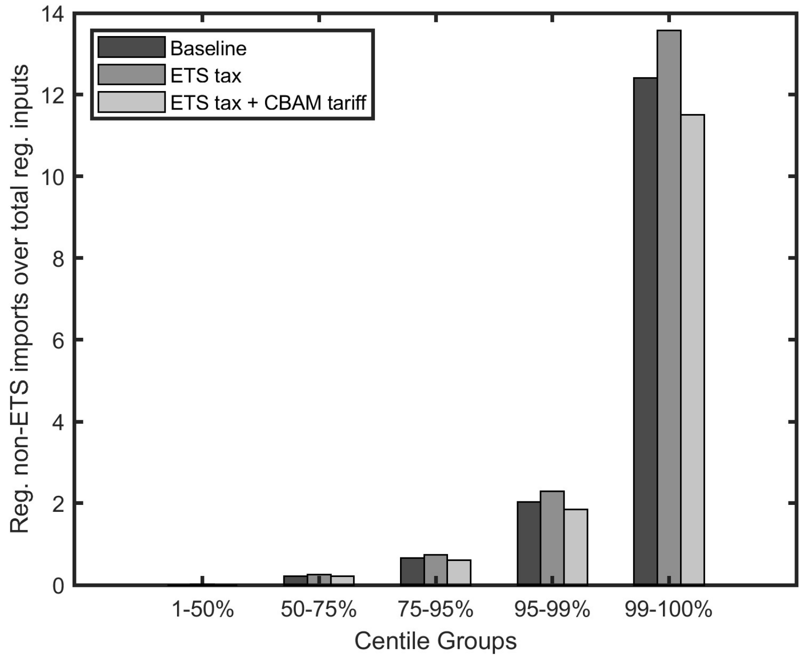
to a decline in nominal expenditures on domestic products of approximately 2.8% under ETS+CBAM, which would further reduce input purchases and thus emissions, at the cost of more emissions in the rest of the world.

### 6.2.3 Heterogeneous leakage effects

We conclude the analysis with evidence on heterogeneous leakage effects depending on the size of the tax and the position of firms in the productivity distribution.

In Figure 9, we illustrate the magnitude of carbon leakage as a function of the tax level. Specifically, we allow carbon taxes to vary between 0 and €300 per ton of $CO_2$. Leakage naturally increases with the tax. The model best matches the data at €70 per ton of $CO_2$, close to levels prevailing during the most recent phase of the ETS. However, the elasticity of leakage with respect to the tax is not constant. The non-linearity arises from adjustments at the extensive margin. Conditional on sourcing from a non-ETS country, the value of imports is log-linear in the level of the tax in our model. However, new investments in sourcing capabilities generate jumps in French firms' sourcing patterns, which explain the discontinuities in the average leakage coefficient in Figure 9. This non-linearity is important from a policy perspective, as reversing these discrete investments may be more difficult in reality than in our model as part of these investments may be irreversible.

**Figure 10.** Model leakage and firm productivity




**Notes:** This figure plots the share of regulated inputs sourced from non-ETS countries, along the distribution of productivities. The dark bars are the pre-ETS values implied by the estimated model and the medium and ligh grey bars correspond the the ETS and ETS+CBAM counterfactuals.

We next examine how the model predicts adjustments along the distribution of firm productivity. Examining the microeconomic underpinnings of the aggregate outcomes not only deepens our understanding of the model's quantitative implications but also allows us to assess the redistributive consequences of carbon policies. Figure 10 plots the share of regulated input purchases sourced from non-ETS countries, both in the baseline estimation and in the counterfactual scenarios. No leakage is observed in the bottom 50% of the firm productivity distribution, as these firms do not import regulated products from non-ETS countries in any of the three scenarios. Beyond the 50th percentile, the share of regulated inputs sourced from non-ETS countries rises with productivity, reaching about 12% of regulated input purchases for firms in the top percentile.

Once the ETS tax is introduced, this import share increases, as does firms' propensity to source from non-ETS countries. The elasticity of import shares with respect to the tariff is particularly strong between the 75th and 99th percentiles, reflecting greater adjustments at the extensive margin. In level terms, however, the aggregate increase in imports from non-ETS countries is driven almost entirely by the top 1% of firms, which can more easily benefit from lower relative prices in non-ETS countries thanks to their already wider sourcing sets.

For the same reason, the top 1% of firms disproportionately adjust to the introduction of carbon tariffs, which sharply raise the prices charged by their existing input suppliers.

# 7 Conclusion

This paper provides evidence on how firms' supply chain decisions adapt in response to carbon taxes. By constructing a novel data set using information from the EU's ETS and CBAM, we demonstrate that French firms modified their sourcing of regulated products as the EU ETS became more stringent. Specifically, firms increased imports from non-ETS countries, leading to carbon leakage both in terms of trade shares and at the extensive margin, as firms established new supply relationships with non-ETS foreign producers of regulated products.

We rationalize these results using a heterogeneous firm model of sourcing decisions. Calibrated to the observed sourcing behavior of French firms, our baseline quantitative findings indicate that implementing a carbon tax to mimic the ETS and a carbon tariff to replicate the CBAM increases the policy's efficiency in reducing emissions sevenfold at the cost of a 60% increase in its economic burden, compared to an ETS-only scenario. The burden of the policy falls predominantly on firms in the top 1% of the productivity distribution, which were already more inclined to source inputs from non-ETS countries prior to the ETS and are thus more strongly affected by input-related carbon taxes.

These results underscore the importance of considering the indirect impacts of policy through supply chain linkages and highlight the benefits of taking a granular approach to firms' choices. There are multiple margins through which firms can adapt to climate policy, making it essential to analyze these options comprehensively.

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# Supplemental Appendix

## A Data Construction and Summary Statistics

### A.1 Regulated and unregulated goods

In addition to the details provided in the main text, below are more precise explanations about the construction of the underlying firm-product level data set and how we delineate unregulated vs. regulated goods.

We begin with a time series-consistent list of products, harmonized over 1995-2020, using the $C^3$ algorithm detailed in Bergounhon, Lenoir and Mejean (2018). Starting from a list of 10,174 CN products in the French customs data, we end up with 7,051 harmonized product codes at this stage. We then use the HS 2002 to Bec Rev.4 conversion table provided by the UN to exclude capital goods (BEC categories 41 and 521).[40] In doing so, we focus on trade in intermediate inputs, the core of our analysis. This removes 784 harmonized product categories.

Then, as described in the main text, we tag as regulated those goods that are listed in the CBAM, or fall into ETS activities (Table A.2 and Table A.3). At this stage of the data construction, the mapping uses the definition of products at the 8-digit level of the CN nomenclature. We can however convert the list into the harmonized product nomenclature (HS) as CN products grouped into the same harmonized product category always fall into the same category of unregulated or regulated products.

Table A.4 provides statistics about the prevalence of regulated products, by HS chapter.[41] 1,464 products are classified as regulated using the combined list of ETS and CBAM products. The list covers some HS chapters entirely such as Mineral Fuels or Chemicals while being defined at a more granular level for products such as cement or fertilisers. See details in Tables A.2 and A.3.

### A.2 Defining regulated and unregulated sectors

In addition to categorizing goods as either regulated or unregulated, it is necessary to measure the intensity of regulated input usage of each sector for two reasons. First, the model-based quantitative analysis requires information on the sectoral composition of firms' input purchases. The administrative firm-level data set only has information on total intermediate usage, so we rely on the intensity of regulated inputs used by a firm's sector to proceed.

[40] See https://unstats.un.org/unsd/classifications/Econ.

[41] Any HS chapter that is not listed in Table A.4 is composed of unregulated products only.

Second, the empirical and quantitative analyses are restricted to a subset of regulated-intensive sectors, which we again define based on the share of regulated products in total input purchases.

We do so using an input-output (IO) table at the sector level. We begin by computing sectoral intensities in regulated and unregulated inputs using the 2011 INSEE IO table, which contains 138 NAF sectors.[42] We first establish a mapping between the NAF nomenclature and the list of ETS sectors to recover a list of regulated-*producing* sectors (see details in Table A.5, column (1) and (4)). For example, ETS activity 31 (manufacture of glass) maps to sector C23A (manufacture of glass and glass products). This procedure yields 14 regulated-producing NAF sectors, including 12 in manufacturing. We then use the IO table to categorize regulated-*intensive* input-user sectors as those manufacturing sectors relying on regulated-producing sectors for at least 10% of their intermediate consumption. This identifies 44 sectors that intensively use regulated inputs for final production (Table A.5, column (2) and (5)).

Lastly, to accurately compute CBAM tariffs and align with policy, it is essential to classify the sectors that produce CBAM goods. According to the list of CBAM goods in Table A.3, there are eight goods at the HS2 level, plus electricity, which is not included in the data set of tradable regulated inputs but is included when we compute the incidence of carbon taxes in our counterfactual exercises. Using our HS to NAF conversion table, we identify seven sectors involved in the production of these eight CBAM goods.[43] This classification is used for calculating the CBAM tariffs, and is depicted in columns (3) and (6) of Table A.5.

## A.3 Core and non-core inputs

The empirical analysis is restricted to a comparison of regulated and unregulated inputs, within a subset of the firm's *core* inputs. In concrete terms, we first use the IO table to identify the list of the most important upstream sectors for each downstream sector, using a 10% intermediate consumption threshold. Then, given a mapping between products and NAF sectors, we are able to identify the set of core inputs for each sector. We restrict our sample to imports of those core products. We restrict the sample this way in order to avoid using, as either a treated or control observation in our reduced-form regressions, a product that is a marginal input in the firm's production function. Indeed, when studying the extensive margin, we will balance the panel with 0's whenever a firm does not import

[42] NAF stands for Nomeclature Agrégée 2008, which is a French sector classification that can be linked to NACE rev.2 sectors. The earliest version for such a disaggregated level is 2011. This is the only instance where we depart from 2004, pre-ETS, as a calibration year.

[43] NAF sectors C20A, C24A, C24B, C25A, C25B, C25E, C27A. We only focus on sectors which produce HS goods which contain more than five cbam NC goods.

a given product. Restricting our sample to core products is hence necessary for practical reasons, but also to avoid marginal products that may pollute the estimation.[44] Table A.7 provides statistics on the number and import share of core products, by importing sector. Overall across manufacturing sectors, focusing on core inputs reduces the number of products from 50K to less than 9K while retaining 64% of the overall value of imports.

## A.4 Firm-level sourcing shares

We next move on to determining the overall mix of types of inputs at the firm level, broken down by origin country. To do so, we exploit three data sets. We first use 2004 (pre-ETS) information from the administrative firm-level balance sheet and income statement data set from INSEE-FICUS, which provides information on firms' total use of intermediate goods and production. We match these data with the detailed sector-level IO data set, which allows us to quantify the share of firm inputs that are either unregulated or regulated (Section A.2). We merge firm- and sector-level information together and assume that every firm mimics its sector's input mix between regulated and unregulated. We make this assumption as we only have information on the total value of intermediate goods used by firms and not the breakdown of this total into types of products. Then, using firm-level customs data and the list of regulated products from Section 2.1, the difference between intermediate consumption of each type of inputs and the corresponding input-specific value of imports is considered to be sourced domestically. This yields a 2004 data set that is used to calibrate the model, in which we have, at the firm level, the share of input purchases by input type and by origin country, including domestic products.

[44] For example, imagine that the data set indicates that a firm in the NAF sector for plastic products (C22B) imports cotton goods (HS classification starting with 52). Since cotton goods are not core products for firms in sector C22B, including them in the estimation and balancing the panel with zeros would significantly increase the number of null values in the data set. This would not only extend computing time but also potentially distort the estimation, as products classified under 52 are not central to the choice set of firms in C22B. For consistency reasons, we keep the same data set when estimating the intensive margin, this time using the share of imports rather than a dummy variable as the dependent variable.

**Table A.1.** Data sources and construction summary

| Dataset | Content | Use |
|---|---|---|
| EU ETS Transaction Log (EUTL) | List of ETS activities/sectors | Defines ETS coverage; mapped to HS/CN goods to tag *regulated* products (authors' mapping). |
| EU CBAM product list (Reg. (EU) 2023/956) | CN8 list of CBAM-covered goods | Complements ETS list to finalize regulated goods; basis for CBAM tariff set. |
| French customs firm-level imports | Firm×origin×product (CN), annual 2000–2019 | Builds firm-level sourcing by product and country; core input panel for reduced form; 2004 baseline shares for calibration. |
| INSEE Producer Price Indices (CPF-4) | Sectoral PPI | Documents higher relative prices for regulated vs. unregulated products. |
| INSEE Input-Output table (2011; 138 NAF) | Sectoral use of intermediates | (i) Identify regulated-*intensive* downstream sectors (10% rule); (ii) define *core inputs* per sector; (iii) impute regulated vs. unregulated input shares to firms. |
| INSEE-FICUS firm accounts (2004) | Firm intermediates and output | Scale firm input use in 2004 calibration; Calibrate $\sigma$ and $\kappa$ |
| WIOD 2016 (IO & emissions) | ISIC Rev. 4 sector×country $CO_2$ (2004); IO tables (2004) | Compute sector×country emission intensities; construct direct (€ /t) and indirect (Leontief) tax incidence; set $\alpha$ from manuf. share |
| UN HS2002 → BEC Rev. 4 conversion | Product → BEC categories | Exclude capital goods to focus on intermediate inputs before building firm panels. |
| World Bank Doing Business: Trading Across Borders (TAB) | Country score $[0, 100]$ | Covariate in gravity-style fixed cost for sourcing |
| Yale EPI: Climate Mitigation sub-index | Country score $[0, 100]$ | Additional covariate in fixed costs *for regulated inputs* only |

*Concordances (authors' construction):* (i) ETS activities → HS/CN; (ii) HS ↔ NAF; (iii) CN harmonization via C3 (per Bergounhon et al. 2018). Used to link policy coverage to products/sectors, define core inputs, and assemble firm-level sourcing shares.

**Table A.2.** Mapping of ETS-covered sectors to HS products

| **ETS sector** | | **HS products** | |
|---|---|---|---|
| Code | Description | Code | Description |
| 1 | Combustion install (thermal input > 20MW) | 27.16 | Electrical energy |
| 2 | Mineral oil refineries | 27.09-27-15,68.07 | Petroleum oils, gases, jelly, coke, bituminen, asphalt (articles thereof) |
| 3 | Coke ovens | 27.01-27.06 | Coal, Lignite, Peat, Coke, Coal Gas, Mineral Tars |
| 4 | Metal ore (including sulphide ore) roasting or sintering Install | 26 ex. 26.18-26.21 | Metal ores and concentrates |
| 5 | Install for the prod of pig iron or steel | 72 ex 72.04 | Iron and steel (ex waste) |
| 6 | Install for the prod of cement clinker or lime | 25.21-25.23 | Lime and cement |
| 7 | Install for the manuf of glass | 70.01-70.06 | Glass and glassware |
| 8 | Install for the manuf of ceramic products | 69 | Ceramic products |
| 9 | Industrial plants for the prod of pulp, paper and board | 47-48 ex 47.07 | Pulp of wood, Paper and paperboard (except waste) |
| 10 | Aircraft operator activities | | |
| 20 | Combustion of fuels | 27.16 | Electrical energy |
| 21 | Refining of mineral oil | 27.09-27.15 | Petroleum oils, gases, jelly, coke, bituminen and asphalt |
| 22 | Prod of coke | 27.04, 27.08, 27.13 | Coke of coal, lignite, petroleum |
| 23 | Metal ore roasting or sintering | 26 ex. 26.18-26.21 | Metal ores and concentrates |
| 24 | Prod of pig iron or steel | 72 ex. 72.04 | Iron and Steel (ex waste) |
| 25 | Prod or processing of ferrous metals | 73 | Articles of iron or steel |
| 26 | Prod of primary aluminium | 76 | Aluminium and articles thereof |
| 27 | Prod of secondary aluminium | 76 | Aluminium and articles thereof |
| 28 | Prod or processing of non-ferrous metals | 74-75,78-81 | Non-ferrous metals and articles thereof |
| 29 | Prod of cement clinker | 25.23 | Cement |
| 30 | Prod of lime, or calcination of dolomite/magnesite | 25.21-25.22, 25.18-25.19 | Lime, dolomite, magnesite |
| 31 | Manuf of glass | 70.01-70.06 | Glass and glassware |
| 32 | Manuf of ceramics | 69 | Ceramic products |
| 33 | Manuf of mineral wool | 68.06 | Slag wool, rock wool and similar mineral wools |
| 34 | Prod or processing of gypsum or plasterboard | 68.09 | Articles of plaster |
| 35 | Prod of pulp | 47 ex 47.07 | Pulp of wood (except waste) |
| 36 | Prod of paper or cardboard | 48 | Paper and paperboard |
| 37 | Prod of carbon black | 28.03 | Carbon blacks and other forms of carbon nes |
| 38 | Prod of nitric acid | 28.08 | Nitric and sulphonitric acids. |
| 39 | Prod of adipic acid | 29.1712 | Adipic acid |
| 40 | Prod of glyoxal and glyoxylic acid | 29.12, 29.18 | Aldehydes, Carboxylic acids |
| 41 | Prod of ammonia | 28.14 | Ammonia, anhydrous or in aqueous solution |
| 42 | Prod of bulk chemicals | 28-29 | Organic and inorganic chemicals |
| 43 | Prod of hydrogen and synthesis gas | 28.04 | Hydrogen, rare gases and other non-metals |
| 44 | Prod of soda ash and sodium bicarbonate | 28.3630 | Sodium hydrogencarbonate (sodium bicarbonate) |
| 45 | Capture of greenhouse gases under Directive 2009/31/EC | | |
| 46 | Transport of greenhouse gases under Directive 2009/31/EC | | |
| 47 | Storage of greenhouse gases under Directive 2009/31/EC | | |
| 99 | Other activity opted-in pursuant to Article 24 of Directive 2003/87/EC | | |

**Notes:** This table shows the mapping between the coverage of ETS and HS products. The list of ETS sectors is taken from the EUTL.

**Table A.3.** List of HS products covered by the CBAM

| Category | Code | Description |
|---|---|---|
| Cement | 25.07 | Other kaolinic clays |
| | 25.2310 | Cement clinkers |
| | 25.2321 | White Portland cement, whether or not artificially coloured |
| | 25.2329 | Other Portland cement |
| | 25.2330 | Aluminous cement |
| | 25.2390 | Other hydraulic cements |
| Electricity | 2716 | Electrical energy |
| Fertilisers | 28.08 | Nitric acid; sulphonitric acids |
| | 28.14 | Ammonia |
| | 28.3421 | Nitrates of potassium |
| | 31.02 | Mineral or chemical fertilisers, nitrogenous |
| | 31.05 | Mineral or chemical fertilisers, other |
| | ex. | Except |
| | 31.0560 | Mineral or chemical fertilisers containing phosphorus and potassium |
| Iron and steel | 72 | Iron and steel |
| | ex. | Except |
| | 72.0220 | Ferro-silicon |
| | 72.0230 | Ferro-silico-manganese |
| | 72.0250 | Ferro-silico-chromium |
| | 72.0270 | Ferro-molybdenum |
| | 72.0280 | Ferro-tungsten and ferro-silico-tungsten |
| | 72.0291 | Ferro-titanium and ferro-silico-titanium |
| | 72.0292 | Ferro-vanadium |
| | 72.0293 | Ferro-niobium |
| | 72.029910 | Ferro-phosphorus |
| | 72.029930 | Ferro-silico-magnesium |
| | 72.029980 | Other |
| | 72.04 | Ferrous waste and scrap; remelting scrap ingots and steel |
| Iron and steel | 26.0112 | Agglomerated iron ores and concentrates, other than roasted iron pyrites |
| | 73.01 | Sheet piling of iron or steel |
| | 73.02 | Railway or tramway track construction material of iron or steel |
| | 73.03 | Tubes, pipes and hollow profiles, of cast iron |
| | 73.04 | Tubes, pipes and hollow profiles, seamless, of iron (other than cast iron) or steel |
| | 73.05 | Other tubes and pipes, the external diameter of which exceeds 406,4 mm, of iron or steel |
| | 73.06 | Other tubes, pipes and hollow profiles of iron or steel |
| | 73.07 | Tube or pipe fittings of iron or steel |
| | 73.08 | Structures and parts of structures of iron or steel |
| | 73.09 | Reservoirs, tanks, vats and similar containers of iron or steel, of a capacity exceeding 300 l |
| | 73.10 | Tanks, casks, drums, cans, boxes and similar containers of iron or steel, of a capacity not exceeding 300 l |
| | 73.11 | Containers for compressed or liquefied gas, of iron or steel |
| | 73.18 | Screws, bolts, nuts, and similar articles, of iron or steel |
| | 73.26 | Other articles of iron or steel |
| Aluminium | 76.01 | Unwrought aluminium |
| | 76.03 | Aluminium powders and flakes |
| | 76.04 | Aluminium bars, rods and profiles |
| | 76.05 | Aluminium wire |
| | 76.06 | Aluminium plates, sheets and strip, of a thickness exceeding 0,2 mm |
| | 76.07 | Aluminium foil not exceeding 0,2 mm |
| | 76.08 | Aluminium tubes and pipes |
| | 76.09 | Aluminium tube or pipe fittings |
| | 76.10 | Aluminium structures and parts of structures; aluminium plates, rods, profiles, tubes and the like |
| | 76.11 | Aluminium reservoirs, tanks, vats and similar containers, of a capacity exceeding 300 litres |
| | 76.12 | Aluminium casks, drums, cans, boxes and similar containers, of a capacity not exceeding 300 litres |
| | 76.13 | Aluminium containers for compressed or liquefied gas |
| | 76.14 | Stranded wire, cables, plaited bands and the like, of aluminium |
| | 76.16 | Other articles of aluminium |
| Chemicals | 28.0410 | Hydrogen |

**Notes:** This table reproduces the list of HS products listed in Regulation (EU) 2023/956 of the European Parliament and of the Council of 10 May 2023 establishing a carbon border adjustment mechanism.

**Table A.4.** Statistics on the prevalence of regulated products, by HS chapter

| | | ETS products | | CBAM products | | ETS+CBAM products | |
|---|---|---|---|---|---|---|---|
| Code | Description | Count | Value Share | Count | Value Share | Count | Value Share |
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| 25 | Salt, sulphur, lime & cement | 20 | .37 | 7 | .25 | 21 | .37 |
| 26 | Ores, slag & ash | 26 | .71 | 1 | .11 | 26 | .71 |
| 27 | Mineral Fuels | 109 | 1 | 1 | .00 | 109 | 1 |
| 28 | Inorganic chemicals | 219 | 1 | 5 | .09 | 219 | 1 |
| 29 | Organic chemicals | 435 | 1 | 0 | 0 | 435 | 1 |
| 31 | Fertilisers | 0 | 0 | 24 | .71 | 24 | .71 |
| 38 | Misc Chemical products | 1 | .03 | 0 | 0 | 1 | .03 |
| 47 | Pulp of wood | 17 | .91 | 0 | 0 | 17 | .91 |
| 48 | Paper | 61 | 1 | 0 | 0 | 61 | 1 |
| 68 | Articles of stone, cement | 7 | .10 | 0 | 0 | 7 | .10 |
| 69 | Ceramic products | 49 | 1 | 0 | 0 | 49 | 1 |
| 70 | Glass and glassware | 131 | 1 | 0 | 0 | 131 | 1 |
| 72 | Iron & steel | 321 | .98 | 308 | .97 | 321 | .98 |
| 73 | Articles of iron & steel | 249 | 1 | 157 | .74 | 249 | 1 |
| 74 | Copper | 65 | 1 | 0 | 0 | 65 | 1 |
| 75 | Nickel | 17 | 1 | 0 | 0 | 17 | 1 |
| 76 | Aluminium | 56 | 1 | 49 | .94 | 56 | 1 |
| 78 | Lead | 11 | 1 | 0 | 0 | 11 | 1 |
| 79 | Zinc | 11 | 1 | 0 | 0 | 11 | 1 |
| 80 | Tin | 8 | 1 | 0 | 0 | 8 | 1 |
| 81 | Other base metals | 69 | 1 | 0 | 0 | 69 | 1 |
| All | | 1444 | .30 | 421 | .07 | 1464 | .31 |

**Notes:** This table shows the number of regulated products and their contribution to the value of French imports, by HS chapter. Columns (1)-(2) considers regulated products that are covered by ETS rules. Columns (3)-(4) is based on the list of CBAM products. Column (5)-(6) is the intersection of both lists.

**Table A.5.** List of regulated and regulated-intensive NAF sectors

| Code | Description | ETS (1) | R-I (2) | CBAM (3) | Code | Description | ETS (4) | R-I (5) | CBAM (6) |
|---|---|---|---|---|---|---|---|---|---|
| C10A | Meat products | 0 | 0 | 0 | C25B | Tanks, reservoir, containers of metal | 1 | 1 | 1 |
| C10B | Fish, crustaceans and molluscs | 0 | 0 | 0 | C25C | Weapons and ammunition | 0 | 0 | 0 |
| C10C | Fruit and vegetables | 0 | 0 | 0 | C25D | Forging of metal; powder metallurgy | 1 | 1 | 0 |
| C10D | Vegetable and animal oils and fats | 0 | 0 | 0 | C25E | Cutlery, tools, general hardware | 0 | 1 | 1 |
| C10E | Dairy products | 0 | 0 | 0 | C26A | Electronic components | 0 | 1 | 0 |
| C10F | Grain mill prods, and starch products | 0 | 0 | 0 | C26B | Computers | 0 | 1 | 0 |
| C10G | Bakery and farinaceous products | 0 | 0 | 0 | C26C | Communication equipment | 0 | 1 | 0 |
| C10H | Other food products | 0 | 0 | 0 | C26D | Consumer electronics | 0 | 0 | 0 |
| C10K | Prepared animal feeds | 0 | 0 | 0 | C26E | Instr. for measuring, testing, navigation | 0 | 1 | 0 |
| C11Z | Beverages | 0 | 1 | 0 | C26F | Electromedical equipment | 0 | 1 | 0 |
| C12Z | Tobacco products | 0 | 0 | 0 | C26G | Optical instruments | 0 | 1 | 0 |
| C13Z | Textile products | 0 | 0 | 0 | C27A | Domestic appliances | 0 | 1 | 1 |
| C14Z | Wearing apparel | 0 | 1 | 0 | C27B | Other electric equipment | 0 | 1 | 0 |
| C15Z | Leather products | 0 | 1 | 0 | C28A | General-purpose machinery | 0 | 1 | 0 |
| C16Z | Wood products | 0 | 0 | 0 | C28B | Agricultural and forestry machinery | 0 | 1 | 0 |
| C17A | Pulp, paper and paperboard | 1 | 1 | 0 | C28C | Metal forming machinery | 0 | 1 | 0 |
| C17B | Articles of paper | 1 | 1 | 0 | C28D | Other special-purpose machinery | 0 | 1 | 0 |
| C18Z | Printing & reprod. of recorded media | 0 | 1 | 0 | C29A | Motor vehicles | 0 | 1 | 0 |
| C19Z | Coke and refined petroleum | 1 | 1 | 0 | C29B | Parts & accessories for motor vehicles | 0 | 1 | 0 |
| C20A | Basic chem., fert., plas. and syn. rubber | 1 | 1 | 1 | C30A | Ships and boats | 0 | 1 | 0 |
| C20B | Soap and detergents | 0 | 1 | 0 | C30B | Railway locomotives | 0 | 1 | 0 |
| C20C | Other chemical products | 0 | 1 | 0 | C30C | Air and spacecraft | 0 | 0 | 0 |
| C21Z | Pharmaceutical products | 0 | 1 | 0 | C30D | Military fighting vehicles | 0 | 0 | 0 |
| C22A | Rubber products | 0 | 1 | 0 | C30E | Other transport equipment | 0 | 1 | 0 |
| C22B | Plastics products | 0 | 1 | 0 | C31Z | Furniture | 0 | 1 | 0 |
| C23A | Glass products | 1 | 1 | 0 | C32A | Jewellery | 0 | 1 | 0 |
| C23B | Other mineral products | 1 | 1 | 0 | C32B | Medical and dental instruments | 0 | 1 | 0 |
| C24A | Basic iron and steel | 1 | 1 | 1 | C32C | Other manufacturing | 0 | 1 | 0 |
| C24B | Basic precious & other non-ferr. metals | 1 | 1 | 1 | C33Z | Repair and installation | 0 | 1 | 0 |
| C24C | Casting of metals | 1 | 1 | 0 | D35A | Electricity, gas, steam, air con. supply | 1 |  | 0 |
| C25A | Structural metal products | 1 | 1 | 1 | D35B | Manufacture & distribution of gas | 1 |  | 0 |

**Notes:** The table summarizes, for each NAF sector, whether a sector is covered by ETS regulations (columns (1) and (4)), whether it is included in the subset of regulated-intensive ('R-I') manufacturing sectors (columns (2) and (5)), and whether it is covered by CBAM (columns (3) and (6)). Sectors D35A and D35B are not in manufacturing and are thus considered within the list of regulated-producing sectors but not in the set of regulated-intensive manufacturing sectors.

**Table A.6.** List of regulated and regulated-intensive ISIC rev.4 sectors

| Code | Description | ETS (1) | CBAM (2) | Code | Description | ETS (3) | CBAM (4) |
|---|---|---|---|---|---|---|---|
| A01 | Crop, animal production | 0 | 0 | G46 | Wholesale trade | 0 | 0 |
| A02 | Forestry and logging | 0 | 0 | G47 | Retail trade | 0 | 0 |
| A03 | Fishing, aquaculture | 0 | 0 | H49 | Land transport | 0 | 0 |
| B | Mining and quarrying | 0 | 0 | H50 | Water transport | 0 | 0 |
| C10-C12 | Food, beverage, tobacco | 0 | 0 | H51 | Air transport | 0 | 0 |
| C13-C15 | Textiles, apparel | 0 | 0 | H52 | Warehousing, support | 0 | 0 |
| C16 | Wood, cork products | 0 | 0 | H53 | Postal, courier | 0 | 0 |
| C17 | Paper products | 1 | 0 | I | Accommodation, food | 0 | 0 |
| C18 | Printing, media reproduction | 0 | 0 | J58 | Publishing | 0 | 0 |
| C19 | Coke, refined petroleum | 1 | 0 | J59-J60 | Media production, broadcasting | 0 | 0 |
| C20 | Chemicals | 1 | 1 | J61 | Telecommunications | 0 | 0 |
| C21 | Pharmaceuticals | 0 | 0 | J62-J63 | IT services, consultancy | 0 | 0 |
| C22 | Rubber, plastic products | 0 | 0 | K64 | Financial services | 0 | 0 |
| C23 | Non-metallic minerals | 1 | 0 | K65 | Insurance, pensions | 0 | 0 |
| C24 | Basic metals | 1 | 1 | K66 | Financial auxiliaries | 0 | 0 |
| C25 | Fabricated metal products | 1 | 1 | L68 | Real estate | 0 | 0 |
| C26 | Computer, electronic goods | 0 | 0 | M69-M70 | Legal, accounting | 0 | 0 |
| C27 | Electrical equipment | 0 | 1 | M71 | Engineering, testing | 0 | 0 |
| C28 | Machinery and equipment | 0 | 0 | M72 | R&D | 0 | 0 |
| C29 | Motor vehicles | 0 | 0 | M73 | Advertising, market research | 0 | 0 |
| C30 | Transport equipment | 0 | 0 | M74-M75 | Professional, vet services | 0 | 0 |
| C31-C32 | Furniture, other mfg | 0 | 0 | N | Administrative support | 0 | 0 |
| C33 | Machinery repair | 0 | 0 | O84 | Public administration | 0 | 0 |
| D35 | Electricity, gas supply | 1 | 0 | P85 | Education | 0 | 0 |
| E36 | Water treatment | 0 | 0 | Q | Health and social work | 0 | 0 |
| E37-E39 | Waste management | 0 | 0 | R_S | Other services | 0 | 0 |
| F | Construction | 0 | 0 | T | Household activities | 0 | 0 |
| G45 | Vehicle trade/repair | 0 | 0 | U | Extraterritorial bodies | 0 | 0 |

**Notes:** The table summarizes, for each ISIC sector, whether a sector is covered by ETS regulations (columns (1) and (3)) and whether it is covered by CBAM (columns (2) and (4)). The table is based on a converting Table A.5 into ISIC rev.4 sectors in order to use WIOD tables.

**Table A.7.** Statistics on core and non-core inputs, by NAF sector

| Code | Description | # Imported products (1) | # Imported core products (2) | Import share core products (3) |
|---|---|---|---|---|
| C11Z | Beverages | 940 | 109 | .36 |
| C14Z | Wearing apparel | 1,853 | 933 | .91 |
| C15Z | Leather products | 1,306 | 177 | .71 |
| C17A | Pulp, paper and paperboard | 769 | 100 | .65 |
| C17B | Articles of paper | 1,297 | 232 | .56 |
| C18Z | Printing and reproduction of recorded media | 984 | 185 | .67 |
| C19Z | Coke and refined petroleum | 484 | 29 | .98 |
| C20A | basic chemicals, fertilisers, plastics and synthetic rubber | 1,738 | 493 | .63 |
| C20B | Soap and detergents | 1,596 | 407 | .68 |
| C20C | Other chemical products | 2,079 | 544 | .54 |
| C21Z | Pharmaceutical products | 1,443 | 454 | .79 |
| C22A | Rubber products | 1,145 | 219 | .74 |
| C22B | Plastics products | 2,049 | 252 | .39 |
| C23A | Glass products | 1,085 | 183 | .65 |
| C23B | Other mineral products | 1,598 | 166 | .52 |
| C24A | Basic iron and steel | 1,272 | 288 | .70 |
| C24B | Basic precious and other non-ferrous metals | 880 | 154 | .77 |
| C24C | Casting of metals | 805 | 184 | .39 |
| C25A | Structural metal products | 955 | 292 | .68 |
| C25B | Tanks, reservoirs and containers of metal | 421 | 80 | .14 |
| C25D | Forging of metal; powder metallurgy | 1,628 | 554 | .65 |
| C25E | Cutlery, tools and general hardware | 1,801 | 526 | .79 |
| C26A | Electronic components | 1,280 | 99 | .04 |
| C26B | Computers | 240 | 12 | .10 |
| C26C | Communication equipment | 396 | 72 | .18 |
| C26E | Instruments for measuring, testing and navigation | 1,125 | 34 | .07 |
| C26G | Optical instruments | 236 | 29 | .24 |
| C27A | Domestic appliances | 708 | 86 | .70 |
| C27B | Other electric equipment | 1,547 | 261 | .33 |
| C28A | General-purpose machinery | 1,789 | 16 | .03 |
| C28B | Agricultural and forestry machinery | 795 | 136 | .05 |
| C28C | Metal forming machinery | 499 | 132 | .25 |
| C28D | Other special-purpose machinery | 1,219 | 315 | .10 |
| C29A | Motor vehicles | 1,139 | 57 | .85 |
| C29B | Parts and accessories for motor vehicles | 1,365 | 61 | .01 |
| C30A | Ships and boats | 695 | 13 | .21 |
| C30B | Railway locomotives | 338 | 12 | .51 |
| C30E | Other transport equipment | 576 | 36 | .29 |
| C31Z | Furniture | 1,434 | 327 | .15 |
| C32A | Jewellery | 695 | 80 | .77 |
| C32B | Medical and dental instruments | 1,237 | 131 | .23 |
| C32C | Other manufacturing | 2,046 | 138 | .33 |
| C33Z | Repair and installation | 2,665 | 277 | .12 |
| | All dirty-intensive manufacturing sectors | 50,363 | 8,885 | .64 |

**Notes:** The table lists, for each manufacturing sector in the estimation sample: (1) the number of distinct products imported by French firms, (2) the number of distinct products that belong to the subset of "core" upstream industries, (3) their share in overall imports.

**Table A.8.** Summary statistics on the population of firms

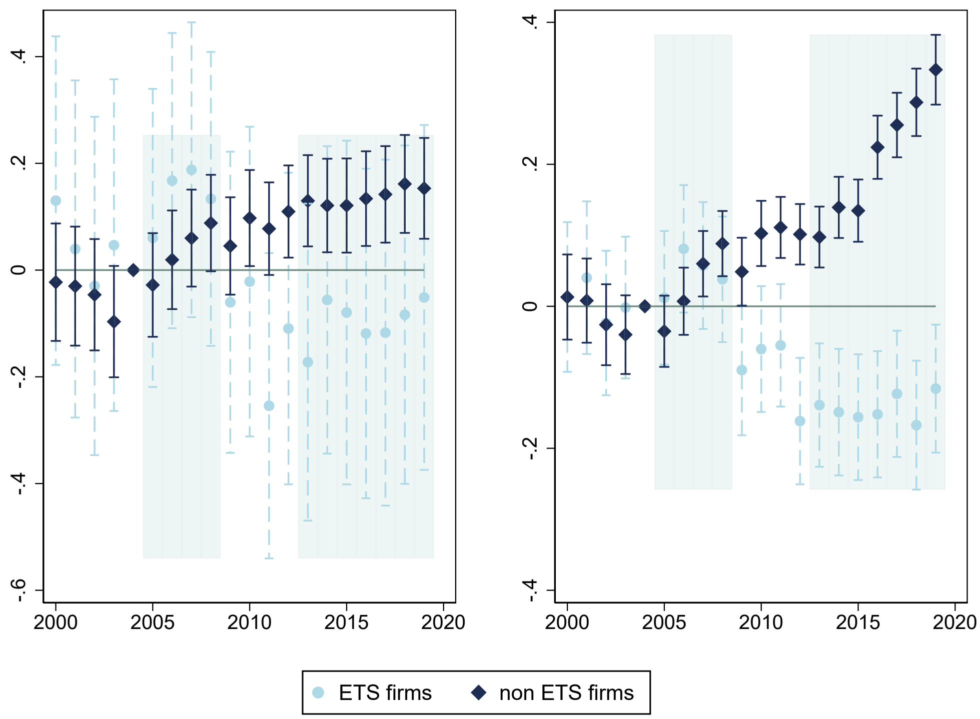
| Variable | Count | Average | Median | Std Dev | Min | Max |
|---|---|---|---|---|---|---|
| Total sales | 62,525 | 8,171 | 954 | 68,528 | 0 | 5,252,972 |
| Input purchases | 62,525 | 5,811 | 530 | 52,633 | 1 | 4,579,392 |
| - (Share of Regulated) | 62,525 | .314 | .291 | .147 | .100 | .626 |
| Probability of ETS coverage | 62,525 | .004 | 0 | .065 | 0 | 1 |
| Value of imports | 62,525 | 1,024 | 0 | 12,263 | 0 | 1,150,147 |
| - (Conditional on importing) | 62,525 | 3,385 | 252 | 22,110 | .013 | 1,150,147 |
| - (Regulated) | 62,525 | 281 | 0 | 5,258 | 0 | 744,381 |
| - (Unregulated) | 62,525 | 743 | 0 | 10,157 | 0 | 1,005,841 |
| Import probability | 62,525 | .303 | 0 | .459 | 0 | 1 |
| - (Regulated) | 62,525 | .193 | 0 | .395 | 0 | 1 |
| - (Unregulated) | 62,525 | .279 | 0 | .448 | 0 | 1 |
| - (Regulated, ETS) | 62,525 | .180 | 0 | .385 | 0 | 1 |
| - (Unregulated, ETS) | 62,525 | .237 | 0 | .425 | 0 | 1 |
| - (Regulated, Non-ETS) | 62,525 | .117 | 0 | .322 | 0 | 1 |
| - (Unregulated, Non-ETS) | 62,525 | .174 | 0 | .379 | 0 | 1 |
| # Import Sources (Conditional on imports) | 18,929 | 5.4 | 4 | 5.1 | 1 | 69 |
| - (Regulated) | 18,929 | 3.3 | 2 | 3.1 | 1 | 36 |
| - (Regulated, ETS) | 18,929 | 2.6 | 2 | 2.3 | 0 | 19 |
| - (Regulated, Non-ETS) | 18,929 | 0.7 | 0 | 1.3 | 0 | 18 |
| - (Unregulated) | 18,929 | 5.0 | 4 | 4.8 | 1 | 68 |
| - (Unregulated, ETS) | 18,929 | 3.4 | 3 | 3.0 | 0 | 23 |
| - (Unregulated, non-ETS) | 18,929 | 1.6 | 1 | 2.6 | 0 | 45 |
| Share of imports in input purchases | 18,929 | .162 | .104 | .169 | .000 | .914 |
| - (Regulated) | 18,929 | .034 | 0 | .121 | 0 | .999 |
| - (Regulated, ETS) | 18,929 | .052 | 0 | .144 | 0 | .999 |

**Notes:** INSEE-Ficus is used to source DGDDI-Intra-EU and extra-EU import flows from 2004. ETS coverage is calculated using EUTL data on French firms that are covered by ETS regulations. All nominal variables are in thousands of euros.

# B Robustness tests on the motivating facts

In this section, we conduct additional robustness tests vis-à-vis the motivating evidence in Section 3.2. As discussed in the main text, Figure B.1 presents our baseline estimations splitting the sample for ETS-regulated versus non-regulated firms, and Figure B.2 presents estimation results based on firm-level imports of regulated inputs for non-ETS vs. ETS origin countries, where we do not control for the change in import status in 2011.

**Figure B.1.** Evolution of firm-level imports from non-ETS countries: regulated vs. unregulated inputs. ETS-regulated versus non-regulated firms

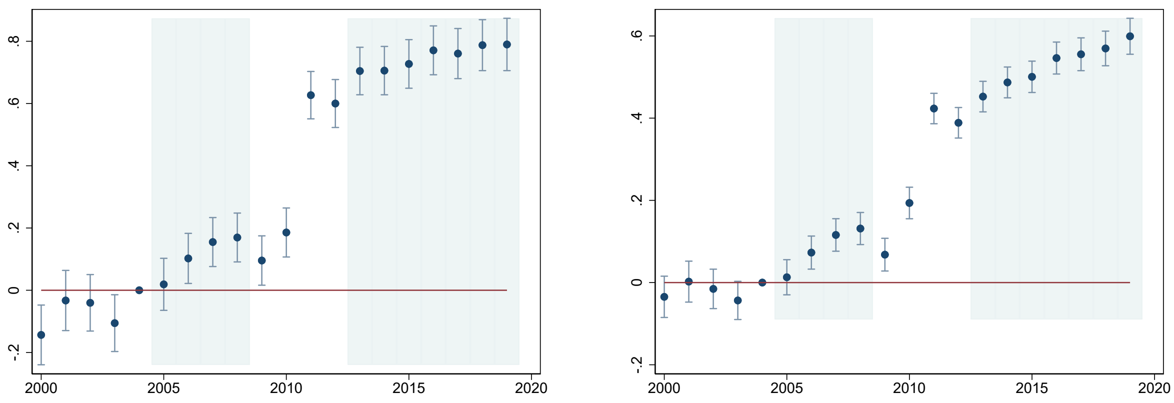



**Notes:** This figure shows the point estimates recovered from the estimation of equation (1), using 2005 as the first "treatment" date. The sample of firms is further divided into ETS regulated and not ETS regulated firms. The treatment group is composed of import flows on regulated inputs sourced in non-ETS countries. The control group covers unregulated inputs imports from non-ETS countries. The equation controls for product×country and year fixed effects. Standard errors are clustered in the product×country×year dimension. The confidence intervals are defined at the 95% level. The blue areas correspond to Phases 1 and 3 of ETS.

In Figure B.3, we test the robustness of the results to heterogeneous treatment effects using the estimator proposed by de Chaisemartin and D'Haultfœuille (2020). Their estimator works for linear models and the point estimates are thus expressed in log points. However, the qualitative results are very similar to the baseline results in Figure 3.

We next check that the average treatment effect discussed in the main text is not driven

**Figure B.2.** Evolution of firm-level imports of regulated inputs, non-ETS vs. ETS origin countries

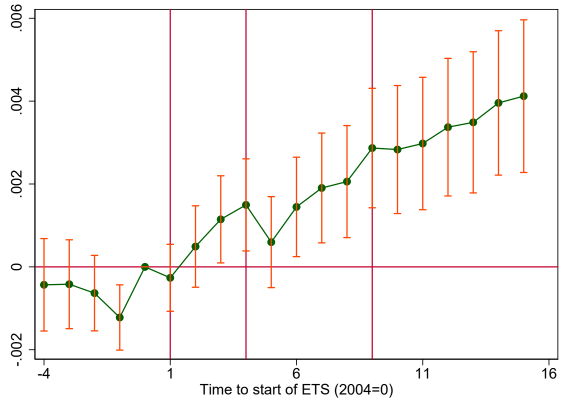



**(a)** Import share **(b)** Import probability

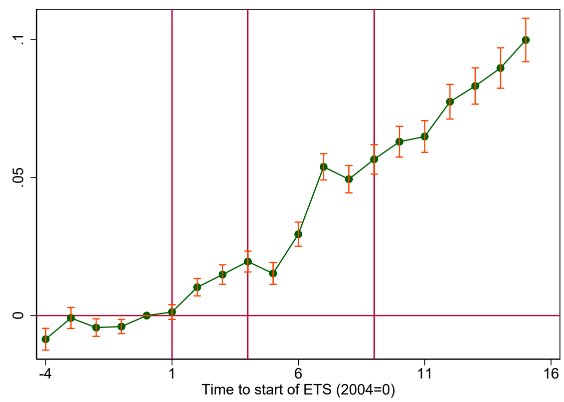
**Notes:** This figure shows the point estimates recovered from the estimation of equation (1), using 2005 as the first "treatment" date. The treatment group is composed of imports flows on regulated inputs sourced in non-ETS countries, with sourcing of regulated inputs from ETS countries taken as control. The equation controls for product×country and year fixed effects. Standard errors are clustered in the product×country×year dimension. The confidence intervals are defined at the 95% level. The blue areas correspond to Phases 1 and 3 of ETS. The discontinuity in 2011 corresponds to the year of the change in the declaration threshold for intra-EU imports.

by any specific source country, as would be the case if the estimation was suffering from omitted variable bias on some country-specific trends. Figure B.4 thus reproduces the estimation in Column (1) of Table 1 on twenty five different sub-samples, each neglecting one possible source country. The coefficients in Figure B.4 are estimated using data for the Phase 3 period of ETS. All coefficients but three are within the confidence interval of the baseline regressions. Overall, our results do not seem to be driven by some obvious omitted variable. Switzerland appears to push the estimated coefficient down in the regression using the share of regulated inputs in imports as regressor. One possible reason is that Switzerland also has a cap-and-trade system, which has converged over time to the European one. Keeping Switzerland in the treatment group is thus conservative. When the variable of interest is the probability of import, two countries are standing apart, namely Morocco and Tunisia. In both cases, removing the country from the estimation sample pushes the estimated coefficients towards zero, thus suggesting that these countries are significant drivers of the carbon leakage phenomenon under study. Given the geographical proximity of these countries, and possible comparative advantages in the production of regulated products, it is not necessarily surprising that these countries stand apart. Note that the estimated coefficient remains positive and significant in both robustness tests, thus suggesting that carbon leakage goes

**Figure B.3.** Evolution of firm-level imports from non-ETS countries: regulated vs. unregulated inputs. Robustness to heterogeneous treatment effects




**(a)** Import share




**(b)** Import probability

**Notes:** This figure shows the point estimates recovered from the estimation of a log-linear version of equation (1), using 2005 as the first "treatment" date (1). The model controls for heterogeneous treatment effects using the estimator in de Chaisemartin and D'Haultfœuille (2020). The underlying equation controls for product×country and year fixed effects. Standard errors are clustered in the product×country×year dimension. The confidence intervals are defined at the 95% level. The vertical bars correspond to the different phases of ETS.

beyond and above the diversion of trade towards any of these single countries.

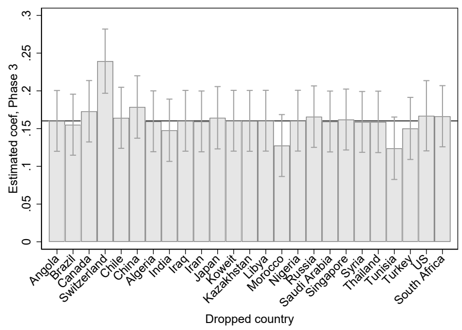
Finally, we investigate the role of multinational firms in driving the results in Section 3.2. To this aim, we merge the estimation sample with data from *LiFi* (INSEE-*Liaisons Financières* survey). Based on these data, we can identify firms that had foreign affiliates in any of the countries included in the estimation sample, prior to the implementation of ETS ($\mathbb{1}(c \notin MNE_f)$ in equation (B.1)).[45] The statistical model is modified to allow for the effect of the treatment to be different between firms with and without ex-ante multinational linkages in the potential source country: [JDG: Drop exp[]?] [IM: not sure. We don't use a linear model]

$$\begin{aligned} y_{fpit} \;=\; \exp\Bigg[ & \sum_{\tau=-4}^{15} \beta_\tau^{MNE} \mathbb{1}(i \notin ETS)\, \mathbb{1}(p \in regulated)\, \mathbb{1}(c \in MNE_f) \\ & + \sum_{\tau=-4}^{15} \beta_\tau^{NotMNE} \mathbb{1}(i \notin ETS)\, \mathbb{1}(p \in regulated)\, \mathbb{1}(c \notin MNE_f) \\ & + \mathbf{X'}_{fpit}\boldsymbol{\theta} + \varepsilon_{fpit} \Bigg], \end{aligned} \tag{B.1}$$

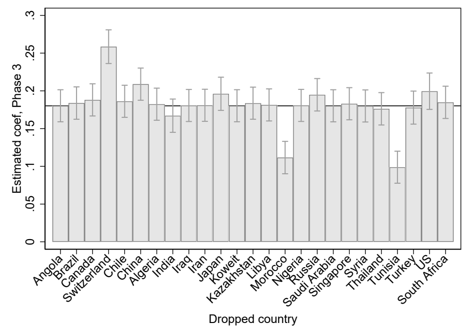
[45] Specifically, we use all multinational linkages identified in the data until 2011. The reason why we do not stop in 2004 is because the coverage of the survey has increased substantially after 2010, thus providing us with a more exhaustive view of multinational linkages.

**Figure B.4.** Difference-in-difference coefficient: regulated vs. unregulated inputs from non-ETS countries. Robustness to the country sample

(a) Import share



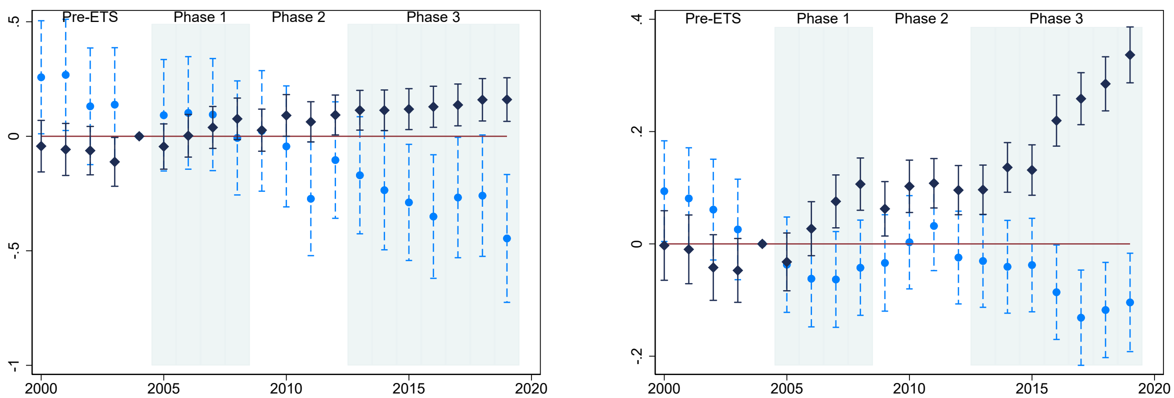

(b) Import probability




**Notes:** This figure shows the coefficient estimated on treated products over Phase 3 of ETS using imports of clean inputs sourced from non-ETS countries as control. The equation controls for product×country and year fixed effects. The estimation is reproduced 25 times removing one sourcing country after the other. The horizontal line is the baseline in the full sample.

Results are reproduced in Figure B.5. The baseline positive trend is still significant among firms that do not have foreign affiliates in the source country. If any, the impact of the treatment goes in the opposite direction for firms that have affiliates in the source country (light blue circles). This effect should however be interpreted cautiously because i) the identification of foreign affiliates is not exhaustive during the estimation period, ii) the data seem to suggest a pre-trend in this sub-sample and iii) the number of firms in our estimation sample that have foreign affiliates in the source country is limited, thus the wide confidence intervals on the corresponding coefficients.

**Figure B.5.** Evolution of firm-level imports from non-ETS countries: regulated vs. unregulated inputs. Controlling for MNE linkages




**(a)** Import share **(b)** Import probability

**Notes:** This figure shows the point estimates recovered from the estimation of equation (B.1), using 2005 as the first "treatment" date. The dark blue diamonds correspond to non-MNE firms and the light blue circles are estimated on firms with a foreign affiliate in the destination. The treatment group is composed of import flows on regulated inputs sourced in non-ETS countries. The control group covers unregulated inputs imports from non-ETS countries. The equation controls for product×country and year fixed effects. Standard errors are clustered in the product×country×year dimension. The confidence intervals are defined at the 95% level. The blue areas correspond to Phases 1 and 3 of ETS.

# C Model details

## C.1 Solving the model with the algorithm

This section derives the parameter conditions under which the types of algorithm described in Jia (2008) and Arkolakis et al. (2023) help us solve our model. We then lay out a new algorithm designed for cases in which only a mixture of the Arkolakis et al. (2023) conditions is met.

### C.1.1 Definitions

It is useful to first define the following objects. Denote by $I = \{I^U, I^R\}$ the finite discrete set of sourcing *options* for the firm, with $I^t$ being the set of countries available to source input $t$ from. Then, define the power set $\mathscr{P}(I) = \{\mathcal{I} \mid \mathcal{I} \subseteq I\}$ as the collection of all possible subsets of $I$. Hence, one can see $I$ as the choice set of the firm, $\mathcal{I}$ as the sourcing strategy set and $\mathscr{P}(I)$ as the sourcing strategy space. We denote by $\mathcal{I}^t(\omega)$ the set of countries for which firm $\omega$ has paid the associated fixed cost of offshoring type $t$ inputs, $\left\{wf_{ij}^t\right\}_{j\in\mathcal{I}^t(\omega)}$. In other words, $\mathcal{I}(\omega) = \left\{\mathcal{I}^U(\omega), \mathcal{I}^R(\omega)\right\} \in \mathscr{P}(I)$ is firm $\omega$'s sourcing strategy set. Then, define the following concepts in our context.

**Definition 1 (Single Cross Differences in Choices (SCD-C) from below)** *Take the firm's profit function (8):*

$$\pi_i(\omega; \mathcal{I}^R(\omega), \mathcal{I}^U(\omega)) = \left(\frac{c(\omega; \mathcal{I}(\omega))}{\omega}\right)^{1-\sigma} B_i - w_i \sum_{j\in\mathcal{I}^R(\omega)} f_{ij}^R - w_i \sum_{j\in\mathcal{I}^U(\omega)} f_{ij}^U.$$

*The profit function is said to obey SCD-C from below when an element $j$ that has positive marginal value for some sourcing strategy set $\mathcal{I}_1(\omega)$ retains a positive marginal value as additional elements are added. That is, if for all elements $j \in I^t$ and sourcing strategies $\mathcal{I}_1(\omega) \subset \mathcal{I}_2(\omega) \in \mathscr{P}(I)$,*

$$\pi_i\left(\omega; \mathcal{I}_1(\omega) \cup j\right) - \pi_i\left(\omega; \mathcal{I}_1(\omega) \setminus j\right) \geq 0 \quad \Rightarrow \pi_i\left(\omega; \mathcal{I}_2(\omega) \cup j\right) - \pi_i\left(\omega; \mathcal{I}_2(\omega) \setminus j\right) \geq 0.$$

**Definition 2 (Single Cross Differences in Choices (SCD-C) from above)** *The profit function is said to obey SCD-C from above when an element $j$ that has positive marginal value for some sourcing strategy set $\mathcal{I}_1(\omega)$ retains a positive marginal value as additional elements are removed. That is, if for all elements $j \in I^t$ and sourcing strategies $\mathcal{I}_1(\omega) \subset \mathcal{I}_2(\omega) \in \mathscr{P}(I)$,*

$$\pi_i\left(\omega; \mathcal{I}_2(\omega) \cup j\right) - \pi_i\left(\omega; \mathcal{I}_2(\omega) \setminus j\right) \geq 0 \quad \Rightarrow \pi_i\left(\omega; \mathcal{I}_1(\omega) \cup j\right) - \pi_i\left(\omega; \mathcal{I}_1(\omega) \setminus j\right) \geq 0.$$

### C.1.2 Conditions for SCD-C to hold

The notions of supermodularity and submodularity are sufficient conditions for SCD-C from below and from above to hold. While SCD-C only requires that the marginal profit of adding any option $j$ crosses zero at most once as the sourcing set expands or contracts, super- and submodularity impose monotonicity of all such marginal profits with respect to the initial set. Specifically, for any $\mathcal{I}_1 \subseteq \mathcal{I}_2$ and $j$,

$$\text{supermodularity:} \quad \pi(\mathcal{I}_1 \cup j) - \pi(\mathcal{I}_1 \setminus j) \ \leq \ \pi(\mathcal{I}_2 \cup j) - \pi(\mathcal{I}_2 \setminus j),$$

$$\text{submodularity:} \quad \pi(\mathcal{I}_1 \cup j) - \pi(\mathcal{I}_1 \setminus j) \ \geq \ \pi(\mathcal{I}_2 \cup j) - \pi(\mathcal{I}_2 \setminus j).$$

Hence, supermodularity is sufficient for SCD-C from below and submodularity is sufficient for SCD-C from above.[46]

In our two-input setting, we distinguish:

- Same-input supermodularity in $U$. For any $\mathcal{I}_1^U \subseteq \mathcal{I}_2^U$, fixed $\mathcal{I}^R$, and any $j_U \in I^U$,

$$\pi(\{\mathcal{I}^R, \mathcal{I}_1^U \cup j_U\}) - \pi(\{\mathcal{I}^R, \mathcal{I}_1^U \setminus j_U\}) \ \leq \ \pi(\{\mathcal{I}^R, \mathcal{I}_2^U \cup j_U\}) - \pi(\{\mathcal{I}^R, \mathcal{I}_2^U \setminus j_U\}).$$

- Same-input submodularity in $U$, which reverses the inequality.

The analogous two statements hold for $R$ with $j_R \in I^R$.

- Cross-input supermodularity for $U$ w.r.t. $R$. For any $\mathcal{I}_1^R \subseteq \mathcal{I}_2^R$, fixed $\mathcal{I}^U$, and any $j_U \in I^U$,

$$\pi(\{\mathcal{I}_1^R, \mathcal{I}^U \cup j_U\}) - \pi(\{\mathcal{I}_1^R, \mathcal{I}^U \setminus j_U\}) \ \leq \ \pi(\{\mathcal{I}_2^R, \mathcal{I}^U \cup j_U\}) - \pi(\{\mathcal{I}_2^R, \mathcal{I}^U \setminus j_U\}).$$

- Cross-input submodularity for $U$ w.r.t. $R$ reverses the inequality.

The analogous two statements hold for $R$ w.r.t. $U$ with $j_R \in I^R$.

Hence, same- or cross-input supermodularity is sufficient for SCD-C from below in the corresponding dimension, and the submodular versions are sufficient for SCD-C from above.

We next derive the conditions for sub/supermodularity to hold.

[46] We refer the reader to figure 1 in Arkolakis et al. (2023) for a visual representation of the difference between SCD-C and modularities.

**Sub/supermodularity of the profit function.** The profit function can be written as:

$$\pi_i(\omega;\mathcal{I}(\omega)) = \omega^{\sigma-1}\left[\mathcal{A}\left(\gamma^R\Theta_i^R(\omega;\mathcal{I}^R(\omega))\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U\Theta_i^U(\omega;\mathcal{I}^U(\omega))\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{1-\sigma}{1-\eta}} B_i$$
$$- w_i \sum_{j\in\mathcal{I}^R(\omega)} f_{ij}^R - w_i \sum_{j\in\mathcal{I}^U(\omega)} f_{ij}^U,$$

where

$$\Theta_i^t\left(\omega;\mathcal{I}^t(\omega)\right) = \sum_{k\in\mathcal{I}^t(\omega)} T_k^t\left(\tau_{ik}^t w_k\right)^{-\theta^t}, \quad t=\{R,U\}$$

is the sourcing capability of firm $\omega$ for inputs of type $t=\{R,U\}$.

Note that the sourcing capability $\Theta_i^t(\omega;\mathcal{I}^t(\omega))$ is monotonically increasing in the sourcing strategy $\mathcal{I}^t(\omega)$. Hence, one can take derivatives with respect to $\Theta_i^t$, and then check for sub/supermodularity by computing the cross and second derivatives.

Start with the first derivative, with some slight simplifications in the notation:

$$\frac{\partial\pi_i}{\partial\Theta_i^t} = \omega^{\sigma-1}B_i\frac{\sigma-1}{\theta^t}\left[\mathcal{A}\left(\gamma^R\Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U\Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{\sigma-\eta}{\eta-1}}\frac{\mathcal{A}^t\left(\gamma^t\Theta_i^t\right)^{\frac{\eta-1}{\theta^t}}}{\Theta_i^t} - w_i\varepsilon,$$

where $\varepsilon>0$ is the added fixed cost element linked to the increase in the size of $\mathcal{I}^t(\omega)$. The first derivative can only be positive if $\sigma>1$. It can also be negative, depending on the value of $w\varepsilon$. Assume it is positive. We now want to check whether this positive change in the profit function remains positive if we increase the original sourcing strategy set, which is the definition of supermodularity, or if it turns negative, hence satisfying submodularity. Note that taking second derivatives will give us modularity properties with respect to the same input type, while taking cross derivatives will give us modularity properties with respect to the cross input type. Taking again the continuous approach, we will hence derive conditions under which the second and the cross derivatives are positive or negative.

Let us now take the cross-derivative:

$$\frac{\partial^2\pi_i}{\partial\Theta_i^U\partial\Theta_i^R} = \omega^{\sigma-1}B_i\frac{\sigma-1}{\theta^R}\frac{\sigma-\eta}{\theta^U}\left[\mathcal{A}\left(\gamma^R\Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U\Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{\sigma-2\eta+1}{\eta-1}}$$
$$\times \mathcal{A}(1-\mathcal{A})\frac{\left(\gamma^R\Theta_i^R\right)^{\frac{\eta-1}{\theta^R}}}{\Theta_i^R}\frac{\left(\gamma^U\Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}}{\Theta_i^U}.$$

Therefore, for $\sigma>1$ and $\sigma>\eta$, the cross derivative is always positive. For $\sigma>1$ and $\sigma<\eta$, it is negative. That is, under those conditions, sub/supermodularity hold for the cross input type case. Note that our main calibration has $\sigma>\eta$, so we will focus on that case below, but a similar logic applies if $\eta>\sigma$.

The next step is to look at the second derivative, which gives us modularity properties for the same input type case:

$$\begin{aligned}
\frac{\partial^2 \pi_i}{\partial \, {\Theta_i^t}^2} &= \omega^{\sigma-1} B_i \frac{(\sigma-1)(\sigma-\eta)}{(\theta^t)^2} \left[\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{\sigma-2\eta+1}{\eta-1}} \left(\frac{\mathcal{A}^t \left(\gamma^t \Theta_i^t\right)^{\frac{\eta-1}{\theta^t}}}{\Theta_i^t}\right)^2 \\
&\quad + \omega^{\sigma-1} B_i \frac{(\sigma-1)(\eta-1-\theta^t)}{(\theta^t)^2} \left[\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{\sigma-\eta}{\eta-1}} \frac{\mathcal{A}^t \left(\gamma^t \Theta_i^t\right)^{\frac{\eta-1}{\theta^t}}}{{\Theta_i^t}^2} \\
&= \left(\frac{\partial \pi_i}{\partial \Theta_i^t} + w_i \varepsilon\right) \times \frac{1}{\theta^t \Theta_i^t} \left[(\sigma-\eta) \frac{\mathcal{A}^t \left(\gamma^t \Theta_i^t\right)^{\frac{\eta-1}{\theta^t}}}{\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}} + (\eta-1-\theta^t)\right].
\end{aligned}$$

We assumed from the first derivative that $\left(\frac{\partial \pi_i}{\partial \Theta_i^t} + w_i \varepsilon\right) > 0$, and $\Theta_i^t$ as well as $\theta^t$ are positive. So the first part of the above expression is positive. Therefore, we are interested in the sign of:

$$(\sigma-\eta) \frac{\mathcal{A}^t \left(\gamma^t \Theta_i^t\right)^{\frac{\eta-1}{\theta^t}}}{\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}} + (\eta-1-\theta^t),$$

which is positive if and only if $\sigma > \eta$ and

$$\frac{\mathcal{A}^t \left(\gamma^t \Theta_i^t\right)^{\frac{\eta-1}{\theta^t}}}{\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}} > \frac{1+\theta^t-\eta}{\sigma-\eta},$$

and is negative if $\sigma > \eta$ and the sign above is flipped. There are other possibilities under which it can be positive or negative depending on the value of $\eta$ vs $\sigma$, but since our calibration verifies $\sigma > \eta$, we will not focus on those cases.

To summarize, our profit function exhibits supermodularity for all input types (and thus SCD-C from below) if the following conditions hold:

1. $\sigma > 1$,

2. $\sigma > \eta$ (from the cross derivatives),

3. $\frac{\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}}}{\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}} > \frac{1+\theta^R-\eta}{\sigma-\eta} \Rightarrow \frac{K\left(\sum_{k\in\mathcal{I}^R(\omega)} \alpha_k^R\right)^{\frac{\eta-1}{\theta^R}}}{K\left(\sum_{k\in\mathcal{I}^R(\omega)} \alpha_k^R\right)^{\frac{\eta-1}{\theta^R}} + \left(\sum_{k\in\mathcal{I}^U(\omega)} \alpha_k^U\right)^{\frac{\eta-1}{\theta^U}}} > \frac{1+\theta^R-\eta}{\sigma-\eta}$,

4. $\frac{(1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}}{\mathcal{A}\left(\gamma^R \Theta_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \Theta_i^U\right)^{\frac{\eta-1}{\theta^U}}} > \frac{1+\theta^U-\eta}{\sigma-\eta} \Rightarrow \frac{\left(\sum_{k\in\mathcal{I}^U(\omega)} \alpha_k^U\right)^{\frac{\eta-1}{\theta^U}}}{K\left(\sum_{k\in\mathcal{I}^R(\omega)} \alpha_k^R\right)^{\frac{\eta-1}{\theta^R}} + \left(\sum_{k\in\mathcal{I}^U(\omega)} \alpha_k^U\right)^{\frac{\eta-1}{\theta^U}}} > \frac{1+\theta^U-\eta}{\sigma-\eta}$,

where points 3 and 4 include a re-writing of the condition with known parameters and objects. If all points hold except for 3, we then have supermodularity for cross inputs and unregulated inputs, and submodularity for regulated inputs. If all points hold except for 4, we then have supermodularity for cross inputs and regulated inputs, and submodularity for unregulated inputs. If all points hold except for 3 and 4, we then have supermodularity for cross inputs, and submodularity for regulated and unregulated inputs.

To verify whether conditions 3 and 4 hold in our setting, consider two cases regarding the value of $\eta$.

**Case 1: regulated and unregulated inputs are substitutes ($\eta > 1$):** Under substitutable inputs, the conditions become:

1. $\sigma > 1$,

2. $\sigma > \eta$ (from the cross derivatives),

3. $\frac{\mathcal{A}\left(\gamma^R \underline{\Theta}_i^R\right)^{\frac{\eta-1}{\theta^R}}}{\mathcal{A}\left(\gamma^R \underline{\Theta}_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \bar{\Theta}_i^U\right)^{\frac{\eta-1}{\theta^R}}} > \frac{1+\theta^R-\eta}{\sigma-\eta}$,

4. $\frac{(1-\mathcal{A})\left(\gamma^U \underline{\Theta}_i^U\right)^{\frac{\eta-1}{\theta^U}}}{\mathcal{A}\left(\gamma^R \bar{\Theta}_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \underline{\Theta}_i^U\right)^{\frac{\eta-1}{\theta^R}}} > \frac{1+\theta^U-\eta}{\sigma-\eta}$,

where $\underline{\Theta}_i^t$ and $\bar{\Theta}_i^t$ denote the lowest and highest bounds of function $\Theta_i^t$, which correspond to a pure domestic sourcing strategy and a sourcing from all possible countries $I^t$, respectively:

$$
\begin{aligned}
\underline{\Theta}_i^t &= T_i^t \left(\tau_{ii}^t w_i\right)^{-\theta^t}, \\
\bar{\Theta}_i^t &= \sum_{k \in I^t} T_k^t \left(\tau_{ik}^t w_k\right)^{-\theta^t},
\end{aligned}
$$

where $I^t$, again, encompasses all countries.

**Case 2: regulated and unregulated inputs are complements ($\eta < 1$):** Under complementary inputs, the conditions become:

1. $\sigma > 1$,

2. $\sigma > \eta$ (from the cross derivatives),

3. $\frac{\mathcal{A}\left(\gamma^R \bar{\Theta}_i^R\right)^{\frac{\eta-1}{\theta^R}}}{\mathcal{A}\left(\gamma^R \bar{\Theta}_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \underline{\Theta}_i^U\right)^{\frac{\eta-1}{\theta^R}}} > \frac{1+\theta^R-\eta}{\sigma-\eta}$,

4. $\frac{(1-\mathcal{A})\left(\gamma^U \bar{\Theta}_i^U\right)^{\frac{\eta-1}{\theta^U}}}{\mathcal{A}\left(\gamma^R \underline{\Theta}_i^R\right)^{\frac{\eta-1}{\theta^R}} + (1-\mathcal{A})\left(\gamma^U \bar{\Theta}_i^U\right)^{\frac{\eta-1}{\theta^R}}} > \frac{1+\theta^U-\eta}{\sigma-\eta}$,

where $A^t\left(\underline{\Theta}_i^t\right)$ and $A^t\left(\bar{\Theta}_i^t\right)$ denote the highest and lowest bounds of function $A^t$, which correspond to a pure domestic sourcing strategy and a sourcing from all possible countries $I^t$, respectively.

Using our parameter values, we find that our profit functions exhibits supermodularity for cross inputs and for unregulated inputs, but sub-modularity for regulated inputs. That is, for any $\mathcal{I}_1^U \subseteq \mathcal{I}_2^U$, $\mathcal{I}_1^R \subseteq \mathcal{I}_2^R$, $j_U \in I^U$ and $j_R \in I^R$, we have

- $\pi\big(\{\mathcal{I}_1^R, \mathcal{I}_1^U \cup j_U\}\big) - \pi\big(\{\mathcal{I}_1^R, \mathcal{I}_1^U \setminus j_U\}\big) \;\leq\; \pi\big(\{\mathcal{I}_1^R, \mathcal{I}_2^U \cup j_U\}\big) - \pi\big(\{\mathcal{I}_1^R, \mathcal{I}_2^U \setminus j_U\}\big)$,
- $\pi\big(\{\mathcal{I}_1^R, \mathcal{I}_1^U \cup j_U\}\big) - \pi\big(\{\mathcal{I}_1^R, \mathcal{I}_1^U \setminus j_U\}\big) \;\leq\; \pi\big(\{\mathcal{I}_2^R, \mathcal{I}_1^U \cup j_U\}\big) - \pi\big(\{\mathcal{I}_2^R, \mathcal{I}_1^U \setminus j_U\}\big)$,
- $\pi\big(\{\mathcal{I}_1^R \cup j_R, \mathcal{I}_1^U\}\big) - \pi\big(\{\mathcal{I}_1^R \setminus j_R, \mathcal{I}_1^U\}\big) \;\leq\; \pi\big(\{\mathcal{I}_1^R \cup j_R, \mathcal{I}_2^U\}\big) - \pi\big(\{\mathcal{I}_1^R \setminus j_R, \mathcal{I}_2^U\}\big)$,
- $\pi\big(\{\mathcal{I}_1^R \cup j_R, \mathcal{I}_1^U\}\big) - \pi\big(\{\mathcal{I}_1^R \setminus j_R, \mathcal{I}_1^U\}\big) \;\geq\; \pi\big(\{\mathcal{I}_2^R \cup j_R, \mathcal{I}_1^U\}\big) - \pi\big(\{\mathcal{I}_2^R \setminus j_R, \mathcal{I}_1^U\}\big)$.

### C.1.3 Algorithm

**Setup.** Theorem 1 in Arkolakis et al. (2023) (AES) develops an algorithm that solves the firm's problem whenever the objective satisfies SCD-C globally – either from above or from below – over the entire strategy space $\mathscr{P}(I)$ (equivalently, the four inequalities stated above have a common direction). In our environment, the profit function displays a *mix* of sub- and supermodularity across input types. We therefore adapt the AES logic to this mixed-modularity setting, exploiting the stronger monotonicity implied by (same-input and cross-input) super/submodularity.[47]

**Delta function.** For $t \in \{R, U\}$ and $j_t \in I^t$, define the marginal gain of adding $j_t$ at $(\mathcal{I}^R, \mathcal{I}^U)$:

$$\Delta(j_U \,|\, \mathcal{I}^R, \mathcal{I}^U) \equiv \pi(\{\mathcal{I}^R, \mathcal{I}^U \cup j_U\}) - \pi(\{\mathcal{I}^R, \mathcal{I}^U\}),$$

$$\Delta(j_R \,|\, \mathcal{I}^R, \mathcal{I}^U) \equiv \pi(\{\mathcal{I}^R \cup j_R, \mathcal{I}^U\}) - \pi(\{\mathcal{I}^R, \mathcal{I}^U\}).$$

**Algorithm (mixed modularity).** The procedure uses the same-input and cross-input monotonicity results established above to classify countries as *always-sourcing*, *never-sourcing*, or *undecided*.

*Step 1: Initial sets that maximize* $\Delta$.

[47] Super/submodularity imply the SCD-C sign-preservation property AES require; see Arkolakis et al. (2023), Def. 3 and the discussion that super/submodularity are sufficient for SCD-C.

**1a.** *Regulated ($j_R$).* Since $\Delta(j_R \,|\, \cdot)$ increases with unregulated inputs and decreases with regulated inputs, the maximizing initial set includes all unregulated countries included and restricts regulated countries to the domestic country. Compute $\Delta(j_R \,|\cdot)$ with that initial set. If $\Delta < 0$, classify $j_R$ as **never-sourcing (R)**.

**1b.** *Unregulated ($j_U$).* Since $\Delta(j_U \,|\, \cdot)$ increases with both sides, the maximizing initial set includes all unregulated and regulated countries. Compute $\Delta(j_U \,|\cdot)$ with that initial set. If $\Delta < 0$, classify $j_U$ as **never-sourcing (U)**.

*Step 2: Initial sets that minimize $\Delta$.*

**2a.** *Regulated ($j_R$).* Using the same monotonicity features, the minimizing initial set includes all regulated countries and the domestic unregulated country. If $\Delta > 0$ using this initial set, classify $j_R$ as **always-sourcing (R)**.

**2b.** *Unregulated ($j_U$).* The minimizing initial set includes domestic countries only for both inputs. If $\Delta > 0$ using that initial sourcing set, classify $j_U$ as **always-sourcing (U)**.

*Step 3 — Update and iterate.*

- Use countries tagged always- and never-sourcing in order to update the initial sets in 1a, 1b, 2a and 2b and recompute $\Delta(\cdot)$ only for the remaining undecided countries.
- By monotonicity, after each pass, the set of countries classified *always* weakly expands and the set classified *never* weakly expands; equivalently, the undecided set weakly shrinks. Because $I$ is finite, the process terminates in finitely many iterations.
- Iterate until no reclassification occurs. If a residual undecided set remains, solve the profit maximization problem by brute force over those residual countries (holding the always/never decisions fixed).

## C.2 Targeted and untargeted moments

**Import probabilities.** These are computed after solving each firm's optimal sourcing strategy, given the set of estimated parameters:

$$\max_{\{\mathbb{1}^R_{ij}(\omega)\}_{j\in I^R},\{\mathbb{1}^U_{ij}(\omega)\}_{j\in I^U}} \quad \pi_i(\omega,\mathcal{I}^R(\omega),\mathcal{I}^U(\omega))$$

with

$$\begin{aligned}
\pi_i(\omega,\mathcal{I}^R(\omega),\mathcal{I}^U(\omega)) &= \left(\frac{c_i(\omega;\mathcal{I}^R(\omega),\mathcal{I}^U(\omega))}{\omega}\right)^{1-\sigma} B_i - w_i\sum_{j\in I^R}\mathbb{1}^R_{ij}(\omega)f^R_{ij}(\omega) - w_i\sum_{j\in I^U}\mathbb{1}^U_{ij}(\omega)f^U_{ij}(\omega)\\
&= \omega^{\sigma-1}\tilde{B}_i\left[K\left(\sum_{k\in I^R}\mathbb{1}^R_{ij}(\omega)\hat{\alpha}^R_{ij}\right)^{\frac{\eta-1}{\theta^R}}+\left(\sum_{k\in I^U}\mathbb{1}^U_{ij}(\omega)\hat{\alpha}^U_{ij}\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{1-\sigma}{1-\eta}}\\
&\quad -w_i\sum_{j\in I^R}\mathbb{1}^R_{ij}(\omega)f^R_{ij}(\omega) - w_i\sum_{j\in I^U}\mathbb{1}^U_{ij}(\omega)f^U_{ij}(\omega)
\end{aligned}$$

where

$$\begin{aligned}
\tilde{B}_i &= B_i(1-\mathcal{A})^{\frac{1-\sigma}{1-\eta}}\left(\gamma^U\right)^{\frac{\sigma-1}{\theta^U}}\left[T^U_i\left(\tau^U_{ii}w_i\right)^{-\theta^U}\right]^{\frac{\sigma-1}{\theta^U}},\\
K &= \left(\frac{\gamma^{R\,-1/\theta^R}}{\gamma^{U\,-1/\theta^U}}\right)^{1-\eta}\left(\frac{\left(T^R_i\left(\tau^R_{ii}w_i\right)^{-\theta^R}\right)^{-1/\theta^R}}{\left(T^U_i\left(\tau^U_{ii}w_i\right)^{-\theta^U}\right)^{-1/\theta^U}}\right)^{1-\eta}\frac{\mathcal{A}}{1-\mathcal{A}}.
\end{aligned}$$

Given the optimal values for $\{\mathbb{1}^t_{ij}(\omega)\}_{t=U,R,j\in I^t,\omega\in\Omega_i}$, the share of importers / of importers from a given source country, can simply be calculated by taking averages.

**Firm-level sales.** These are defined using the optimal demand function:

$$\begin{aligned}
p_i(\omega)y_i(\omega) &= \left(\frac{p_i(\omega)}{P_i}\right)^{1-\sigma}B_i\\
&= \sigma B_i\left(\frac{c_i(\omega)}{\omega}\right)^{1-\sigma}\\
&= \sigma\omega^{\sigma-1}\tilde{B}_i\left[K\left(\sum_{k\in I^R}\mathbb{1}^R_{ij}(\omega)\hat{\alpha}^R_{ij}\right)^{\frac{\eta-1}{\theta^R}}+\left(\sum_{k\in I^U}\mathbb{1}^U_{ij}(\omega)\hat{\alpha}^U_{ij}\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{1-\sigma}{1-\eta}},
\end{aligned}$$

which can then be compared with the value of the median firm in the data to compute the share of firms with sales below the median value.

**Firm-level input purchases.** These are aggregated across countries and/or products starting from

$$\begin{aligned}
M_{ij}^t(\omega) &= \chi_{ij}^t(\omega)\mathcal{A}^t\left(\frac{c_i^t(\omega)}{c_i(\omega)}\right)^{1-\eta}(\sigma-1)\left(\frac{c_i(\omega)}{\omega}\right)^{1-\sigma}B_i \\
&= \chi_{ij}^t(\omega)\chi_i^t(\omega)\omega^{\sigma-1}(\sigma-1)\tilde{B}_i\left[K\left(\sum_{k\in I^R}\mathbb{1}_{ij}^R(\omega)\hat{\alpha}_{ij}^R\right)^{\frac{\eta-1}{\theta^R}}+\left(\sum_{k\in I^U}\mathbb{1}_{ij}^U(\omega)\hat{\alpha}_{ij}^U\right)^{\frac{\eta-1}{\theta^U}}\right]^{\frac{1-\sigma}{1-\eta}},
\end{aligned}$$

with

$$\begin{aligned}
\chi_{ij}^t(\omega) &= \frac{\alpha_{ij}^t}{\sum_{k\in\mathcal{I}_i^t(\omega)}\alpha_{ik}^t}, \quad \text{if} \quad j\in\mathcal{I}_i^t(\omega) \quad / \quad 0 \quad \text{otherwise}, \\
\chi_i^R(\omega) &= \frac{K\left[\sum_{k\in\mathcal{I}^R(\omega)}\alpha_k^R\right]^{\frac{\eta-1}{\theta^R}}}{K\left(\sum_{k\in\mathcal{I}^R(\omega)}\alpha_k^R\right)^{\frac{\eta-1}{\theta^R}}+\left(\sum_{k\in\mathcal{I}^U(\omega)}\alpha_k^U\right)^{\frac{\eta-1}{\theta^U}}}, \\
\chi_i^U(\omega) &= \frac{\left[\sum_{k\in\mathcal{I}^U(\omega)}\alpha_k^U\right]^{\frac{\eta-1}{\theta^U}}}{K\left(\sum_{k\in\mathcal{I}^R(\omega)}\alpha_k^R\right)^{\frac{\eta-1}{\theta^R}}+\left(\sum_{k\in\mathcal{I}^U(\omega)}\alpha_k^U\right)^{\frac{\eta-1}{\theta^U}}}.
\end{aligned}$$

**Free-entry, mass of firms and counterfactual estimation.** The model delivers the following free-entry condition:

$$\int_{\tilde{\omega}}^{\infty}\left[\left(\frac{c(\omega;\mathcal{I}^R(\omega),\mathcal{I}^U(\omega))}{\omega}\right)^{1-\sigma}B_i-w_i\sum_{j\in\mathcal{I}^R(\omega)}f_j^R-w_i\sum_{j\in\mathcal{I}^U(\omega)}f_j^U\right]dG(\omega)=w_if_e, \tag{C.2}$$

where $\tilde{\omega}$ denotes the minimum productivity for profitable entry into the manufacturing sector. Using this equation, any counterfactual proceeds as follows. We take the cost of entry and all other parameters as fixed, except for $\tilde{B}_i$, solve for firms optimal sourcing decisions, and then solve for a value of $\tilde{B}_i'$ which allows equation (C.2) to hold. This new value of $\tilde{B}_i'$ takes into account both the new market demand, and the updated tax. That is, it is defined as

$$\tilde{B}_i'=B_i'(1-\mathcal{A})^{\frac{1-\sigma}{1-\eta}}\left(\gamma^U\right)^{\frac{\sigma-1}{\theta^U}}\left[T_i^U\left(\tau_{ii}^Uw_i\right)^{-\theta^U}\right]^{\frac{\sigma-1}{\theta^U}}{t_i^U}^{1-\sigma}.$$

We then solve our economy with the updated sourcing potentials and market demand $\tilde{B}_i'$.

Finally, the equilibrium measure $\Omega_i$ of entrants in the manufacturing sector is solved for using the above free-entry condition together with the definition of $\tilde{B}_i$ under constant mark-ups:

$$\Omega_i=\frac{E_i}{\sigma\left[\int_{\tilde{\omega}}^{\infty}\left(\sum_{j\in\mathcal{I}^R(\omega)}f_{ij}^R(\omega)+\sum_{j\in\mathcal{I}^U(\omega)}f_{ij}^U(\omega)\right)dG(\omega)+f_e\right]}. \tag{C.3}$$

**Firm-level and aggregate price index.** Each firm charges a markup over marginal cost:

$$p_i(\omega) \;=\; \frac{\sigma}{\sigma-1}\,\frac{c_i(\omega)}{\omega},$$

Using firm-level sales, this simplifies to:

$$p_i(\omega) \;=\; \frac{\sigma}{\sigma-1}\left(\frac{\text{sales}(\omega)}{\sigma B_i}\right)^{\frac{1}{1-\sigma}}.$$

Aggregate this price index to compute $P_i$:

$$\begin{aligned}
P_i &= \left[\int_{\omega\in\Omega_i} p(\omega)^{1-\sigma}\,d\omega\right]^{\frac{1}{1-\sigma}} \\
&= \left[\int_{\omega\in\Omega_i}\left(\frac{\sigma}{\sigma-1}\left(\frac{\text{sales}(\omega)}{\sigma B_i}\right)^{\frac{1}{1-\sigma}}\right)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}} \\
&= \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{1}{\sigma B_i}\right)^{\frac{1}{1-\sigma}}\left[\int_{\omega\in\Omega_i}(\text{sales}(\omega))\,d\omega\right]^{\frac{1}{1-\sigma}}.
\end{aligned}$$

Since we only have a value for $\tilde{B}_i$, defined as:

$$\tilde{B}_i = B_i(1-\mathcal{A})^{\frac{1-\sigma}{1-\eta}}\left(\gamma^U\right)^{\frac{\sigma-1}{\theta^U}}\left[T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}\right]^{\frac{\sigma-1}{\theta^U}},$$

We are only able to compute a version of the price index scaled by the unknown:

$$(1-\mathcal{A})^{\frac{1}{\eta-1}}\left(\gamma^U\right)^{\frac{1}{\theta^U}}\left[T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}\right]^{\frac{1}{\theta^U}}.$$

As such, when computing counterfactual price changes $\frac{P_i'}{P_i}$, in which a carbon tax is applied in the counterfactual setting, one must multiply $P_i'$ by $\frac{1}{t_i^U}$. To see why, note the following

$$\begin{aligned}
\frac{\tilde{B}_i'}{\tilde{B}_i} &= \frac{B_i'(1-\mathcal{A})^{\frac{1-\sigma}{1-\eta}}\left(\gamma^U\right)^{\frac{\sigma-1}{\theta^U}}\left[T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}\right]^{\frac{\sigma-1}{\theta^U}}\;{t_i^U}^{1-\sigma}}{B_i(1-\mathcal{A})^{\frac{1-\sigma}{1-\eta}}\left(\gamma^U\right)^{\frac{\sigma-1}{\theta^U}}\left[T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}\right]^{\frac{\sigma-1}{\theta^U}}} \\
&= \frac{B_i'\,{t_i^U}^{1-\sigma}}{B_i},\text{ so} \\
\left(\frac{\tilde{B}_i}{\tilde{B}_i'}\right)^{\frac{1}{1-\sigma}} &= \left(\frac{B_i}{B_i'}\right)^{\frac{1}{1-\sigma}}\frac{1}{t_i^U}.
\end{aligned}$$

# D Model Estimation and Counterfactuals

## D.1 Sample and random shocks construction

To draw the fixed costs shocks and construct the sample of firms, we follow Antràs et al. (2017) closely.

First, we construct the sample of firms. To do so, we first create a set of bounds on the unit interval, that define 25 productivity bins. Then, we simulate 15 firms in each productivity bin. In doing this, we oversample the upper tail. With fixed effects on importing, we indeed expect most of the action to take place at the top of the productivity distribution, thus explaining why we want to simulate relatively more high-productivity firms.[48] Finally, we use the inverse-CDF of a Pareto distribution with scale 1 and shape $\kappa$ to recover the productivity of each of the simulated firms. Note that all statistics and regression coefficients later correct for the oversampling using sampling weights.

We then construct the fixed costs shocks. We first draw a van der Corput sequence of size $S = 15$ on $[0, 1]$: 1/2, 1/4, 3/4, 1/8, 5/8, 3/8, 7/8, 1/16, 9/16, .... For each country×input pair, we take an independent random permutation of this sequence and map each element $u$ to a shock via the inverse CDF of the standard normal, $\Phi^{-1}(u)$. For instance, $u = 1/4$ yields $-0.6745$ and $u = 1/2$ yields 0. Thus, each country×input pair gets assigned a vector of 15 distinct shocks, and all pairs share the same values of shocks, but with independent permutations.

Finally, we combine the productivity values with the random shocks. For each productivity draw $\omega$ (375 total), we create 15 duplicates and assign to the $k$-th duplicate the $k$-th shock for every country×input pair (i.e., a full vector across pairs). This yields $375 \times 15 = 5,625$ firms.

Note the slight abuse of notation when we introduce heterogeneous fixed costs. When introducing heterogeneous fixed costs, $\omega$ no longer indexes a unique firm. In the SMM with heterogeneous fixed costs, a "firm" is identified by its productivity $\omega$ together with its fixed-cost vector $f_{ij}^{t}(\omega)$, $t \in \{R, U\}$.

## D.2 Estimation of the technical coefficients

We estimate the following function that confounds the impact of technical coefficients and relative production costs using the model-implied and empirical counterparts of the relative

[48]In practice, the oversampling involves drawing the same number of firms in the following 25 percentile bins: $[0; 0.10]$, $[0.10; 0.20]$, $[0.20; 0.30]$, $[0.30; 0.40]$, $[0.40; 0.50]$, $[0.50; 0.55]$, $[0.55; 0.60]$, $[0.60; 0.65]$, $[0.65; 0.70]$, $[0.70; 0.75]$, $[0.75; 0.80]$, $[0.80; 0.85]$, $[0.85; 0.90]$, $[0.90; 0.925]$, $[0.925; 0.95]$, $[0.95; 0.96]$, $[0.96; 0.97]$, $[0.97; 0.98]$, $[0.98; 0.99]$, $[0.99; 0.995]$, $[0.995; 0.996]$, $[0.996; 0.997]$, $[0.997; 0.998]$, $[0.998; 0.999]$, $[0.999; 1]$.

demand of regulated and unregulated inputs:

$$\frac{\mathcal{A}c_i^R(\omega)y_i^R(\omega)}{(1-\mathcal{A})c_i^U(\omega)y_i^U(\omega)} = \left(\frac{c_i^R(\omega)}{c_i^U(\omega)}\right)^{1-\eta} \frac{\mathcal{A}}{1-\mathcal{A}}$$

$$= \left(\frac{\gamma^{R\,-1/\theta^R}}{\gamma^{U\,-1/\theta^U}}\right)^{1-\eta} \left(\frac{\left(T_i^R\left(\tau_{ii}^R w_i\right)^{-\theta^R}\right)^{-1/\theta^R}}{\left(T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}\right)^{-1/\theta^U}}\right)^{1-\eta} \frac{\mathcal{A}}{1-\mathcal{A}} \frac{\left(\sum_{k\in\mathcal{I}_i^R(\omega)} \frac{T_k^R\left(\tau_{ki}^R w_k\right)^{-\theta^R}}{T_i^R\left(\tau_{ii}^R w_i\right)^{-\theta^R}}\right)^{(\eta-1)/\theta^R}}{\left(\sum_{k\in\mathcal{I}_i^U(\omega)} \frac{T_k^U\left(\tau_{ki}^U w_k\right)^{-\theta^U}}{T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}}\right)^{(\eta-1)/\theta^U}}.$$

Taking logs and using the definition of $\alpha_{ij}^t$ from Section 5.1:

$$\log \frac{\mathcal{A}c^R(\omega)y^R(\omega)}{(1-\mathcal{A})c^U(\omega)y^U(\omega)} = \log \underbrace{\left(\frac{\gamma^{R\,-1/\theta^R}}{\gamma^{U\,-1/\theta^U}}\right)^{1-\eta} \left(\frac{\left(T_i^R\left(\tau_{ii}^R w_i\right)^{-\theta^R}\right)^{-1/\theta^R}}{\left(T_i^U\left(\tau_{ii}^U w_i\right)^{-\theta^U}\right)^{-1/\theta^U}}\right)^{1-\eta} \frac{\mathcal{A}}{1-\mathcal{A}}}_{K}$$

$$+ \frac{\eta-1}{\theta^R}\log\left(\sum_{k\in\mathcal{I}_i^R(\omega)} \alpha_{ik}^R\right) - \frac{\eta-1}{\theta^U}\log\left(\sum_{k\in\mathcal{I}_i^U(\omega)} \alpha_{ik}^U\right), \quad \text{(D.4)}$$

which we can estimate using OLS, with the constant term capturing the (log of) the parameters of interest.

Results of the estimation of equation (D.4) are reported in Table D.1. The odd columns are estimated using data on all firms, and the even columns correspond to estimates recovered using only firms with some foreign input sourcing. In columns (1) and (2), the coefficients scaling the impact of the firm's sourcing choices are left unconstrained, while we force them to equal their calibrated values in columns (3) and (4). Results are very stable across specifications, with a value for the parameter $K$ varying between 0.39 and 0.42. In the rest of the analysis, we retain the value from column (3).

## D.3 SMM estimation and sensitivity analysis

To obtain initial parameter values for the method of moments estimation, we employ Latin Hypercube Sampling (LHS), generating 1,500 distinct sets of starting points. LHS is particularly well-suited for this context as it ensures a more systematic and comprehensive exploration of the parameter space compared to purely random sampling. This approach thus reduces the risk of poor initializations leading to local optima. We put bounds on the initial parameter values for the LHS at $-5$ and $+5$. There are a few exceptions, especially for variables that take logs: $B_i$ is set between 0 and .2, both fixed costs shocks betwen 0 and 10, the EU and the distance variables between 0 and 5, and the constant between 0 and 10.

**Table D.1.** Results of estimating technical coefficients from relative input purchases

| | Dep.var: log of Relative input purchases (overall) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\log\left(\sum_{k\in\mathcal{I}^R(\omega)}\alpha_k^R\right)$ | 13.82*** | 13.90*** | | |
| | (.375) | (.391) | | |
| $\log\left(\sum_{k\in\mathcal{I}^U(\omega)}\alpha_k^U\right)$ | -20.30*** | -20.28*** | | |
| | (.509) | (.519) | | |
| $\log K$ | -0.866*** | -0.875*** | -0.883*** | -0.924*** |
| | (.003) | (.009) | (.003) | (.006) |
| Nb Observations | 62,517 | 18,918 | 62,517 | 18,918 |
| $R^2$ | .026 | .075 | .000 | .000 |
| Sample | All | Inter | All | Inter |

**Notes:** The left-hand side variable is the relative share of regulated input purchases in the firm's overall input purchases. The right-hand side variables measure the sum of the sourcing potential variables, over all the countries that the firm purchases from, where sourcing potentials are estimated in Section 5.1. In columns (3) and (4), the coefficients on the firm's sourcing potential are constrained to their calibrated value.

We begin by running optimizations in parallel with twenty four workers in Matlab, using those 1,500 different initial guesses for the parameters. Initially, we apply the `patternsearch` function with relatively relaxed convergence criteria. Based on these results, we re-optimize using the `fminsearchbnd` function, keeping similar convergence thresholds. At this stage, both algorithms are limited to 200 and 100 iterations respectively, and they stop when either the change in parameter values or the objective function value falls below 0.4. Next, we keep the 15 best (lowest) value functions and the associated vectors of parameters. We then re-optimize this reduced set of parameter vectors: each one is optimized using both `fminsearchbnd` and `patternsearch`, with the results of `fminsearchbnd` as the starting point. Convergence parameters are now more stringent, set to 1000 iterations and thresholds of 0.05. If the objective function values from the second optimization are sufficiently close to those from the first, we proceed; otherwise, the optimization process continues until the difference is below the defined criteria. We then proceed with the set of parameters that yield the lowest objective function.

With the parameters at hand, we estimate their variance-covariance matrix as

$$\left(J'W^{-1}J\right)^{-1} + \left(J'\tilde{W}^{-1}J\right)^{-1},$$

where $W$ is the variance-covariance matrix of the data moments. Variation is obtained by bootstrapping the data 150 times. $\tilde{W}$ is the simulated data equivalent. That is, we fix the parameters to the ones estimate in the SMM procedure, and sample firms 150 times. $J$ is the Jacobian matrix around the SMM estimate. The full procedure can for example be found in the online appendix of Catherine et al. (2022).

Last, it is important to validate our moment selection. We do so by plotting the moments' sensitivities to parameter values in Figure D.1. We do so by fixing all parameters, and varying the parameter of interest above and below its equilibrium value. All moments (we only depict 6 of them) increase or decrease smoothly with parameters' values, hence corroborating that our selection helps us calibrate parameters accurately.

## D.4 Calculation of carbon taxes

We calculate the input $\times$ country level of taxes using WIOD's environmental accounts. This data set provides yearly emissions levels (in tons of $CO_2$) for 56 ISIC Rev.4 sectors across 44 countries (including EU28, Rest Of The World – RoW, and 15 other major economies). The data set covers the period from 2000 to 2016, and we use the year 2004 for our analysis. By leveraging WIOD's 2016 IO table for 2004, we can determine the total production for each sector $\times$ country combination, enabling us to compute an emission intensity for each combination. We use WIOD's IO table rather than INSEE's because the emissions data is tailored to WIOD's IO structure. From this, using a given price of euro per ton of $CO_2$, we can calculate the level of direct taxes for our counterfactuals.

We also account for input-output linkages to compute the full tax incidence of the vector of taxes on each sector $\times$ country. We proceed as follows. Denote WIOD's IO matrix as $\Omega$, a $(56 \times 44) \times (56 \times 44)$ matrix of technical coefficients. We then compute the Leontieff inverse $\Psi = (I - \Omega)^{-1}$, where each entry $\Psi_{ij}$ captures both the direct and indirect ways through which $i$ (a sector $\times$ country) uses $j$ (another sector $\times$ country).

Next, we calculate the level of direct taxes under our counterfactual scenario. Direct taxes are calculated as the product of a dummy equal to one if the country$\times$sector is covered in the corresponding counterfactual, times the emissions intensity recovered from the WIOD, times the level of output, times the assumed price of carbon.

We then multiply this direct tax burden by the Leontief inverse $\Psi$ to determine the total tax burden for any firm purchasing from these 56 sectors $\times$ 44 countries. Finally, we aggregate the corresponding tax rates into two broad sectors (regulated and unregulated) using weights based on French input purchases. Countries in our sample that are not included in WIOD are assigned the values calculated for the Rest of the World aggregate of the WIOD.

Finally, we take into account the slightly different coverages of the ETS and CBAM systems (see Tables A.2 and A.3). For the carbon tax counterfactual, we classify the sectors listed in columns (1) and (4) of Table A.6 as regulated, with all other sectors considered unregulated.[49] For the ETS + CBAM counterfactual, we additionally expand taxation to the regulated CBAM sectors listed in columns (2) and (5) of Table A.6.

With the tax levels in hand, counterfactual exercises feed in the following modified elements into the model:

- The sourcing potentials:

$$\begin{aligned}\hat{\alpha}_{ij}^{t}{}' &= \frac{T_j^t \left(\tau_{ji}^t w_j\right)^{-\theta^t} \; t_j^{t\,-\theta^t}}{T_i^t \left(\tau_{ii}^t w_i\right)^{-\theta^t} \; t_i^{t\,-\theta^t}} \\ &= \hat{\alpha}_{ij}^t \left(\frac{t_j^t}{t_i^t}\right)^{-\theta^t} .\end{aligned}$$

- The relative cost in France of regulated products:

$$\begin{aligned}K' &= \left(\frac{\gamma^{R\,-1/\theta^R}}{\gamma^{U\,-1/\theta^U}}\right)^{1-\eta} \left(\frac{\left(T_i^R \left(\tau_{ii}^R w_i\right)^{-\theta^R}\right)^{-1/\theta^R}}{\left(T_i^U \left(\tau_{ii}^U w_i\right)^{-\theta^U}\right)^{-1/\theta^U}}\right)^{1-\eta} \frac{\mathcal{A}}{1-\mathcal{A}} \left(\frac{t_i^R}{t_i^U}\right)^{1-\eta} \\ &= K \left(\frac{t_i^R}{t_i^U}\right)^{1-\eta} .\end{aligned}$$

- The demand term, scaled by unregulated elements:

$$\begin{aligned}\tilde{B}_i' &= B_i (1-\mathcal{A})^{\frac{1-\sigma}{1-\eta}} \left(\gamma^U\right)^{\frac{\sigma-1}{\theta^U}} \left[T_i^U \left(\tau_{ii}^U w_i\right)^{-\theta^U}\right]^{\frac{\sigma-1}{\theta^U}} \; t_i^{U\,1-\sigma} \\ &= \tilde{B}_i \; t_i^{U\,1-\sigma} .\end{aligned}$$

  In fact, the modified market demand term also allows $B_i$ to change, such that $\tilde{B}_i' = B_i'(1-\mathcal{A})^{\frac{1-\sigma}{1-\eta}} \left(\gamma^U\right)^{\frac{\sigma-1}{\theta^U}} \left[T_i^U \left(\tau_{ii}^U w_i\right)^{-\theta^U}\right]^{\frac{\sigma-1}{\theta^U}} \; t_i^{U\,1-\sigma}$. See section C.2 for more details.

## D.5 Calibration of $\mu_i$

We borrow from Shapiro (2021). In particular, we express agents' utility in country $i$ as:

$$U_i = H_i^{1-\alpha} C_i^{\alpha} \left[1 + \mu_i \left(CO_2 - CO_{2,baseline}\right)\right]^{-1},$$

where $H_i$ is the homogeneous good and $C_i$ is the CES manufacturing aggregator. $CO_2$ is the amount of $CO_2$ emissions (in tons) associated with producing the inputs for the household's manufacturing goods, and $\mu_i$ is a term to be calibrated. As explained in the main text, this

[49] Note that sectors in Table A.5 follow the NAF nomenclature, whereas WIOD uses ISIC Rev.4. This is why we use Table A.6 to classify them as regulated and unregulated

specification is designed to measure damages from changes in emissions only, and we thus abstract from baseline climate damages.

Indirect utility is given by

$$V_i = \frac{I_i}{N_i^{1-\alpha} P_i^{\alpha}} \left[1 + \mu_i \left(CO_2 - CO_{2,baseline}\right)\right]^{-1},$$

where $I_i$ is total nominal spending, $N_i$ denotes the price of the homogeneous good, and $P_i$ represents the CES price index of the manufactured final goods.

We calibrate the value of $\mu_i$ so that one additional ton of carbon reduces welfare by a given monetary amount (in euros) $D_i$. Hence, we compute $\frac{\partial V_i}{\partial CO_2} = D_i$, and find $\mu_i$ accordingly. As explained in the main text, we assume that one extra ton of carbon has a global net damage of €200 in the main counterfactual. We also use €1500 to reflect higher recent estimates (Rennert et al., 2022; Bilal and Känzig, 2024; Moore et al., 2024).

Only a share of these €200 falls on France. If we assume that all countries are affected by climate change in similar way, then France should receive a damage proportional to its share of global GDP, about 2.96%. We would thus get that $D_i = -2.96\% \times$ €200 $= -$ €5.92.[50]

However, in addition to GDP differences, countries are affected heterogeneously. Nordhaus and Boyer (2000) calculate the damage $d_i$ due to a 2.5°C warming for each of 13 regions, expressed as a portion of GDP, as follows: US 0.45%, China 0.22%, Japan 0.50%, OECD Europe 2.83%, Russia $-0.65\%$, India 4.93%, Other High Income $-0.39\%$, High Income OPEC 1.95%, Eastern Europe 0.71%, Middle Income 2.44%, Lower-middle Income 1.81%, Africa 3.91%, and Low Income 2.64%. Denoting country $i$'s GDP as $Y_i$, we then proceed as in Shapiro (2016) and compute $D_i = -\frac{d_i Y_i}{\sum_j d_j Y_j} \times$ €200.

Would all countries have identical $d_i$'s, we would get back to $D_i = -2.96\% \times$ €200 $= -$ €5.92. However, since France has a value of $d_i$ which is higher than average (2.83%), we then get that $D_i = -6.75\% \times$ €200 $= -$ €13.5. This is the value we use for $D_i$. When turning to a social cost of carbon of €1500, we thus get $D_i = -$ €101.25.

Having computed $D_i$, we then turn to the computation of $\mu_i$. To do so, we take the derivative of $V_i$ with respect to $CO_2$, set it equal to $D_i$, rearrange terms and get that $\mu_i = \frac{-D_i \cdot \left[1+\mu_i\left(CO_2 - CO_{2,\text{baseline}}\right)\right]^2}{\frac{I_i}{N_i^{1-\alpha} P_i^{\alpha}}}$. We evaluate this term at baseline values, i.e. with $CO_2 = CO_{2,baseline}$, so our formula yields $\mu_i = \frac{-D_i}{\frac{I_i}{N_i^{1-\alpha} P_i^{\alpha}}}$. Since our model does not deliver a value for $N_i$ and $I_i$, we proxy the denominator with real GDP.

Note that both the numerator and denominator of $\mu_i$ are affected by the change in geographical area considered. Going from a French household to an EU one increases the numerator and the denominator in similar proportions, such that for a given social cost of

[50] 2.96% is obtained using the 2022 value of the 2015 constant USD GDP series from the World Bank.

carbon, the two $\mu_i$'s would not differ widely. This is due to the fact that we model damages as multiplicative, and thus real income shows up in the partial derivative of $V_i$. Only a change in the social cost of carbon affects $\mu_i$ significantly.

**Table D.2.** SMM model parameter estimates

| | Regulated | Unregulated |
|---|---|---|
| $B_i$ | 0.003 | |
| | (0.000) | |
| $\delta^t$ | 4.954 | 1.254 |
| | (0.034) | (0.018) |
| $\beta_0^t$ | 211.113 | 9.196 |
| | (7.756) | (0.272) |
| $\beta_{[1,2]}^t$ | 2.117 | 2.880 |
| | (0.032) | (0.034) |
| $\beta_{[2,5]}^t$ | 2.069 | 2.745 |
| | (0.049) | (0.055) |
| $\beta_{[5,\infty]}^t$ | 1.181 | 2.274 |
| | (0.034) | (0.042) |
| $\beta_{non-EU}^t$ | 0.495 | 0.691 |
| | (0.014) | (0.009) |
| $\beta_{TAB}^t$ | -1.427 | -1.292 |
| | (0.012) | (0.005) |
| $\beta_{Climate}^t$ | 0.820 | |
| | (0.007) | |

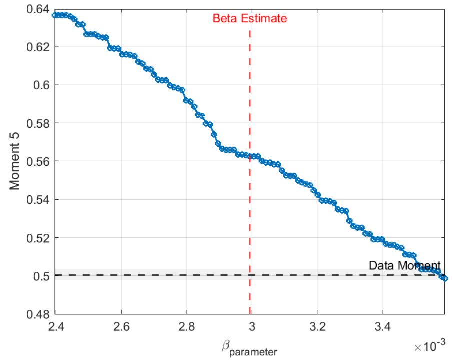
**Notes:** The table reports the estimated coefficients for the parameters of equation (11), together with the variance of fixed costs ($\delta^t$) and the demand parameter ($B_i$). All coefficients are estimated by SMM. Bootstrapped standard errors in parentheses. See details of the bootstrapping in Section D.3.

**Table D.3.** Targeted moments: model and data

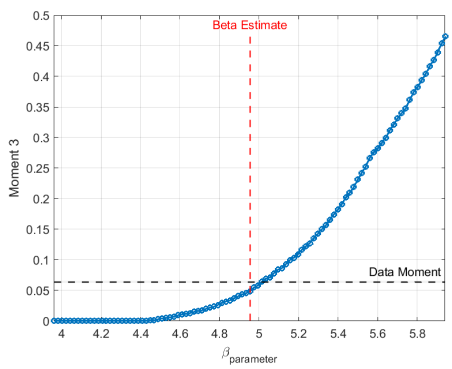
| Parameter | Moment: Share of | Sector | Model | Data |
|---|---|---|---|---|
| $\boldsymbol{\beta}^t$ | Importers among all firms | Unregulated | 0.283 | 0.278 |
| | | Regulated | 0.214 | 0.193 |
| | Firms importing from each country | Unregulated<br>Regulated | See Figure 6 | |
| $\delta^t$ | Importer from most popular country among importers | Unregulated | 0.572 | 0.597 |
| | | Regulated | 0.217 | 0.542 |
| | Importers among firms with sales below p75 | Unregulated | 0.096 | 0.135 |
| | | Regulated | 0.060 | 0.064 |
| $B_i$ | Firms with sales below data median value | | 0.553 | 0.500 |

**Notes:** This table presents the data and model moments that are estimated by SMM, as described in Section 5.4 and Table 2.

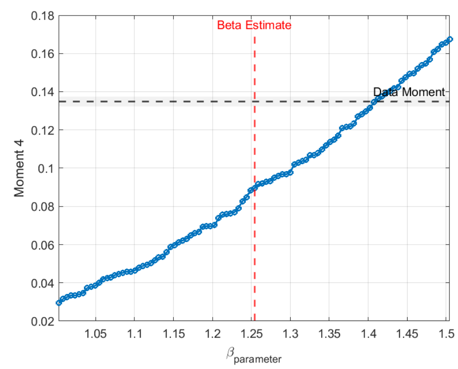
**Figure D.1.** Moments' sensitivity to parameter values



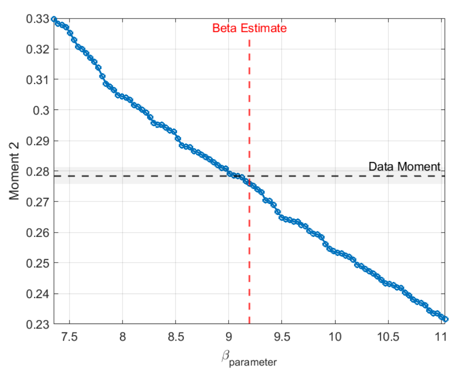

**(a)** *Share of firms with sales below data median*'s sensitivity to $B_i$



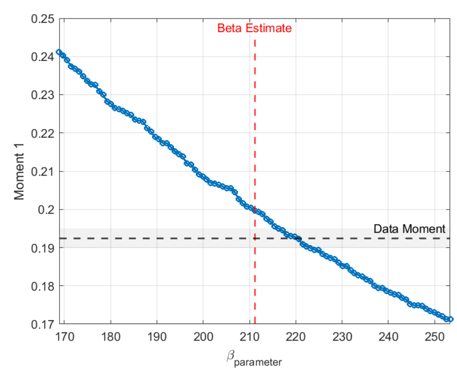

**(b)** *Share of importers of regulated inputs among firms with sales below p75*'s sensitivity to $\delta^R$




**(c)** *Share of importers of unregulated inputs among firms with sales below p75*'s sensitivity to $\delta^U$



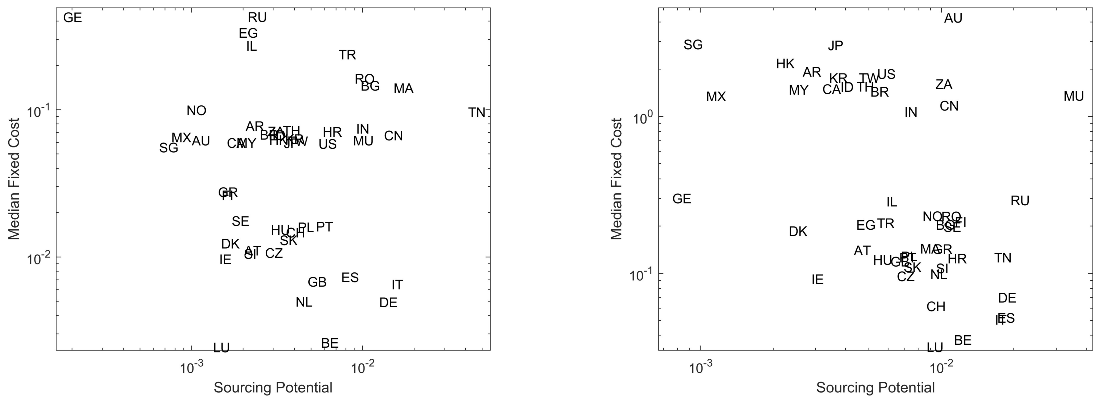

**(d)** *Share of importers of C goods as a fraction of all firms*' sensitivity to $\beta_0^U$




**(e)** *Share of importers of D goods as a fraction of all firms*' sensitivity to $\beta_0^R$

**Notes:** The x-axis is the parameter value, the y-axis is the model moment. The red vertical bar points the parameter value the model settles on. The horizontal black bar is the moment in the data. The gray area around that bar depicts the 5th and 95th percentiles of this data moment, obtained from the 150 bootstraps.

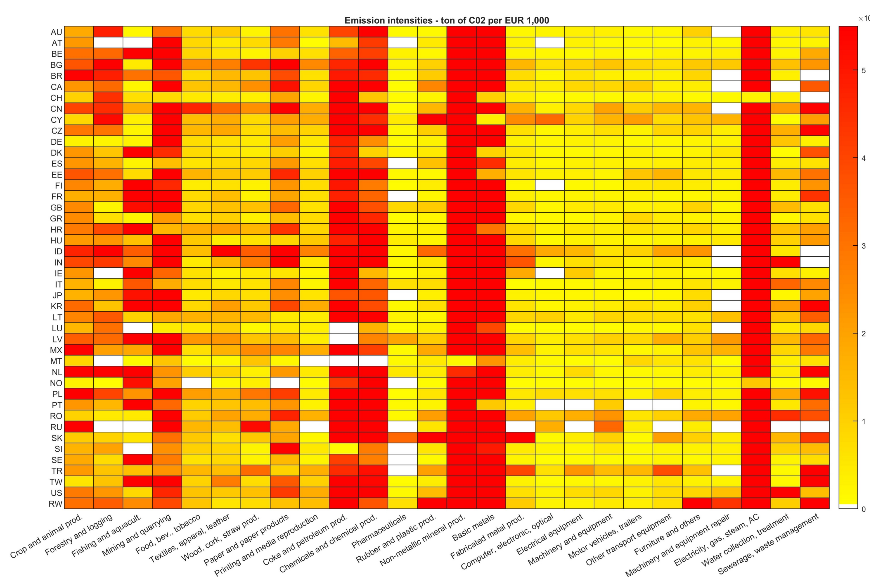
**Figure D.2.** Fixed costs and Sourcing potential




**(a)** Unregulated **(b)** Regulated

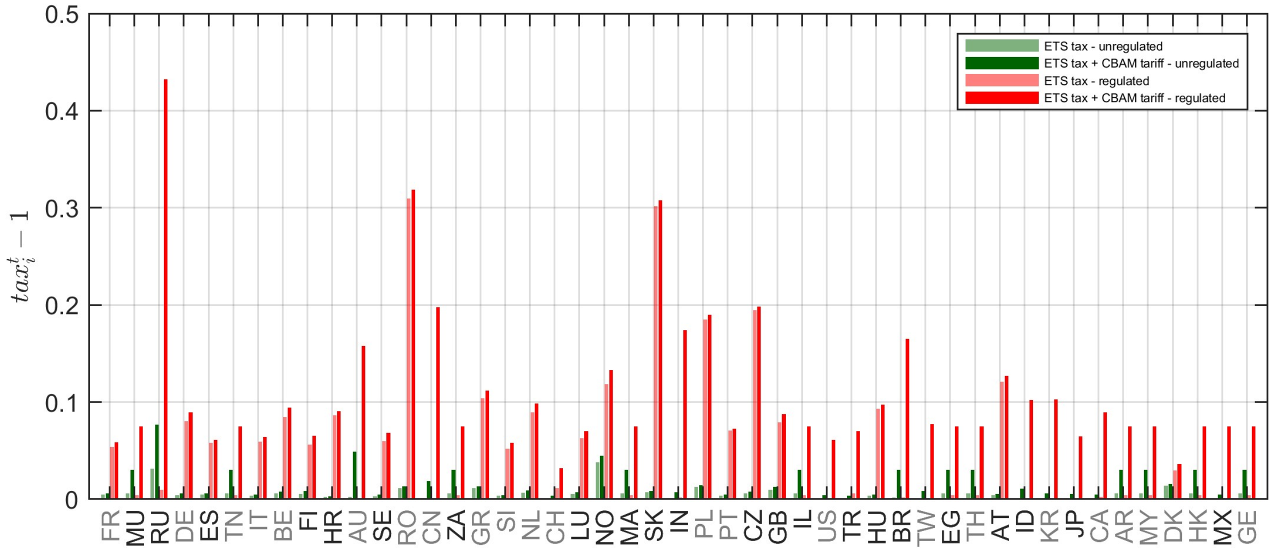
**Notes:** This figure plots the median fixed cost to source from a given country generated by the model against the source country's estimated sourcing potential for unregulated inputs in panel (a) and regulated inputs in panel (b). Data used are from 2004.

**Figure D.3.** Country-sector variation of $CO_2$ emissions in production in 2004



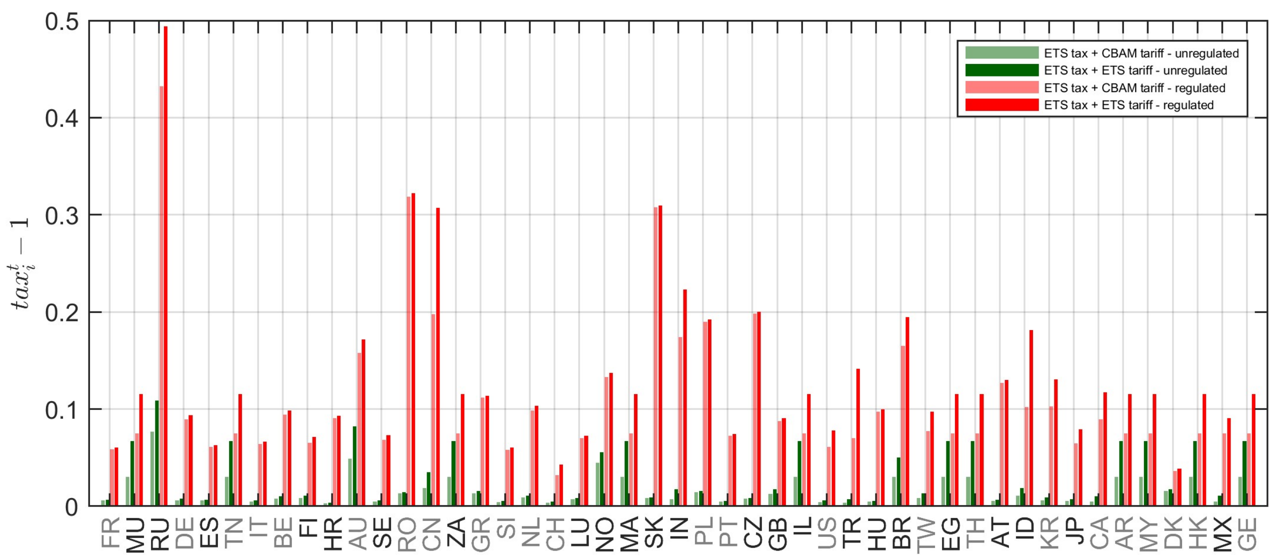

**Notes:** This figure plots a heat map of sectoral emissions intensities, measured as tons of $CO_2$ emitted per 1,000 euros of goods produced. The data are sourced from the WIOD's Environmental Acccounts and Input Output table.

**Figure D.4.** Country-level taxes



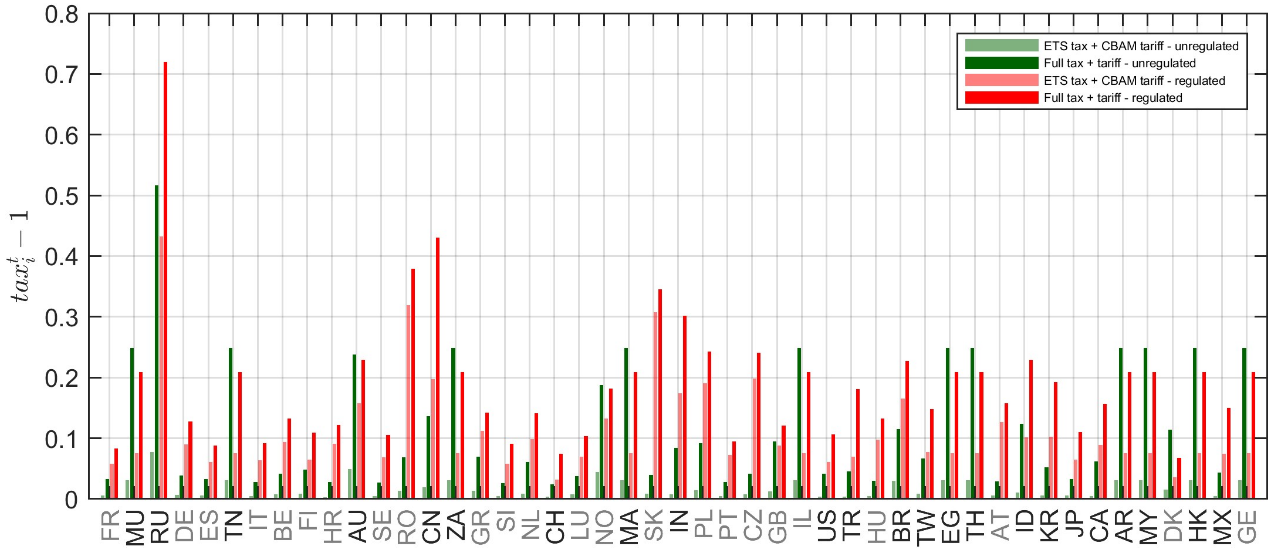

**Notes:** This figure presents country rates for each input type for ETS (grey labels) and non-ETS countries (black labels), in the ETS tax and ETS tax + CBAM tariff scenarios. Based on authors' calculations using data from WIOD's sector-level emissions + WIOD IO tables.

**Figure D.5.** Country-level taxes when taxing all regulated inputs using ETS coverage



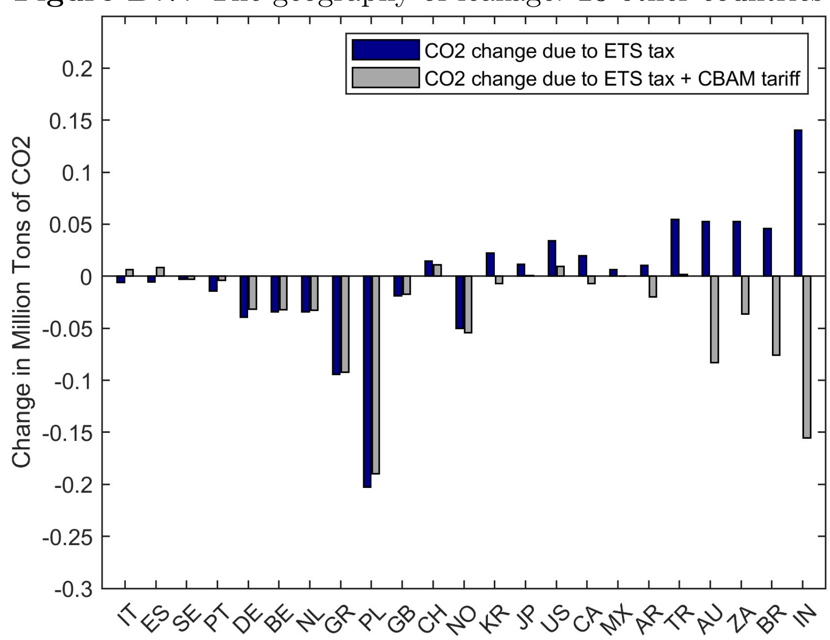

**Notes:** This figure presents country rates for each input type for ETS (grey labels) and non-ETS countries (black labels), in the ETS tax + CBAM tariff, vs and ETS tax + ETS tariff scenarios. The baseline CBAM tariff scenario uses the CBAM coverage displayed in Table A.3. The ETS tariff scenario applies the same coverage displayed in Table A.2 to both ETS and non-ETS countries. Based on authors' calculations using data from WIOD's sector-level emissions + WIOD IO tables.

**Figure D.6.** Country-level taxes when taxing all emissions




**Notes:** This figure presents country rates for each input type for ETS (grey labels) and non-ETS countries (black labels), in the ETS tax + CBAM tariff, compared with a scenario in which the sectoral coverage is uniform and all emissions are taxed. Based on authors' calculations using data from WIOD's sector-level emissions + WIOD IO tables.

**Figure D.7.** The geography of leakage: 23 other countries




**Notes:** This figure plots the change in emissions in millions of tons when imposing the carbon tax, and then both the carbon tax and tariff. We plot a subset of 23 countries.