Firms' Supply Chain Adaptation to Carbon Taxes*

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Abstract

This paper investigates how firms adapt their sourcing of clean and dirty inputs in response to changes in climate policy. We use information from the European Union's Emissions Trading System (EU ETS) and the Carbon Border Adjustment Mechanism (CBAM) to create a new classification of clean and dirty products based on whether they are subject to a domestic or a border carbon tax. We then combine this dataset with French firms' product-level import data over 2000–2019 and estimate that firms' propensity to import dirty inputs from non-EU countries increased in the 2010s, reflecting *carbon leakage*. A heterogeneous firm model is then used to quantify the impact of changes in firms' sourcing of clean and dirty inputs given the implementation of a carbon tax and a carbon tariff. The simulated ETS carbon tax scenario is able to match leakage observed in the data and leads to a higher price level and a modest decline in emissions. The scenario that further includes the CBAM carbon tariff reverses carbon leakage at the cost of an additional rise in prices. Overall, household welfare declines because the higher costs associated with the carbon policies outweigh the benefits of reduced emissions.

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

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1 Introduction

A prevailing consensus among economists asserts that establishing a sufficiently high carbon price serves as a fundamental pillar for tackling climate change.[1] The implementation of national carbon taxes or cap-and-trade systems have been common approaches to achieve higher carbon prices. The effectiveness of such unilateral policies in decreasing global emissions is questionable, however, given the ability for firms to shift production and thus emissions across borders to avoid being taxed, a behavior that is commonly referred to as *carbon leakage*.[2] One proposed solution to address this leakage is the implementation of a carbon border adjustment mechanism (CBAM), which taxes the emissions' content of imported goods.

European Union (EU) member countries have been at the forefront of such carbon policies. In particular, the EU implemented a cap-and-trade system, called the EU Emissions Trading System (ETS) in 2005. This scheme sets a maximum amount of emissions every year and allows EU firms to trade emissions rights within this limit.[3] While this system set a common price for carbon across EU countries, it did not eliminate the possibility of carbon leakage outside the union. To eliminate the remaining leakage and incentivize foreign firms to produce low-carbon intensive goods, the EU thus introduced a CBAM framework in 2023, which will take hold in 2026.

The questions of whether a cap-and-trade system, such as the EU ETS, creates significant carbon leakage and what CBAM's potential impact on both emissions and economic efficiency will be are still not well understood. In this paper, we take a *granular* approach to answering these questions in the context of the EU's experience. We first build a novel *product-level* dataset of French firms' intermediate imports from different source countries over 2000–2019 to track the impact of the ETS on carbon leakage over time. Crucially, this dataset allows us to differentiate the importing of *clean* vs. *dirty* goods from ETS and non-ETS member countries. Using the product and spatial dimensions, we can identify carbon leakage from

[1]For example, 34 out of 43 leading economists surveyed by the Clark Center at Chicago Booth in March 2021 strongly agree with the following statement: "Sound policy would involve increasing significantly the currently near-zero price of emissions of carbon dioxide and other greenhouse gases" (https://www.kentclarkcenter.org/surveys/pricing-emissions/). In addition, in 2019 more than 3,600 economists, including 28 Nobel laureates released a statement advocating that a " ... carbon tax offers the most cost-effective lever to reduce carbon emissions," and that it " ... should increase every year until emissions reductions goals are met" (https://www.econstatement.org/).

[2]The term *carbon leakage* is used in the literature to designate two distinct consequences of unilateral carbon policies: i) their impact on production costs, which induces a shift in production away from countries with stringent climate policies (the *trade channel*), and ii) their impact on global fossil fuel prices through a decline in domestic demand (the *international energy price channel*). In this paper, our focus is on the former trade effect.

[3]This system complements EU members' domestic carbon taxes, which vary by country and target mostly the production of non-tradable goods such as energy production. This production cannot generate carbon leakage easily as it is difficult to shift consumption of fuel away from national distributors.

changes in trade patterns both across and within firms. We use these data to show that French firms shifted their imports of dirty products to non-ETS country suppliers over time, with the extensive margin playing an important role in this change of sourcing behavior.

Motivated by our empirical findings, we set up a model of endogenous firm sourcing decisions by extending the work of Antràs, Fort and Tintelnot (2017) to multiple input types (clean and dirty). This model allows us to embed different layers of carbon policy-induced costs of production, which are meant to mimic the impacts of both ETS and CBAM on French firms' sourcing decisions across countries, as well as between clean and dirty inputs. Specifically, we model the policy-induced costs as taxes, which take the form of domestic and foreign iceberg costs, in the sourcing of different inputs. Importantly, the model allows for firms to adjust their import decisions at both the extensive and intensive margins. Our firm-level focus on extensive adjustments is motivated by the high costs of finding new intermediate goods suppliers along with the uncertainty of climate policy. To the best of our knowledge, such types of climate adaptation costs have not been studied.

We then combine the French firm-level import data with an administrative dataset on firms' balance sheets in order to estimate the model's key parameters and run counterfactual analysis to study the effect of various carbon tax policies. In doing so, we quantify the aggregate impact of the ETS on French carbon leakage and household welfare and compare these outcomes to a system in which the ETS is complemented with a carbon tariff such as the CBAM. We show that the French carbon leakage resulting from the ETS would be reversed when adding the CBAM since domestic firms increase their propensity to source from EU suppliers, who on average have lower emission intensities than non-ETS producers. Both policies lead to a fall in emissions embedded in French firms' intermediate goods used in production, but at a cost of higher prices faced by domestic households. On net, both the ETS and the CBAM lead to a fall in domestic welfare, as the associated rise in prices from these policies outweigh the utility gain households obtain from the fall in emissions.

An important contribution of this paper is the construction of a new product-level dataset that defines clean vs. dirty goods. Our methodology differs from common approaches taken in the literature that either rely on emissions data to measure a sector's or firm's exposure to environmental policies, or comparing the impact of a policy on regulated vs. non-regulated firms. We instead define clean vs. dirty goods based on which products are subject to an environmental policy rather than the emissions generated in production. The definition of a type of good leverages information about the actual scope of the European policies. The EU ETS applies to several sectors for all EU member states plus the European Free Trade Association countries (Iceland, Liechtenstein and Norway). The sectoral coverage is used to define a list of *dirty* inputs.[4] We then compare the geographic structure of import sourcing for these dirty inputs to a control group composed of the remaining set of *clean* inputs. By focusing on firms' input usage, we capture the indirect impact of a policy on downstream customer firms. Further, a key and novel benefit to our approach is that it allows us to capture the input mix across types of goods *within* a firm, using a granular approach to differentiate clean and dirty inputs.

The first empirical result we document is that, relative to clean imports, the import share of dirty products that a French manufacturing firm sources from outside of the EU has increased after the implementation of the ETS. In 2019, the relative share of these imports had increased by 10 to 20% relative to 2004 values.[5] The magnitude of this change is economically meaningful and accumulates over time as the impact of the ETS becomes increasingly binding. Second, we show that the reshuffling of import portfolios is in part driven by the *extensive margin*, i.e., French firms starting to import dirty products from new suppliers outside of the ETS zone.

Our quantitative analysis takes into account this extensive margin of sourcing using a model built on the seminal contribution of Antràs et al. (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 clean and dirty inputs, (ii) country- and input-specific carbon taxes, and (iii) carbon damages incorporated into households' utility. This framework allows us to think about 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.

We first estimate key model parameters using pre-ETS firm-level and firm×product-type×source country imports from 50 countries, within and outside the EU ETS. We extend the approach of Antràs et al. (2017) in estimating the fixed cost a firm faces in sourcing dirty products from a given country to allow for the existence of environmental policies in the country.[6] We then borrow other relevant parameters from the literature and apply

[4]The sectoral scope of the ETS has somewhat evolved over time but mostly concerns electricity, heat generation and energy-intensive manufacturing sectors (oil refineries, steel works, and production of iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals).

[5]The increased import share is observed when focusing on French firms' sourcing from outside of the ETS zone using the sourcing of clean inputs from the same countries as controls. We also confirm the qualitative results in a difference-in-differences model that compares dirty 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 blurs the comparison of intra- and extra-ETS sourcing strategies during the period under study, as EU and ETS countries largely overlap.

[6]Furthermore, the estimation for France rather than the U.S. also forces us to adjust the empirical specification to account for the differential impact of geography on the fixed cost of sourcing given high intra-EU trade and France's relative closeness to many EU countries.

simulated methods of moments (SMM) to estimate the remaining structural parameters for each type of inputs. The model is able to match the observed trading patterns in the data fairly well along the lines of Antràs et al. (2017).

Given the simulated model parameters, we run policy experiments that allow for the imposition of a carbon tax on dirty inputs sourced from within the EU ETS, including domestically produced goods. We then apply an equally-sized carbon tax to dirty 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.[7] Furthermore, we also use data on sector×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.

Our baseline quantitative exercise, which applies a tax level of €100 per ton of CO_2, yields several interesting results. The ETS-only simulation produces statistics of carbon leakage via firms' adaptation at the intensive and extensive margins that are comparable to those calculated in the data. More specifically, we replicate the motivating stylized facts within simulated firm-level data. The reshuffling of import portfolios towards dirty 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 choice of a €100 tax 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. 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 distribution. In relative terms, the most affected firms are those displaying intermediate productivities, as these firms lie close to the productivity cutoff for imports in the baseline model without carbon taxes.

On aggregate and holding total French expenditures constant, the ETS-system simulation leads to a relatively small fall in the emission-content of inputs sourced by French firms, −1.84M of tons relative to a no-tax equilibrium. This result is driven by supply chain reallocation across two margins: while the economy experiences carbon leakage as French firms substitute to non-ETS dirty producers, the tax also leads domestic firms to substitute towards cleaner 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 increase is modest, at 0.05% relative to a no-tax equilibrium. Applying the utility function of Shapiro (2021) which considers emissions damages, we still find that welfare decreases slightly, −0.005% relative

[7] 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.

to a no-tax equilibrium, as the price rise dominates the utility gain from lower emissions.

Next, turning to the baseline ETS+CBAM simulation, the application of the €100 border tax in addition to the ETS one 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 and are significant, 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 CBAM is driven by French firms decreasing their imports from Russia, China and India.[8] Meanwhile, high input emission ETS-countries, such as Bulgaria, Romania and Poland, now increase their exports slightly to France relative to an ETS-only equilibrium. However, this increase in imports, relative to the ETS-only system, is not sufficient to reverse the fall of France's imports from these countries relative to a no-tax equilibrium.

Across countries, the addition of the CBAM to the ETS decreases the emission-content of inputs sourced by French firms to -6.94M tons relative to a no-tax equilibrium, which is roughly four times larger than the decline with only the ETS. This fall reflects a large decrease in the use of dirty inputs overall as leakage is reversed. The fall in emissions comes at a cost, however, as the price index now increases by 0.54%. Again, the real consumption effect dominates the utility gains associated with lower global emissions and welfare decreases (-0.542%). Rebating tax revenues to households generates positive welfare effects.

Related literature. We contribute to several strands of the literature. First, our work contributes to 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 firms or multinationals, and by drilling down to the product level to study the potential for leakage. Furthermore, building on our new empirical stylized facts, we provide a model of firms' sourcing decisions that can be taken to the data and be used to provide policy analysis.

It is useful to compare our results with those of Colmer et al. (2024) who also use French micro data. Those authors provide evidence that ETS-regulated firms were largely unaffected by the ETS given their ability to innovate. One of their findings is that ETS-regulated firms' imports did not change relative to a control group of similar non-regulated

[8] In our partial equilibrium model, total sales and hence total imports are fixed across simulations. Hence, a decrease in imports from a country in a given counterfactual is equivalent to a lower share of imports coming from this country.

firms, which the authors interpret as evidence against leakage. Our analysis complements their work on several grounds. First, we focus our attention to carbon leakage, rather than other adjustment margins such as innovation. In doing so, we account for the possibility that carbon leakage may extend beyond regulated firms to downstream industries. For this reason, our sample is not restricted to having only ETS firms as the treatment group. We instead focus on a set of manufacturing firms that use dirty (i.e., regulated) inputs in production.[9] Beyond the difference in coverage, we also develop a novel empirical strategy to identify carbon leakage, which leverages product-level data rather than total firm imports. Based on these data, we can compare the geographic structure of individual firms' imports of dirty inputs, and in relative terms with the same firms' purchases of clean (i.e., unregulated) inputs. Therefore, we present complementary evidence to the innovation channel on how manufacturing firms adapt to carbon policy.

Our focus on the impact of the ETS on firms located downstream from the regulated sectors relates to literature studying the impact of carbon policies on production networks (e.g., King, Tarbush and Teytelboym, 2019; Devulder and Lisack, 2020; Aghion, Barrage, Hemous and Liu, 2024). In recent work, Martin, Muûls and Stoerk (2024) use data on Beligium firm-to-firm input-output relationships to estimate the spillover effects of the ETS on customer and supplier of regulated firms. The authors study the spillover effects of variables such as value added, employment, or innovation, but omit firms' import behavior as a channel for adaptation.

The empirical results add to the literature estimating the magnitude of the effect of climate policies on actual trade. A number of papers test for a link between net trade flows and the stringency of pollution control measures using US data on local pollution regulations. In their survey of the literature, Dechezleprêtre and Sato (2017) conclude that there is some evidence in favor of the pollution haven hypothesis. Aldy and Pizer (2015) and Sato and Dechezleprêtre (2015) estimate the elasticity of net imports to energy prices using panel data and find small positive elasticities.[10] A few papers have tested the carbon leakage hypothesis using the EU ETS as a natural experiment. For instance, Naegele and Zaklan (2019) use product-level trade data over 2004–2011 and do not find any significant carbon leakage. In our data, carbon leakage is not found to be significant before the early 2010s.

Our findings also complement those in the nascent literature that studies how firms adapt their supply chain and production decisions in response to climate shocks. Balboni, Boehm and Waseem (2024), Blaum, Esposito and Heise (2024), Castro-Vincenzi (2024), Castro-

[9] We show in a robustness check that our findings do not hold when focusing only on ETS firms.

[10] In Sato and Dechezleprêtre (2015), a €40-65/ton CO_2 price of carbon in the EU ETS would increase Europe's imports from the rest of the world by only 0.04%.

Vincenzi, Khanna, Morales and Pandalai-Nayar (2024) use granular data to study the impact of weather shocks on firms and production networks. Those papers find that firms' sourcing decisions of intermediate goods are impacted by climate shocks, but that firms may adapt by alternating between suppliers. Further, such types of shocks may propagate throughout the production network as originally shown by Barrot and Sauvagnat (2016) and Carvalho, Nirei, Saito and Tahbaz-Salehi (2020). Our study complements these papers by showing the importance of firms' sourcing adaptation to climate *policy* and quantifying the impact of these changes on emissions and household welfare.

Our modeling approach is in the spirit of recent contributions in the quantitative trade and environmental literature, such as Shapiro (2016, 2021) and Bellora and Fontagné (2023), and other work discussed in the review by Copeland, Shapiro and Taylor (2022).[11] 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 (France in our case), 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 on the impact of policy on global emissions. On the other hand, by focusing on the firm and product levels, we are able to perform analysis that highlights potentially important mechanisms that firms can use to adapt to climate policy. Furthermore, by using granular data, we are also able to gauge potential future carbon leakage via extensive margin adjustments that would not be possible using sector-level data.

Finally, while our work remains silent on the global implications of climate policy, we hope to provide a granular view of the impact of environmental policy, both within a country and at the border, that can be used to inform theoretical models that evaluate such policies like the contributions of Nordhaus (2015), Larch and Wanner (2017), Weisbach, Kortum, Wang and Yao (2022), and Farrokhi and Lashkaripour (2024).

Section 2 describes the construction of the new dataset. Section 3 provides evidence on firms' sourcing choices of clean and dirty products from within and outside of the EU ETS. Section 4 presents the theoretical framework that is used to model firms' domestic and foreign sourcing decisions. 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.

[11] 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.

2 Data

A key aspect of our analysis is the identification of firms' sourcing of clean and dirty 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 "dirty" goods by the actual coverage of these policies. This methodology follows several steps and relies on information at the product, firm and sector levels.[12] In this section, we sketch the main approaches taken in the construction of this new dataset, with details relegated to Appendix A.

2.1 Defining clean and dirty products

We use information from the EU Transaction Log (EUTL) to recover a list of regulated sectors under the ETS.[13] We complement these data with information from the European Commission on the list of products that will be covered by the CBAM.[14] We use these two datasets to create a list of dirty 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 C.1). For example, the ETS covers firms that refine mineral oil (activity 21 in the ETS classification), so we categorize as dirty 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 dirty products and then use these data to supplement the ETS list of dirty products (see Table C.2).

This manual approach may introduce measure error and not capture the true dirtiness of sourced intermediates as measured by their emissions, which is the common metric used in the literature. However, two factors help to assuage these concerns. First, there is substantial overlap of products that are classified as dirty using the ETS classification approach and the CBAM list of products. Second, while the delineation of goods into dirty and clean sets is legislation-based rather than emissions-based, the ETS and CBAM cover the most heavily polluted sectors according to their emissions, so the differential in emissions between clean

[12] 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.

[13] See https://www.euets.info/ for a link to the underlying dataset.

[14] 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 the Combined Nomenclature (CN) 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.

and dirty products should also be reflected in our approach. Finally, a further benefit of our approach is that defining dirty products based on policies rather than based on their emissions content avoids erroneously classifying products as dirty when they are not actually taxed by either ETS or CBAM. Further details about the classification of clean and dirty goods can be found in Appendix A.1, which includes the prevalence of dirty goods across HS categories in Table C.3.

2.2 Firm-level variables

Using the above categorization of HS products, we can first leverage firm-level import data and run the reduced-form regressions. Our main source of information is the customs dataset, which contains import flows by firm, origin country and product category, from 2000 to 2019.[15] Import flows are aggregated at the annual level. Origin countries are divided into ETS and non-ETS countries and product categories into clean and dirty inputs, based on the actual coverage of ETS. The sample of firms is restricted to 44 dirty-intensive manufacturing sectors, using information recovered from the 2011 INSEE input-output (IO) table.[16] Finally, our empirical analysis focuses on a subset of firms' core inputs. The purpose of the restriction is to avoid including in the treatment or the control groups product categories that are either marginal in a firm's intermediate usage, or purchased occasionally.[17] To this aim, 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 given a mapping between products and NAF sectors, we are able to 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 dataset from INSEE-FICUS, which provides information on firms' total use of intermediate goods and production. The model requires information on the dirtiness intensity of firms' input purchases. In the absence of firm-level information, we match the data with the detailed sector-level IO dataset described in the previous paragraph, and apply the sector-specific

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

[16] We first establish a mapping between the 138 sectors composing the French IO table and the list of ETS sectors listed in Table C.1 to recover a list of dirty-*producing* sectors. We then use the IO table to categorize dirty-*intensive* input-use sectors. The analysis is restricted to manufacturing sectors relying on dirty-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$\times$product$\times$country dimension. In doing so, we expand the dataset significantly, since every product$\times$country pair that is observed once in a firm's portfolio is considered a sourcing option in every other year. Restricting the dataset to the firm's core products avoids inflating the sample with too many zeros.

dirtiness intensity 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 yields a 2004 dataset which will be 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.

3 Motivating Facts

In this section, we explore the dynamics of French firms' imports before and after the introduction of ETS. We are interested in exploring the time variation of potential leakage since adjustments to the ETS were made over three phases (Phase 1: 2005–08, Phase 2: 2009–12, Phase 3: 2013–2020) after its announcement in 2003.[18] Moreover, 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 (see Figure D.2). 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. The proportion of free allowances was still high however, around 90%. This changed during Phase 3, when auctioning became the default method for allocating allowances. We next explore how French manufacturing imports adjusted to these phases, first at the macro and then the micro level.

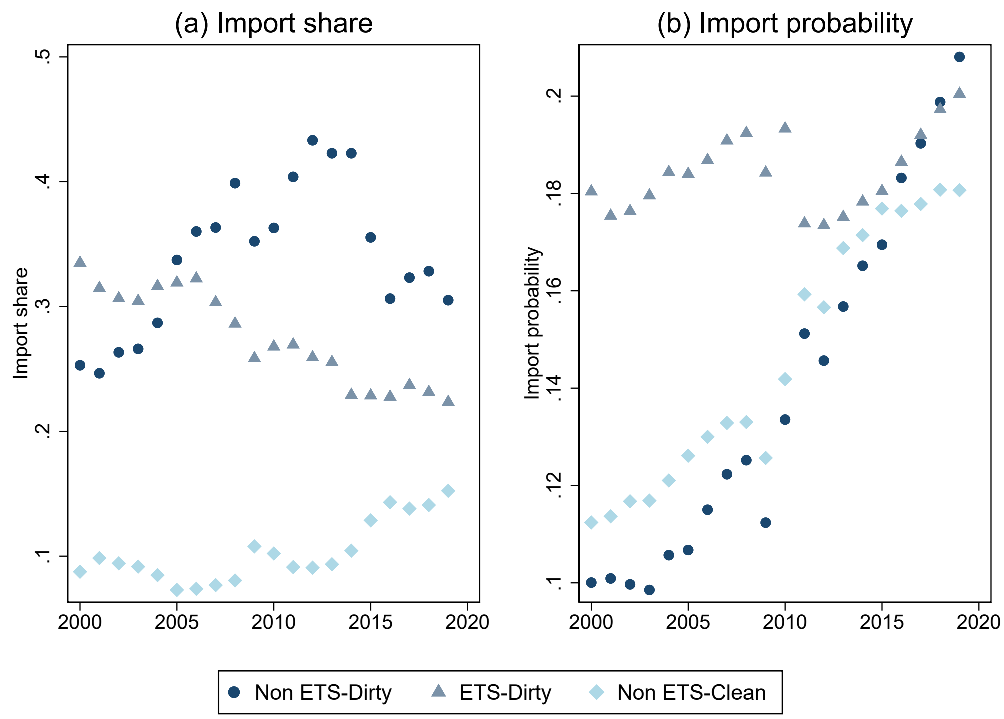
3.1 Aggregate statistics

We first present aggregate evidence on French imports using our newly constructed dataset. 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 dirty inputs. Figure 1 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

[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 1. Aggregate import shares and probability of sourcing from a new supplier market: control vs. treatment groups



Notes: This figure presents aggregate import statistics based on the firm× product import dataset that classifies products as either clean or dirty. 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 Dirty', vs. both control groups: (i) 'non-ETS Clean' or (ii) 'ETS-Dirty'.

country. Averaging across firms, products and countries within each product type (clean or dirty) × 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 (clean or dirty) × 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 dirty 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 clean import share from non-ETS countries (light

[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.

blue diamonds) exhibits a less volatile upward trend. The share of non-ETS dirty imported goods is always larger than its clean counterpart, but this difference has fallen over time. The second control group, the dirty 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 clean and dirty products, though the rate of increase has been stronger in recent years for dirty 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 dirty product from ETS member countries has not changed greatly over time, we do see a substantial increase in the extensive margin of importing dirty products from non-ETS countries, where now a firm appears to be equally likely to source a dirty 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 dataset 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 1.

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 will become binding in the future. We use a difference-in-differences model that can be generally written as:

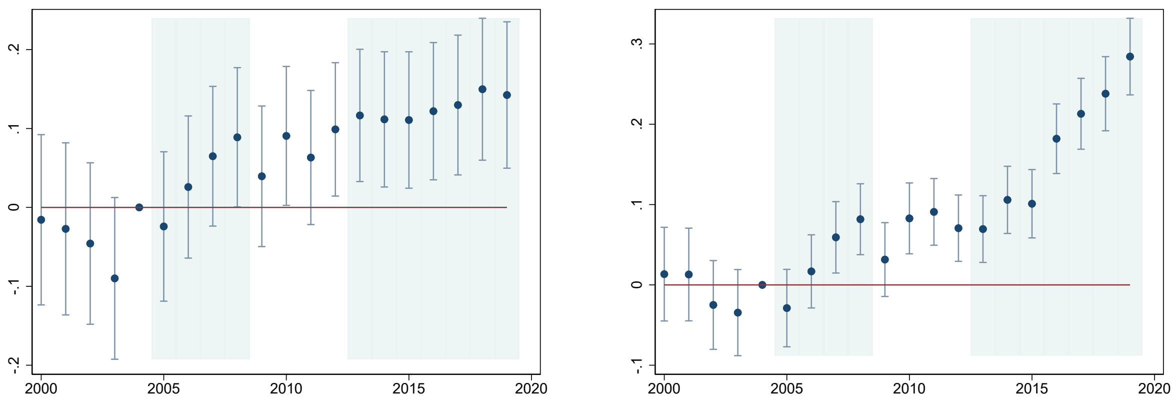
$$y_{fpit} = \exp\left[\sum_{\tau=-4}^{15} \beta_\tau \mathbf{1}\left(i \notin ETS\right) \mathbf{1}\left(p \in Dirty\right) \mathbf{1}\left(t = \tau\right) + \mathbf{X}'_{fpit}\boldsymbol{\theta} + \varepsilon_{fpit}\right], \tag{1}$$

where y_{fpit} is either the share of product p sourced from country i in the firm's overall imports at time t or a dummy variable for whether the firm imports product p from country

[20] The declaration threshold is defined over annual imports across all EU member states, which constitute the majority of ETS countries.

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

Figure 2. Evolution of firm-level imports from non-ETS countries: Dirty vs. Clean 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 dirty inputs sourced in non-ETS countries. The control group covers clean 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.

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. Note that the notation $\mathbf{1}()$ is used for dummy variables in (1), where $\mathbf{1}\,(i \notin ETS)$ is a dummy variable which equals one if i is not an ETS member country, $\mathbf{1}\,(p \in Dirty)$ identifies dirty products, and $\mathbf{1}\,(t = \tau)$ is equal to one for trade flows observed at time τ. $\mathbf{X}_{fpit}$ 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 clean inputs sourced from non-ETS countries or dirty 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 within and between manufacturing firms. Results are

[22] We also tried exploiting a triple interaction regression specification in which we compared the dynamics of dirty versus clean 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 clean inputs sourced from ETS member countries in the early 2000s.

summarized in Figure 2, 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. Following Silva and Tenreyro (2006), equation (1) is estimated by Poisson pseudo-maximum-likelihood (PPML) so that the exponential of the coefficients are interpreted as the expected ratio of the left-hand-side variable, for dirty relative to clean inputs.

Consider first panel (a) which compares import shares across countries and products. Results point to an upward trend in the relative share of dirty 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 dirty inputs sourced from non-ETS countries had increased by 15% relative to the share of clean inputs sourced from the same area.

Whereas panel (a) studies the evolution of a firm's import portfolio, panel (b) shows that this evolution is in part driven by extensive margin adjustments, namely an increasing propensity for French firms to source their dirty 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.[23]

Table 1 next presents 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 2000–2004 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 2 (column (1)). From column (2), we restrict our attention to variation happening within a firm, 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 most impactful set of fixed effects encompass the sectoral controls, which halves 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.

In column (6), we further control 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

[23]In Figure D.3, we show that these results are robust to controlling for heterogeneous treatment effects following de Chaisemartin and D'Haultfœuille (2020). 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 clean inputs from non-ETS countries is 1.6% (resp. 18%).

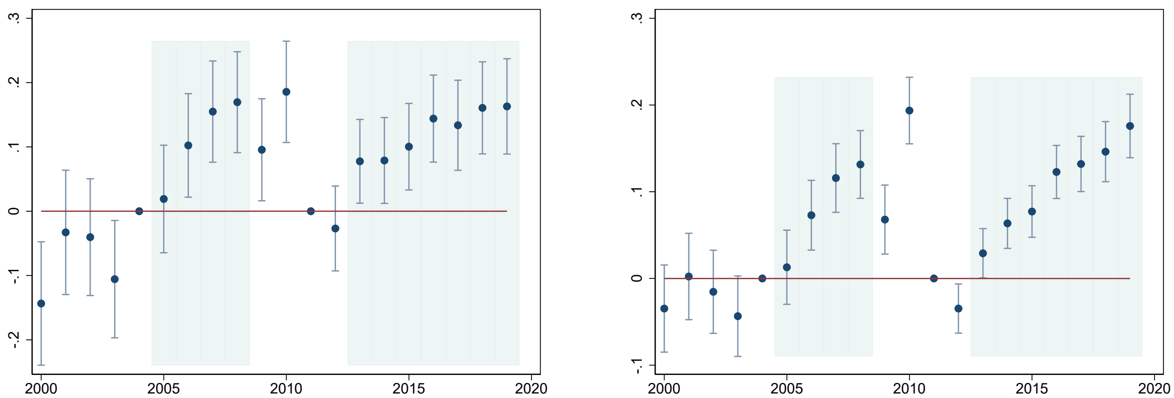
Table 1. Firm-product-level evidence on carbon leakage, Imports from non-ETS countries: Dirty vs. Clean inputs

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel (a) Import Share					
Dirty product × Non-ETS						
× ETS Phase 1	0.056**	0.085***	0.159***	0.050	0.083**	0.083***
	(0.025)	(0.024)	(0.024)	(0.037)	(0.035)	(0.024)
× ETS Phase 2	0.109***	0.169***	0.276***	0.066**	0.119***	0.174***
	(0.021)	(0.021)	(0.021)	(0.032)	(0.030)	(0.021)
× ETS Phase 3	0.161***	0.268***	0.359***	0.067**	0.133***	0.277***
	(0.021)	(0.021)	(0.020)	(0.031)	(0.029)	(0.021)
Pseudo R^2	.162	.384	.388	.390	.390	.384
	Panel (b) Import Probability					
Dirty product × Non-ETS						
× ETS Phase 1	0.024*	0.018	0.043***	0.031*	0.030*	0.017
	(0.013)	(0.013)	(0.012)	(0.018)	(0.018)	(0.013)
× ETS Phase 2	0.079***	0.078***	0.097***	0.082***	0.076***	0.091***
	(0.011)	(0.011)	(0.010)	(0.015)	(0.015)	(0.011)
× ETS Phase 3	0.181***	0.183***	0.141***	0.074***	0.072***	0.205***
	(0.011)	(0.011)	(0.010)	(0.015)	(0.015)	(0.011)
Pseudo R^2	.044	.158	.166	.161	.169	.158
Observations	7,553,888					
# Firms	27,240					
Control group	Non-ETS Clean products					
Fixed effects	pc,t	fpc,t	fpc,ct	fpc,st	fpc,ct,st	fpc,ETSt

Notes: This table presents the estimated β 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.

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 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. The vast majority of firms in our estimation

Figure 3. Evolution of firm-level imports of dirty 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 dirty inputs sourced in non-ETS countries, with sourcing of dirty 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 later 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.

sample (26,900 out of 27,240) 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 dirty inputs increasing.[24]

As explained in Section 3.1, evidence of carbon leakage could in principle be recovered from the comparison of dirty input sourcing from non-ETS versus ETS source countries. Unfortunately, the change in the declaration threshold for intra-EU imports involves an additional difficulty, as this break in the data shifts all the treatment effects after 2011.[25] In Figure 3, 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 2 despite the estimation sample and

[24] Figure D.4 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 dirty inputs sourced from non-ETS countries seems to decrease during Phase 3 of the ETS.

[25] See evidence for this shift in Figure D.5. 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.

[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

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.

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 out a quantitative multi-country sourcing model that provides a methodology to solve firm's problem with interdependencies following the approach of Antràs et al. (2017), referred to as AFT henceforth.[27] We include the following additional ingredients to the baseline model to capture heterogeneous environmental taxes and their impact: (i) clean and dirty inputs, (ii) country- and input-specific carbon taxes, and (iii) carbon damages to 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 clean and dirty *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 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.

4.1 Households

A representative household in country i values the consumption of a CES aggregate of differentiated varieties purchased from domestic final good producers, along with a homogeneous

from EU countries, exploiting this discrepancy is not possible. In Figure 3, 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] Appendix B provides details and proofs.

good that is included to pin down the equilibrium wage. The CES utility 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 Ω_i denotes the set of varieties available to a household and σ measures the elasticity of substitution between varieties ω.

It will be useful to summarize the demand side of the model later by a demand term B_i 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 $P_i \equiv \left[\int_{\omega \in \Omega_i} p(\omega)^{1-\sigma} \, d\omega \right]^{\frac{1}{1-\sigma}}$.

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 (φ), and a bundle of intermediate goods, which are sourced from around the world to minimize costs. We depart from AFT and modify the supply-side of the model by introducing two categories of inputs, clean and dirty inputs. To this end, we introduce a nested-CES structure involving a firm-specific bundle of clean inputs $y^C(\varphi)$ and a bundle of dirty inputs $y^D(\varphi)$, which can be sourced domestically or imported:

$$y_i(\varphi) = \varphi \left[y_i^C(\varphi)^{\frac{\eta-1}{\eta}} + y_i^D(\varphi)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}},$$

with

$$y_i^C(\varphi) = \left[\int_{\nu \in \mathcal{A}^C} y_i^C(\varphi, \nu)^{\frac{\rho-1}{\rho}} \, d\nu \right]^{\frac{\rho}{\rho-1}}, \quad y_i^D(\varphi) = \left[\int_{\nu \in \mathcal{A}^D} y_i^D(\varphi, \nu)^{\frac{\rho-1}{\rho}} \, d\nu \right]^{\frac{\rho}{\rho-1}},$$

where η is the elasticity of substitution between clean and dirty input bundles, and each bundle is itself a CES aggregate of a mass of differentiated varieties, which are substituted at rate $\rho > 1$, assumed to be the same across clean and dirty inputs. We index each variety of input, $y_i^t(\varphi, \nu)$, $t = C, D$, by the final good firm's productivity parameter, φ, and the variety of the intermediate good, ν. Each firm treats the mass of clean and dirty varieties, $\mathcal{A}^C$ and $\mathcal{A}^D$, as exogenous parameters. We calibrate these using data on the relative contribution of clean and dirty inputs to intermediate consumption, and normalize $\mathcal{A}^C$ so that $\mathcal{A}^C + \mathcal{A}^D = 1$. All else equal, an increase in $\mathcal{A}^D$ puts more weight in firms' cost on dirty inputs, which makes firms more sensitive to the taxation of these inputs.

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

Cost minimization implies the following demand for input bundles of type $t = C, D$:

$$c^t(\varphi)y^t(\varphi) = \left(\frac{c^t(\varphi)}{c(\varphi)}\right)^{1-\eta} c(\varphi)y(\varphi),$$

with

$$c(\varphi) = \left[c^D(\varphi)^{1-\eta} + c^C(\varphi)^{1-\eta}\right]^{\frac{1}{1-\eta}},$$

$$c^t(\varphi) = \left[\int_{\nu\in\mathcal{A}^t} c^t(\varphi,\nu)^{1-\rho}\, d\nu\right]^{\frac{1}{1-\rho}},$$

where $c(\varphi)$ is the unit cost of the firm's input bundle given the vectors of unit costs for individual clean and dirty inputs, $c^t(\varphi)$, which are in turn a function of each variety's unit cost, $c^t(\varphi,\nu)$.

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 ν 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 intermediate input efficiency, $1/a_j^t(\nu)$, is the realization of draws from a Fréchet distribution:

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

where these draws are assumed to be independent across locations and inputs. T_j^t governs the state of technology in country j for type t input while θ^t determines the variability of productivity draws across inputs of type t. Firms in country i must pay fixed cost f_{ij}^t to source a type-t intermediate good from country j. We can then define $\mathcal{I}^t(\varphi) \subset I^t$ as the set of countries from which a firm can source t-type inputs (has paid fixed cost f_{ij}^t), which following *AFT* is called the Global Sourcing Strategy (GSS).

Sourcing problem. The cost of a French firm sourcing from country j is a function of trade costs and Ricardian comparative advantage:

$$c^t\left(\varphi, \nu; \mathcal{I}^t(\varphi)\right) = \min_{j \in \mathcal{I}^t(\varphi)} \left\{\tau_{ij}^t a_j^t(\nu) w_j\right\}.$$

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

$$\chi_{ij}^t(\varphi; \mathcal{I}^t(\varphi)) = \begin{cases} \frac{T_j^t\left(\tau_{ij}^t w_j\right)^{-\theta^t}}{\Theta_i^t(\varphi;\mathcal{I}^t(\varphi))} & \text{if} \quad j \in \mathcal{I}^t(\varphi), \\ 0 & \text{if} \quad j \notin \mathcal{I}^t(\varphi), \end{cases} \tag{4}$$

with

$$\Theta_i^t(\varphi; \mathcal{I}^t(\varphi)) \equiv \sum_{k \in \mathcal{I}^t(\varphi)} T_k^t \left(\tau_{ik}^t w_k\right)^{-\theta^t}. \tag{5}$$

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 clean and dirty goods from potential source countries:

$$\pi_i(\varphi; \mathcal{I}^D(\varphi), \mathcal{I}^C(\varphi)) = \left(\frac{c(\varphi; \mathcal{I}^D(\varphi), \mathcal{I}^C(\varphi))}{\varphi}\right)^{1-\sigma} B_i - w_i \sum_{j \in \mathcal{I}^D(\varphi)} f_{ij}^D(\varphi) - w_i \sum_{j \in \mathcal{I}^C(\varphi)} f_{ij}^C(\varphi), \tag{6}$$

with

$$c(\varphi; \mathcal{I}^D(\varphi), \mathcal{I}^C(\varphi)) = \left[\left(c^D(\varphi; \mathcal{I}^D(\varphi))\right)^{1-\eta} + \left(c^C(\varphi; \mathcal{I}^C(\varphi))\right)^{1-\eta}\right]^{\frac{1}{1-\eta}},$$

$$c^t(\varphi; \mathcal{I}^t(\varphi)) = \left(\mathcal{A}^t\right)^{\frac{1}{1-\rho}} \left(\gamma^t \Theta^t(\varphi; \mathcal{I}^t(\varphi))\right)^{-1/\theta^t},$$

$$\gamma^t \equiv \left[\Gamma\left(\frac{\theta^t + 1 - \rho}{\theta^t}\right)\right]^{\theta^t/(1-\rho)}, \ \Gamma \text{ the gamma function}, \rho < 1 + \theta^t.$$

Firms trade-off the reduction in costs associated with a large GSS and the payment of additional fixed costs given demand (B_i) and productivity (φ). 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*, the model can be solved using an algorithm from Jia (2008), extended by Arkolakis, Eckert and Shi (2023). While our approach follows the previous literature, it is worthwhile noting that applying this approach is further complicated given that firms are now sourcing two types of goods, clean and dirty, and these decisions are interdependent. We show in Appendix B what bounds must be placed on parameter values in order to make the solution method tractable.

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., $T_j^t \left(\tau_{ij}^t w_j\right)^{-\theta^t}$. Second, we borrow estimates of elasticities and productivity parameters from the literature. Third, given the model structure, we apply simulated method of moments (SMM) to firm-level data to estimate the vector of average fixed costs and their variance across firms, the mass of varieties for intermediate goods, and market demand. Crucially, 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.

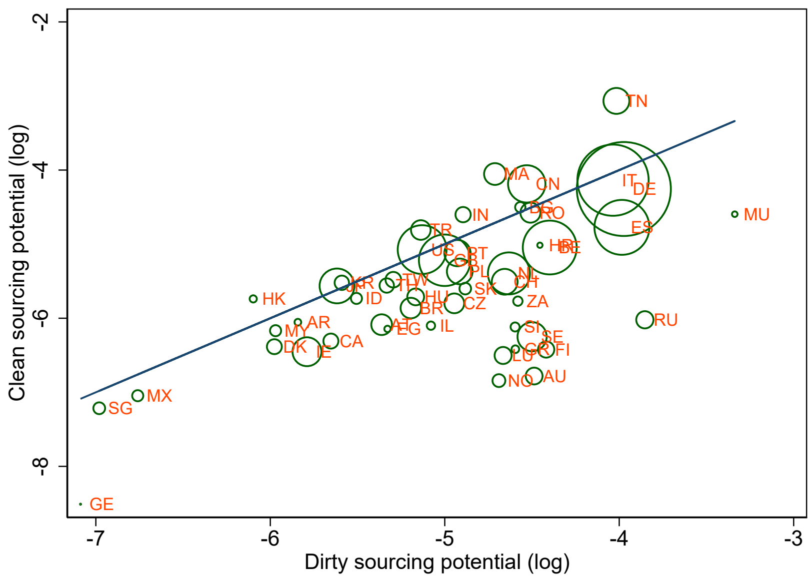
5.1 Estimation of sourcing potential

Given the model structure, we can use equations (4) and (5) to motivate the following fixed effect regression to back out a firm's sourcing potential for each type of good:

$$\log \chi_{fi,j}^t - \log \chi_{fi,i}^t = \alpha_{ij}^t + \varepsilon_{fi,j}^t, \tag{7}$$

where $\chi_{fi,j}^t$ is firm f in country i's import share of type-t from country j, where i refers to home market (France), and α_{ij}^t are source-country-type fixed effects, which in the model relate to the country's sourcing potential $\alpha_{ij}^t = \log T_j^t \left(\tilde{\tau}_{ij}^t w_j\right)^{-\theta^t} - \log T_i^t \left(\tilde{\tau}_{ii}^t w_i\right)^{-\theta^t}$. The regression is estimated using deviations from country i's sourcing potential (i.e., relative to use of domestic intermediates, $\chi_{fi,i}^t$). Note that since equation (7) 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 30,225 observations for clean inputs and 11,448 observations for dirty inputs.

Figure 4. Estimated sourcing potential for Clean and Dirty inputs



Notes: This figure plots the exponential of $\alpha_{i,j}^{t}$ for $t = C, D$. The size of the bubbles is proportional to the value of overall imports. The blue line is the 45 degree line.

Figure 4 plots the estimated sourcing potential for clean inputs on the y-axis vs. dirty inputs on the x-axis in log-log scale. We also include a 45-degree line and 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 45 degree line, indicating that they have a comparative advantage over France on dirty inputs relative to clean inputs. These include non-ETS countries such as Russia (RU) and Australia (AU), and the ETS member Norway (NO), which are major exporters of petroleum products and dirty raw materials. Interestingly, both China (CN) and India (IN) have slightly larger cleaning sourcing potential than dirty ones. With the estimated sourcing potentials in hand, we can now proceed to back-out other necessary structural parameters.

5.2 Elasticities and productivity parameters

To proceed in the estimation of the model's other key variables, such as the fixed cost of accessing a supplier market, we need to take a stand on the distribution of domestic firms' productivity, the distribution of intermediate inputs efficiency, the elasticity of substitution between clean and dirty input aggregates, as well as the household's elasticity of substitution across varieties of goods.

We borrow the Pareto shape parameter of firms productivity, $\kappa = 4.25$, from Melitz and Redding (2015). We set the value of the shape parameter of input efficiency, $\theta = 1.789$, to be the same for both $t = C, D$ and equal to the value estimated in AFT. We use the elasticity of substitution between clean and dirty energy, estimated using international input-output tables from Papageorgiou, Saam and Schulte (2017), as the value of the parameter $\eta = 3$, which governs the substitution between clean and dirty inputs. The elasticity of substitution in consumption σ 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 markup as the ratio of sales to total input purchases and taking the mean across firms and arrive at a $\sigma = 6.9$.

5.3 Simulated method of moments

The rest of the model's parameters, namely fixed costs of sourcing, the mass of dirty inputs sourced by French firms, and market demand 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 new country, 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:

$$\begin{aligned}\log \bar{f}^t_{ij} = \log \beta^t_0 + \beta^t_{short} D_{ij} \log dist_{ij} + \beta^t_{long}(1 - D_{ij}) \log dist_{ij} + contig_{ij} \log \beta^t_{cont} \\ - \beta^t_{corr} corr_j + EU_{ij} \log \beta^t_{EU} - \beta^t_{TAB} TAB_j \left[-\beta^t_{Climate} Climate_j \text{ if } t = D\right],\end{aligned} \tag{8}$$

where $dist_{ij}$ is country j's distance from country i and $D_{ij} \equiv 1[dist_{ij} < 5,000\text{km}]$. $contig_{ij}$ identifies neighboring countries and $EU_{ij} \equiv 1[(i,j) \in \text{EU}]$ EU member states. $corr_j$ is j's control of corruption.[28] 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. Finally, $Climate_j$ is j's score in Yale's Environmental Protection sub-index on climate mitigation policy (continuous $\in [0; 100]$, higher is better). Further, following the methodology in AFT we also add some idiosyncratic randomness in fixed costs faced by firms in sourcing a given variety, where δ^t is an additional parameter to be estimated:

$$f^t_{ij}(\varphi) = \bar{f}^t_{ij} \times \exp\left(x^t\right), \; x^t \sim \mathcal{N}(0, \sqrt{\delta^t}). \tag{9}$$

The set of variables used to estimate (8) differ from AFT given that we are examining French firms rather than US ones. Specifically, given the geographical closeness of Europe and high volume of intra-European trade, we include a dummy variable to capture the non-linear fit of the distance variable for trade with other countries ($D_{ij} = 1$ if i and j are less

[28]Source: World Development Indicators, World Bank. The indicator is a continuous variable $\in [-2.5; 2, 5]$, with higher values indicating better control of corruption.

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 Share of importers of t goods from each country
δ^t	# firms importing t goods from most popular country over # of firms that import t goods Share of importers of t goods among firms below the sales median
$\mathcal{A}^D$	Share of dirty inputs aggregated across firms
B_i	Share of firms with sales below data median value

Notes: $\boldsymbol{\beta}^t$ explain avg. source-country fixed costs; δ^t generates randomness in fixed costs across firms; $\mathcal{A}^D$ is the mass of dirty goods sourced; B is market demand.

than 5,000 kilometers apart). 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 entry in international trade for different countries. Second, given that we are also interested in differing sourcing behavior for clean and dirty 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.

Table 2 presents the calibrated moments that we target to estimate the OLS coefficients of gravity equation (8) and the δ^t parameters for equation (9). The first set of moments are used to estimate the vector of $\boldsymbol{\beta}$ 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 β_0^t. Second, the share of importers of t goods from each country allows us to identify parameters on country-specific variables, $\{\beta_{short}^t, \beta_{long}^t, \beta_{cont}^t, \beta_{corr}^t, \beta_{EU}^t, \beta_{TAB}^t, \beta_{Climate}^t\}$. Turning to the estimation of the variance parameters, δ^t, we target (i) the number of firms importing t goods from 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 with (i) is the following. 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

GSS, it is also necessarily part of the GSS 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 equate 1. Any deviation from 1 is indicative of the value of δ^t.[29] The intuition behind 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 B.3, adjusting δ^t will allow us to match data moment (ii).[30]

The final two parameters that we estimate are $\mathcal{A}^D$, the mass of dirty goods in production, and market demand, B_i. We target the share of dirty inputs aggregated across firms to estimate $\mathcal{A}^D$, and the share of firms with sales below the median data value to target B_i. Note that our strategy to estimate B_i differs slightly from AFT who target costs directly. We target total sales given the two-input type setup we are using as we treat costs heterogeneously for clean and dirty inputs.

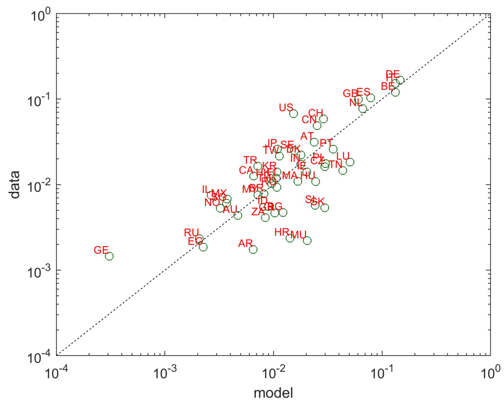
Figure 5 presents scatter plots to gauge the model fit of the SMM estimation, with the data on the y-axis and the model predictions on the x-axis. Panel I presents results for the extensive margin of imports. We plot the share of importers by country for clean and dirty inputs in subplots (a) and (b), respectively. 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, the fit of clean inputs exhibiting somewhat less variance than dirty inputs. Panel II next presents results for import shares, with clean in subplot (c) and dirty in subplot (d). Similarly to the extensive margin fit, we see that the model and data points falling around the forty-five degrees line, though the fit exhibits more variation for both clean and dirty importer sources. We further report the estimated parameters in Table C.7, the data and model moments in Table C.8, and the estimated fixed costs and sourcing potential for clean and dirty source countries in Figure D.6.

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

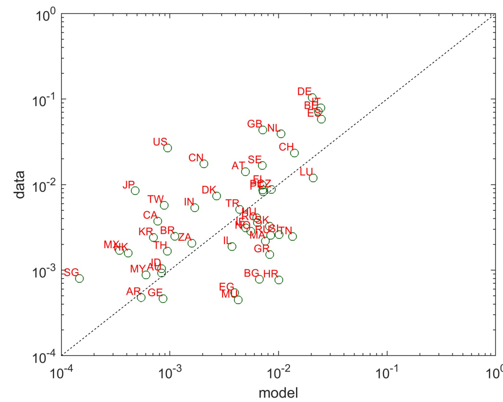
[30] As explained, in Appendix B.3, each productivity level φ is duplicated 100 times, such that each entry of this productivity level has a unique vector of fixed costs shocks. Also, each entry of each productivity level is applied the same level of fixed costs shocks. This means that the first firm with productivity level φ_L has the same vector of shocks as the first firm with productivity level $\varphi_H > \varphi_L$. However, since in the model φ_H will be less sensitive to fixed costs changes, increasing or decreasing δ^t will change lower productivity firms' import strategies relatively more than higher productivity firms, helping us match moment (ii).

Figure 5. Model estimation and fit for France's manufacturing sector

Panel I. Share of importers by source country

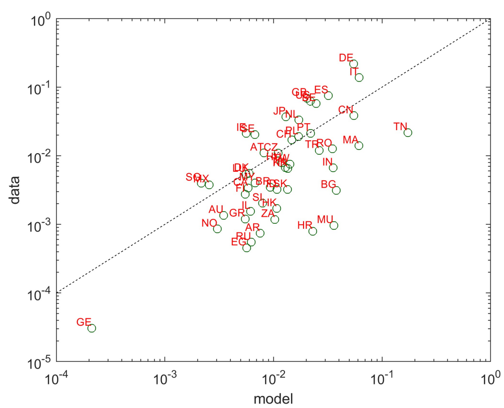


(a) Clean

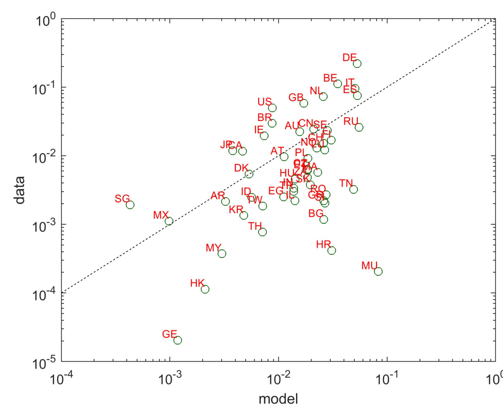


(b) Dirty

Panel II. Share of imports by source country



(c) Clean



(d) Dirty

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 clean products in (a) and dirty products in (b). Panel II plots the share of manufacturing sector imports by source country for clean products in (c) and dirty products in (d). All data used in the model and for actual moments in the data are source for 2004.

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 border tax 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.

To quantify the welfare impact of the tax policies, we introduce a carbon damage function into the household's utility function, so that it faces a trade-off between aggregate consumption and the environmental damages that come from more production/consumption. Specifically, we define utility of the representative household in country i as:

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

where CO_2 is the amount of CO_2 emissions (in tons) associated with producing the inputs for the household's consumption goods, and μ_i is a term to be calibrated. This carbon damage function takes the same form as in Shapiro (2021) and has several useful properties. First, including it as multiplicative of aggregate consumption in utility facilitates counterfactual analysis using ratios. Second, normalizing by the $CO_{2,baseline}$ term allows us to abstract from baseline emissions damages, and simply study counterfactual damages. Third, the indirect utility form implies that damages are proportional to real income, allowing the calibration of μ_i to match a specific cost of carbon in real euro terms.[31] CO_2 emissions include all emissions from the production of inputs used by French firms, both domestically and abroad. This applies to both the baseline scenario and the counterfactual scenario. These emissions are calculated using the emissions intensity data from the World Input-Output Database environmental accounts (Corsatea et al., 2019).

6.1 Carbon taxes and tariffs

To quantify the impacts of implementing a carbon tax and a carbon tariff, we run two policy 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 C.4). 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 C.4).

The first scenario is meant to capture the incidence of ETS regulations on production costs for dirty-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.[32] Likewise, the geographical scope uses the actual borders of the ETS system while

[31] The latest "Technical Support Document on Social Cost of Carbon, Methane, and Nitrous Oxide" of the US government's Interagency Working Group on Social Cost of Greenhouse Gases indicates that under a discount factor slightly above 3%, the social cost of a ton of carbon is around €40 in 2020. Following Nordhaus and Boyer (2000), we further assume that France only bears part of this global cost. Overall, we end up with the calibration of μ_i such that one extra ton of CO_2 reduces French real income by €10.58. More details on the calibration of μ_i are available in Appendix B.4.

[32] In Figure D.9, we compare these scenarios with a counterfactual policy that would cover all sectors in

the ETS+CBAM scenario applies the tax to all products imported from outside of the ETS.[33] We calibrate the nominal tax rates using information on sectoral emissions intensities from WIOD for each country in our sample.[34] This amounts to computing the embodied carbon emissions using a sector-based approach in which all producers within a sector are taxed at the average emissions intensity. 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 this analysis is not fully general equilibrium as we do not capture changes in trade and production abroad, the inclusion of IO linkages in calculating the incidence of taxation maps into the actual impact of the tax on French firms.[35] Finally, 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 6 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.7 for the underlying country-level tax rates. We present taxes for clean (green bars) and dirty (brown 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 dirty sectors, but taxes are not zero for clean 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.[36]

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-

the economy. As European policies target the most emissions-intensive sectors, the difference is not huge for most countries. For some non-ETS countries like China or Russia, broadening the carbon border tax to all sectors would almost double the average tax level though.

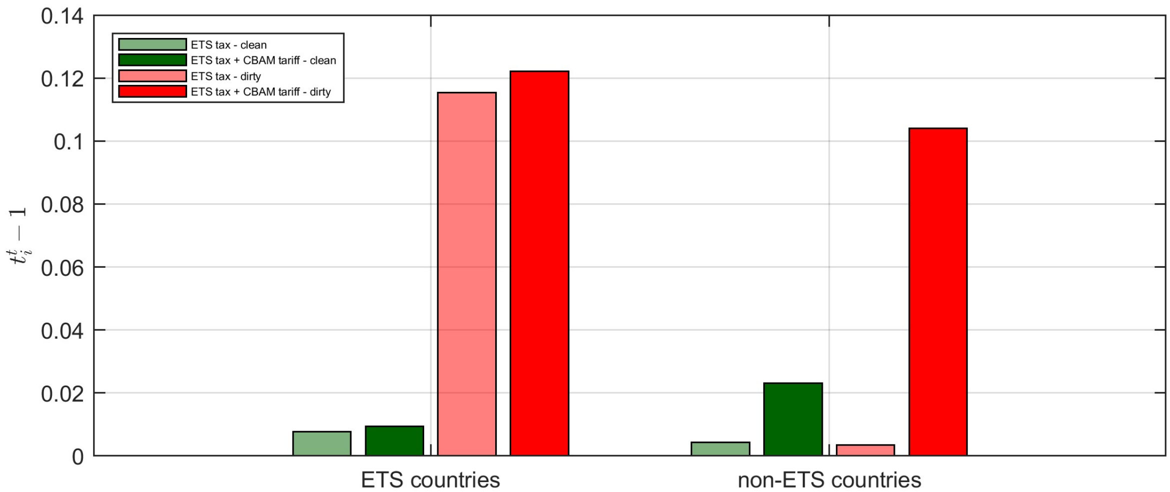
[33] As discussed in OECD (2020), the European Union should introduce exemptions for products that have already been taxed under national carbon policies. Moreover, it has been argued that exemptions for least-developed countries could be justified. In our stylized setting, we abstract from political 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.

[34] The WIOD sectoral classification follows ISIC rev. 4. In Table C.5, similar to Table C.4 for NAF sectors, we present the classification of ETS and CBAM sectors according to ISIC rev. 4. Figure D.1 reproduces a heat graph of country-sector emissions.

[35] See Appendix A.5 for details.

[36] When taxing all dirty inputs with the same ETS coverage, tax rates are much higher for non-ETS countries, as seen in Figure D.8. 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.9.

Figure 6. Tax rates for dirty and clean 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.7.

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 Ω_i.[37] It is important to note that nominal expenditures on manufacturing goods (E_i in equation (3)) are held constant across simulations. As a result, aggregate input purchases also remain the same, 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 cleaner 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

[37]See details in Appendix B.2.

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),[38] again using a control group composed of clean inputs sourced from ETS countries. Table 3 presents the regression estimates. Column (1) reproduces our most conservative estimates from the data, while column (2) presents estimates based on the model-generated ETS scenario with a €100 per ton tax. Results in panel (a), where the regressand is a firm's import share, show that the model generates an estimated coefficient comparable to that from the data regressions – the model reproduces 80% of the leakage estimated in the data. Turning to the extensive margin adjustment in panel (b), we find that the model's generated data only reproduce one fifth of the estimated leakage in comparison to the estimate based on the data regressions.

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 dirty inputs from

[38]Specifically, we simulate 36,000 firms across 50 countries with two types of inputs, so that for each simulation we generate a matrix of import values with dimensions $36,000 \times 100$. Since the model includes only two types of inputs, compared to the much larger number of products in the dataset, 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.

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

	Data (1)	ETS (2)	ETS + CBAM (3)
	Panel (a) Import Share		
Dirty product × Non-ETS			
× $\mathbb{1}\,(tax = €100$ or Post)	0.129***	0.106***	-0.046***
	(0.019)	(0.002)	(0.002)
Pseudo R^2	0.162	0.118	0.119
Observations	7,560,435	402,579	398,892
	Panel (b) Import Probability		
Dirty product × Non-ETS			
× $\mathbb{1}\,(tax = €100$ or Post)	0.126***	0.025***	-0.016***
	(0.010)	(0.001)	(0.001)
Pseudo R^2	0.044	0.002	0.000
Observations	7,560,435	402,579	398,892
# (Simulated) Firms	27,240	36,000	
Control group	Non-ETS Clean products		
Fixed effects	pc,t	pc,t	

Notes: This table presents the estimated β from regression (1) using both the reduced form dataset and two model-generated datasets (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. (*, **, ***) denote significance levels at 10%, 5%, and 1%, respectively.

ETS countries compared to clean inputs. This happens despite the CBAM scheme having a lower sectoral coverage than ETS. The reason is that non-ETS countries display relatively high pollution 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 for aggregate emissions, the geography of sourcing and welfare in Table 4. The first set of results presented in panel (a) show the change in millions of tons of emissions embedded in inputs sourced

Table 4. Quantitative results: change from baseline

Variable	ETS	ETS + CBAM
Panel (a) Δ Million tons emissions embedded in inputs		
Total	-1.84	-6.94
... *from clean inputs only*	0.02	-0.39
... *from dirty inputs only*	-2.13	-6.55
... *from FR inputs only*	0.06	0.89
... *from ETS (ex. FR) inputs only*	-5.65	-3.45
... *from non-ETS inputs only*	3.48	-4.39
Panel (b) Δ Million EUR in inputs purchases		
Total	0	0
... *from clean inputs only*	189.14	1845.37
... *from dirty inputs only*	-189.14	-1845.37
... *from FR inputs only*	211.41	3160.36
... *from ETS (ex. FR) inputs only*	-1575.62	-1338.99
... *from non-ETS inputs only*	1364.21	-1821.37
Panel (c) Δ Welfare		
$\% \, \Delta P_i$	0.051	0.542
$\% \, \Delta \left(\frac{E_i}{P_i^{\alpha}} \left[1 + \mu_i \left(CO_2 - CO_{2,\text{ baseline}}\right)\right]^{-1} \right)$	-0.005	-0.052
$\% \, \Delta \left(\frac{E_i + T_i}{P_i^{\alpha}} \left[1 + \mu_i \left(CO_2 - CO_{2,\text{ baseline}}\right)\right]^{-1} \right)$	1.767	2.728

Notes: Δ denotes changes. All simulations apply a carbon tax of €100 per ton of CO_2. Through μ_i, the indirect utility (last row) assumes a marginal cost of carbon of €40 per ton. Total nominal input purchases are unchanged across simulations in the model, as E_i is fixed. The baseline level of emissions embedded in input purchases is equal to 168.5M tons of CO_2. The ETS policy (resp. ETS+CBAM policy) thus reduces emissions by -1.09% (resp. -4.12%). The last row depicts the change in welfare under the assumption that total tax revenues T_i are rebated lump-sum to households. ΔP_i is adjusted by α, the share of manufacturing expenditures in France ($\sim 10\%$), to calculate welfare changes for the whole economy.

globally by French firms. These values can be compared to the impact of a policy on the flow of input purchases, which are shown in panel (b) of the table. Panel (c) presents the change in the ideal price index along with the welfare changes for the baseline where taxes are treated as a deadweight loss as well as when they are rebated to households.

ETS tax scenario. Implementing the ETS scenario in column (1) results in a 1.84 million tons reduction in emissions, driven by a fall in the use of dirty inputs (-2.13M tons). Meanwhile, firms substitute towards using clean inputs, which are not emission-free given supply chain linkages, so emissions embedded in the use of intermediate goods rises slightly (0.02M 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 5.65 million tons decrease in emissions embedded in these countries' inputs, while emissions embedded in inputs from non-ETS countries rise by 3.48 million tons. Interestingly, the third row indicates a 0.06 million tons increase in emissions embedded in inputs from France. This increase is largely similar for both inputs types – not depicted in table. This rise in emissions is due to an increase in sourcing from France, which the model delivers because the tax applied to France is on average smaller than the one applied to other countries with high sourcing potentials. Overall, the net effect of increased emissions from sourcing clean inputs and from leakage to non-ETS inputs is outweighed by the reduction in emissions from decreased sourcing of dirty inputs within the ETS zone, leading to the overall decrease in emissions. This happens despite our model assumption that total input purchases are constant, through E_i. Hence, this emissions decrease is simply the result of a reshuffling of firms' input purchases, as illustrated in the second panel of Table 4.

The last panel 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 0.05%. This holds true despite tax rates reaching more than 20% for dirty inputs sourced from ETS countries (Figure 6). 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 -0.005%. 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).[39] One way of improving the welfare balance of this type of policies is to rebate tax revenues to households. In the last row of Table 4, we illustrate this point in an extreme scenario in which all tax revenues are rebated to domestic households. Welfare now *increases* by 1.767%.

[39]See Appendix B.4 for further details on the calibration of μ_i, and the utility trade-off between emission declines vs. price increases. No realistic specification on the cost of carbon implies a utility gains associated with less emissions that outweighs the welfare cost associated with price increases. This is true even if we consider the much higher cost of carbon estimated in the recent literature (Bilal and Känzig, 2024).

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 almost quadrupled. In this scenario, both clean and dirty 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. Overall emissions from domestically-produced inputs increase slightly, together with domestic sourcing. The fall in emissions embedded in inputs sourced from other ETS-countries' inputs is still large, although now dominated by inputs sourced from non-ETS countries. 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 0.54%, which leads to a further fall in utility. Again, the fall in emissions does not outweigh loss of purchasing power. For the policy to be welfare-improving, tax revenues must be entirely refunded to domestic households.

6.2.3 Geography of leakage

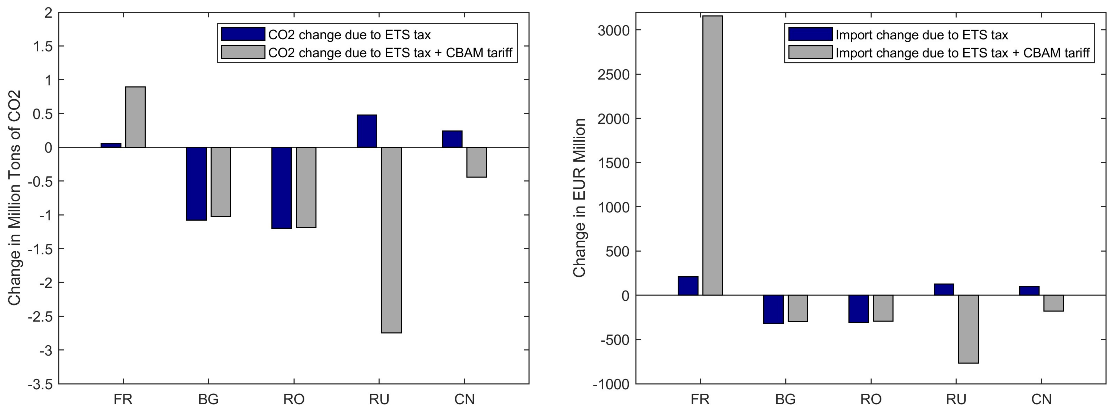
We next dig deeper into the geography of input portfolio reshuffling. Results are summarized in Figure 7 for a subset of the most affected countries. Panel (a) illustrates the change in emissions (in millions of tons of CO_2) under the ETS and ETS+CBAM scenarios. Panel (b) displays the corresponding change in input purchases (in millions of euros). Results for the rest of the sample are provided in Figure D.10.

As discussed earlier, both carbon policies increase domestic input sourcing. This is due to French producers' relatively lower emission intensities, combined with the fact that all firms source some inputs domestically given the model's assumptions. Second, imports from two highly taxed ETS countries – Bulgaria (BG) and Romania (RO) – drop significantly under the ETS tax regime, and this decline is only slightly mitigated by the CBAM tariff. For non-ETS countries, imports from Russia (RU) and China (CN) initially rise following the ETS tax but then decrease more than proportionately under the CBAM tariff. In value terms, the portfolio reshuffling towards French inputs is massive. However, the impact on local emissions is relatively mild, an increase of 1 million tons, while emissions from other countries fall by 0.5 to 3 million tons given much larger emission intensities.

6.2.4 Heterogeneous leakage effects

We next focus on the model's predictions regarding leakage along the distribution of firm productivity. Digging into the microeconomic underpinnings of the aggregate results not

Figure 7. The geography of leakage



(a) Emissions leakage **(b)** Import leakage

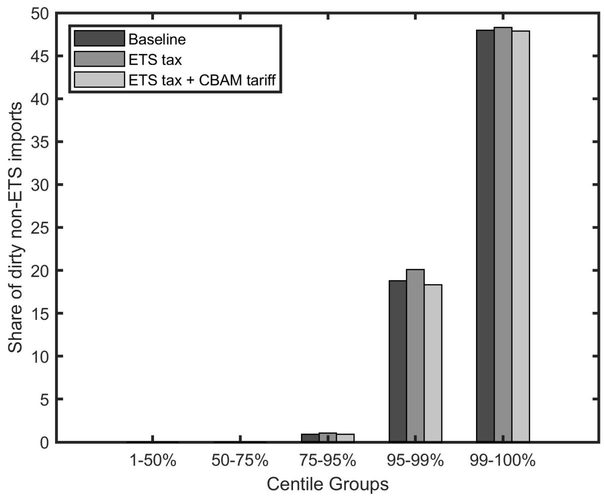
Notes: This figure plots the change in imports in emissions in millions of tons (panel (a)) and in millions of euros (panel (b)) when imposing either a carbon tax, or a carbon tax and a carbon tariff. Results are restricted to the 5 most impacted countries. The breakdown by input type is displayed in Figure D.11.

only improves our understanding of the model's quantitative results, but further allows us to examine the redistributive consequences of carbon policies. Figure 8 plots statistics on leakage of dirty imports to non-ETS suppliers in terms of import shares (Panel I) and the extensive margin (Panel II) for different firm-level productivity bins.

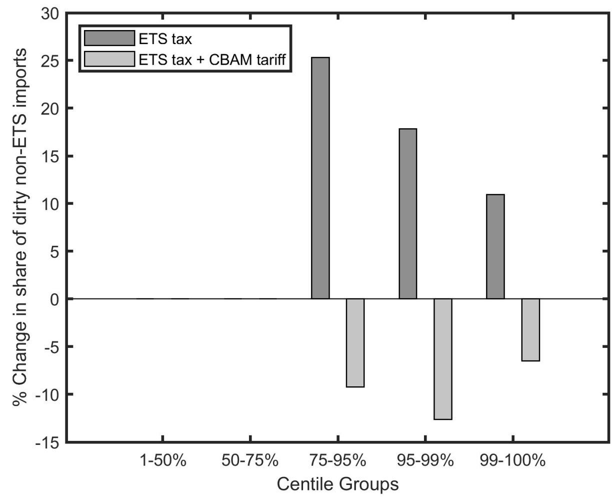
The first point to note is that there is no leakage observed in the bottom 75% of the firm productivity distribution as these firms do not import dirty products from non-ETS countries in any of the three scenarios. Beyond the 75th percentile, the share of dirty inputs sourced from non-ETS countries increases with productivity, reaching almost 50% of intermediate consumption in the top percentile of the distribution. Once the ETS tax is introduced, this import share increases, together with firms' propensity to import from non-ETS countries. The elasticity of import shares to the tariff is especially strong between the 75th and 95th percentiles, largely driven by the extensive margin contribution of a 16% increase in the share of firms that start to import dirty products from non-ETS countries. Leakage in percentage change falls for firms in the 95-99% and top 1% bins, and the contribution of the extensive margin to that change becomes marginal. The reversal of carbon leakage from the implementation of the CBAM reveals some interesting patterns along the productivity distribution. Specifically, there is no longer a monotonic change in leakage, instead firms in the 95-99% bin tend to reverse the largest proportion of their previous leakage.

Figure 8. Model leakage and firm productivity

Panel I. Import share leakage

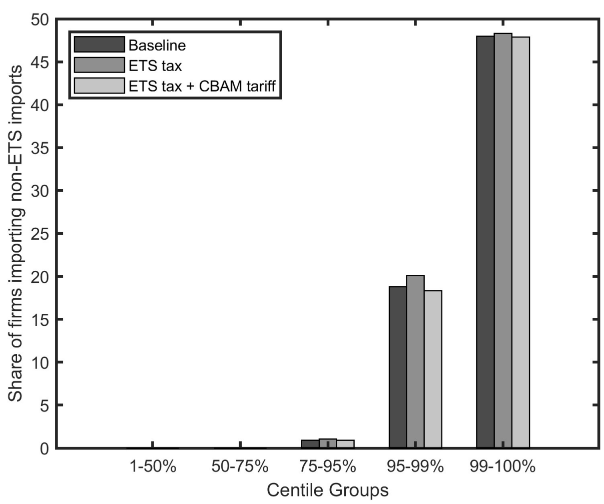


(a) Absolute terms

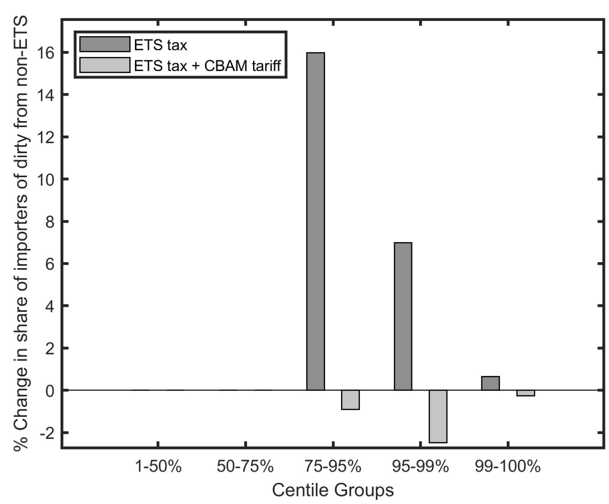


(b) Percentage change from baseline

Panel II. Extensive margin leakage



(c) Absolute terms



(d) Percentage change from baseline

Notes: This figure plots model-based leakage values along the firm productivity dimension. Panel I plots the import share of dirty products from non-ETS countries, while panel II plots the share of firms importing dirty inputs from non-ETS countries within each productivity bin. Sub-figures (a) and (c) present statistics in absolute values, while the sub-figures (b) and (d) present percentage changes from baseline.

7 Conclusion

This paper provides evidence on how firms' supply chain decisions adapt in response to carbon taxes. By constructing a novel dataset using information from the EU's ETS and

CBAM, we demonstrate that French firms modified their sourcing of dirty products as the EU ETS tightened. Specifically, firms increased imports from non-ETS countries, leading to carbon leakage both in terms of trade shares and at the extensive margin, as they established new supply relationships with dirty non-ETS foreign producers.

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 leads to higher price levels. These effects persist even as firms adjust their sourcing strategies across clean and dirty products, as well as between ETS and non-ETS countries. Notably, the quantitative analysis reveals only small decreases in emissions associated with the inputs used by French producers.

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 dynamics comprehensively.

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Online Appendix

A Data Construction Details

A.1 Clean vs. Dirty 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 dataset and how we delineate clean vs. dirty 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 dirty those goods that are listed in the CBAM, or fall into ETS activities (Table C.1 and Table C.2). 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 clean or dirty products.

Table C.3 provides statistics about the prevalence of dirty products, by HS chapter.[41] 1,464 products are classified as dirty 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 C.1 and C.2.

A.2 Defining clean and dirty sectors

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

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

[41] Any HS chapter that is not listed in Table C.3 is composed of clean products only.

and quantitative analyses are restricted to a subset of dirty-intensive sectors, which we again define based on measures of dirtiness intensities.

We do so using an Input-Output (IO) table at the sector level. We begin by computing sectoral dirtiness intensities 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 dirty-*producing* sectors (see details in Table C.4, 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 dirty-producing NAF sectors, including 12 in manufacturing. We then use the IO table to categorize dirty-*intensive* input-user sectors as those manufacturing sectors relying on dirty-producing sectors for at least 10% of their intermediate consumption. This identifies 44 sectors that intensively use dirty inputs for final production (Table C.4, 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 C.2, there are eight goods at the HS2 level, excluding electricity, which is not included in our dataset. Using our HS to NAF conversion table, we identify 7 sectors involved in the production of these 8 CBAM goods.[43] This classification will be used for calculating the CBAM tariffs, and is depicted in columns (3) and (6) of Table C.4.

A.3 Core and non-core inputs

The empirical analysis is restricted to a comparison of dirty and clean 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 a given product. Restricting our sample to core products is hence necessary for practical reasons, but also to avoid marginal products to pollute the estimation.[44] Table C.6 provides statistics on the number and 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 5 cbam NC goods.

[44] For example, imagine that the dataset 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

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 datasets. We first use 2004 (pre-ETS) information from the administrative firm-level balance sheet and income statement dataset 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 dataset, which allows us to quantify the share of firm inputs that are either clean or dirty (Section A.2). We merge firm- and sector-level information together and assume that every firm mimics its sector's input mix between clean and dirty. 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 dirty 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 dataset which will be 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.

A.5 Calibration of carbon taxes

We calculate the input $\times$ country level of taxes using WIOD's environmental accounts. This dataset 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 dataset 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.

in sector C22B, including them in the estimation and balancing the panel with zeros would significantly increase the number of null values in the dataset. 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 dataset when estimating the intensive margin, this time using the share of imports rather than a dummy variable as the dependent variable.

We also account for input-output linkages to compute the full tax incidence of the vector of taxes on each sector × country. We proceed as follows. Denote WIOD's IO matrix as Ω, 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 Ψ_{ij} captures both the direct and indirect ways through which i (a sector × country) uses j (another sector × 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×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 Ψ to determine the total tax burden for any firm purchasing from these 56 sectors × 44 countries. Finally, we aggregate the corresponding tax rates into two broad sectors (clean and dirty) 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 C.1 and C.2). For the carbon tax counterfactual, we classify the sectors listed in columns (1) and (4) of Table C.5 as dirty, with all other sectors considered clean.[45] For the carbon tax + carbon tariff counterfactual, we additionally expand taxation to the dirty CBAM sectors listed in columns (2) and (5) of Table Table C.5.

B Model Details

B.1 Solving the model with the algorithm

In this sub-section, we derive the parameter conditions under which the types of algorithm described in Jia (2008); Arkolakis, Eckert and Shi (2023) help us solve our model.

B.1.1 Definitions

It is useful to first define the following objects. Denote by $I = \{I^C, I^D\}$ 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 $\mathcal{I}^t(\varphi)$ the set of countries for which firm φ has paid the associated fixed cost of offshoring type t inputs, $\left\{wf^t_{ij}\right\}_{j\in\mathcal{I}^t(\varphi)}$. In

[45] Note that sectors in Table C.4 follow the NAF nomenclature, whereas WIOD uses ISIC Rev.4. This is why we use Table C.5 to classify them as dirty and clean

other words, $\mathcal{I}(\varphi) = \left\{\mathcal{I}^C(\varphi), \mathcal{I}^D(\varphi)\right\} \in \mathscr{P}(J)$ is firm φ's sourcing strategy. Then, define the following concepts in our context.

Definition 1 (Single Cross Differences in Choices (SDC-C) from below) *Take the firm's profit function (6):*

$$\pi_i(\varphi; \mathcal{I}(\varphi)) = \left(\frac{c(\varphi; \mathcal{I}(\varphi))}{\varphi}\right)^{1-\sigma} B_i - w_i \sum_{j \in \mathcal{I}^D(\varphi)} f_{ij}^D - w_i \sum_{j \in \mathcal{I}^C(\varphi)} f_{ij}^C,$$

The profit function is said to obey SDC-C from below, if an element j, which addition to a given sourcing strategy set results in a positive marginal value, also retains its positive marginal value when other elements are added to the initial sourcing strategy set. That is, if for all elements $j \in I^t$ and sourcing strategies $\mathcal{I}_1(\varphi) \subset \mathcal{I}_2(\varphi) \in \mathscr{P}(J)$,

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

Definition 2 (Single Cross Differences in Choices (SDC-C) from above) *The profit function is said to obey SDC-C from above, if an element j, which addition to a given sourcing strategy set results in a positive marginal value, also retains its positive marginal value when other elements are removed from the initial sourcing strategy set. That is, if for all elements $j \in I^t$ and sourcing strategies $\mathcal{I}_1(\varphi) \subset \mathcal{I}_2(\varphi) \in \mathscr{P}(J)$,*

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

B.1.2 Conditions for SDC-C to hold

We next derive the sufficient and necessary conditions for the SDC-C from below and from above conditions to hold.

SDC-C from below versus from above of the profit function. The profit function can be written as:

$$\begin{aligned}\pi_i(\varphi; \mathcal{I}(\varphi)) = \varphi^{\sigma-1} &\left[\left(\mathcal{A}^D\right)^{\frac{1-\eta}{1-\rho}} \left(\gamma^D \Theta_i^D(\varphi; \mathcal{I}^D(\varphi))\right)^{\frac{\eta-1}{\theta^D}} + \left(\mathcal{A}^C\right)^{\frac{1-\eta}{1-\rho}} \left(\gamma^C \Theta_i^C(\varphi; \mathcal{I}^C(\varphi))\right)^{\frac{\eta-1}{\theta^C}}\right]^{\frac{1-\sigma}{1-\eta}} B_i \\ &- w_i \sum_{j \in \mathcal{I}^D(\varphi)} f_{ij}^D - w_i \sum_{j \in \mathcal{I}^C(\varphi)} f_{ij}^C,\end{aligned}$$

where

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

is the sourcing capability of firm φ for inputs of type $t = C, D$.

Note that the sourcing capability $\Theta_i^t(\varphi; \mathcal{I}^t(\varphi))$ is monotonically increasing in the sourcing strategy $\mathcal{I}^t(\varphi)$. Hence, one can take derivatives with respect to Θ_i^t to check for SDC-C from below/above.

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

$$\frac{\partial \pi_i}{\partial \Theta_i^t} = \varphi^{\sigma-1} B_i \frac{\sigma-1}{\theta^t} \left(A^D(\Theta_i^D) + A^C(\Theta_i^C)\right)^{\frac{\sigma-\eta}{\eta-1}} \frac{A^t(\Theta_i^t)}{\Theta_i^t} - w\varepsilon,$$

where $A^t(\Theta^t) \equiv (\mathcal{A}^t)^{\frac{1-\eta}{1-\rho}} (\gamma^t \Theta_i^t)^{\frac{\eta-1}{\theta^t}}$, and $\varepsilon > 0$ is the added fixed cost element linked to the increase in the size of $\mathcal{I}^t(\varphi)$. 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 SDC-C from below. Taking again this continuous approach, we will hence derive conditions under which the second and the cross derivatives are positive.

Let us now take the cross-derivative:

$$\frac{\partial^2 \pi_i}{\partial \Theta_i^C \partial \Theta_i^D} = \varphi^{\sigma-1} B_i \frac{\sigma-1}{\theta^D} \frac{\sigma-\eta}{\theta^C} \left(A^C(\Theta_i^C) + A^D(\Theta_i^D)\right)^{\frac{\sigma-2\eta+1}{\eta-1}} \frac{A^D(\Theta_i^D)}{\Theta_i^D} \frac{A^C(\Theta_i^C)}{\Theta_i^C}.$$

Therefore, for $\sigma > 1$ and $\sigma > \eta$, the cross derivative is always positive.

The next step is to look at the second derivative:

$$\begin{aligned}
\frac{\partial^2 \pi_i}{\partial\, {\Theta_i^t}^2} &= \varphi^{\sigma-1} B_i \frac{(\sigma-1)(\sigma-\eta)}{(\theta^t)^2} \left(A^C(\Theta_i^C) + A^D(\Theta_i^D)\right)^{\frac{\sigma-2\eta+1}{\eta-1}} \left(\frac{A^t(\Theta_i^t)}{\Theta_i^t}\right)^2 \\
&\quad + \varphi^{\sigma-1} B_i \frac{(\sigma-1)(\eta-1-\theta^t)}{(\theta^t)^2} \left(A^C(\Theta_i^C) + A^D(\Theta_i^D)\right)^{\frac{\sigma-\eta}{\eta-1}} \frac{A^t(\Theta_i^t)}{(\Theta_i^t)^2} \\
&= \left[\varphi^{\sigma-1} B_i \frac{\sigma-1}{\theta^t} \left(A^D(\Theta_i^D) + A^C(\Theta_i^C)\right)^{\frac{\sigma-\eta}{\eta-1}} \frac{A^t(\Theta_i^t)}{\Theta_i^t}\right] \\
&\quad \times \frac{1}{\theta^t \Theta_i^t} \left[(\sigma-\eta) \frac{A^t(\Theta_i^t)}{A^C(\Theta_i^C) + A^D(\Theta_i^D)} + (\eta-1-\theta^t)\right].
\end{aligned}$$

We assumed from the first derivative that $\varphi^{\sigma-1} B_i \frac{\sigma-1}{\theta^t} \left(A^D(\Theta_i^D) + A^C(\Theta_i^C)\right)^{\frac{\sigma-\eta}{\eta-1}} \frac{A^t(\Theta_i^t)}{\Theta_i^t} > 0$, and Θ_i^t as well as θ^t are positive. So the first part of the above expression is positive. Therefore, we are interested in the sign of:

$$(\sigma-\eta) \frac{A^t(\Theta_i^t)}{A^C(\Theta_i^C) + A^D(\Theta_i^D)} + (\eta-1-\theta^t),$$

which is positive if and only if (we have $\sigma > \eta$ from the cross derivatives):

$$\frac{A^t(\Theta_i^t)}{A^C(\Theta_i^C) + A^D(\Theta_i^D)} > \frac{1+\theta^t-\eta}{\sigma-\eta}.$$

To summarize, our profit function exhibits SCD-C from below if the following conditions hold:

1. $\sigma > 1$,

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

3. $\frac{A^D(\Theta_i^D)}{A^C(\Theta_i^C)+A^D(\Theta_i^D)} > \frac{1+\theta^D-\eta}{\sigma-\eta}$,

4. $\frac{A^C(\Theta_i^C)}{A^C(\Theta_i^C)+A^D(\Theta_i^D)} > \frac{1+\theta^C-\eta}{\sigma-\eta}$.

On the other hand, our profit function exhibits SCD-C from above if the second- and cross-derivatives are negative, while the first derivative is still assumed to be positive. This holds if the following conditions are met:

1. $\sigma > 1$,

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

3. $\frac{A^D(\Theta_i^D)}{A^C(\Theta_i^C)+A^D(\Theta_i^D)} > \frac{1+\theta^D-\eta}{\sigma-\eta}$,

4. $\frac{A^C(\Theta_i^C)}{A^C(\Theta_i^C)+A^D(\Theta_i^D)} > \frac{1+\theta^C-\eta}{\sigma-\eta}$.

Note that the only difference between SCD-C from above and from below is how η compares to σ. Since in the SCD-C from above case $\sigma < \eta$, the sign on the conditions (3.) and (4.) are unchanged. In the next section, we will derive the necessary conditions for either of these cases to apply.

Necessary conditions for SCD-C from below. The conditions for SCD-C from below are:

SCD-C from below:

1. $\sigma > 1$,

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

3. $\frac{A^D\left(\Theta_i^t\right)}{A^C\left(\Theta_i^C\right)+A^D\left(\Theta_i^D\right)} > \frac{1+\theta^D-\eta}{\sigma-\eta}$,

4. $\frac{A^C\left(\Theta_i^t\right)}{A^C\left(\Theta_i^C\right)+A^D\left(\Theta_i^D\right)} > \frac{1+\theta^C-\eta}{\sigma-\eta}$.

Note that $A^t\left(\Theta_i^t\right) = \left(\mathcal{A}^t\right)^{\frac{1-\eta}{1-\rho}}\left(\gamma^t\Theta_i^t\right)^{\frac{\eta-1}{\theta^t}}$ is increasing (resp. decreasing) in Θ_i^t if $\eta > 1$ (resp. $\eta < 1$).

As the left-hand side of conditions 3 and 4 is bounded between 0 and 1, a set of sufficient conditions is $\sigma > 1$, $\sigma > \eta$ and $Max(1+\theta^C, 1+\theta^D) < \eta$. These conditions are very constraining though and we will thus rely on necessary conditions. Conditional on conditions 1 and 2 being met, we need to find the two lower bounds of the left hand side, and make sure the two inequalities hold in that case.

From here, we need to consider two cases depending on whether the clean and dirty inputs are substitutes or complements ($\eta > 1$ or $\eta < 1$).

Case 1: Clean and dirty inputs are substitutes ($\eta > 1$): Under substitutable inputs, a set of necessary conditions for the problem to exchibit SCD-C from below is:

1. $\sigma > 1$,
2. $\sigma > \eta$ (from the cross derivatives),
3. $\frac{A^D\left(\underline{\Theta}_i^D\right)}{A^C\left(\bar{\Theta}_i^C\right)+A^D\left(\underline{\Theta}_i^D\right)} > \frac{1+\theta^D-\eta}{\sigma-\eta}$,
4. $\frac{A^C\left(\underline{\Theta}_i^C\right)}{A^C\left(\underline{\Theta}_i^C\right)+A^D\left(\bar{\Theta}_i^D\right)} > \frac{1+\theta^C-\eta}{\sigma-\eta}$,

where $A^t\left(\underline{\Theta}_i^t\right)$ and $A^t\left(\bar{\Theta}_i^t\right)$ denote the lowest and highest bounds of function A^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: Clean and dirty inputs are complements ($\eta < 1$): Under complementary inputs, a set of necessary conditions for the problem to exhibit SCD-C from below is:

1. $\sigma > 1$,
2. $\frac{A^D\left(\bar{\Theta}_i^D\right)}{A^C\left(\underline{\Theta}_i^C\right)+A^D\left(\bar{\Theta}_i^D\right)} > \frac{1+\theta^D-\eta}{\sigma-\eta}$,
3. $\frac{A^C\left(\bar{\Theta}_i^C\right)}{A^C\left(\bar{\Theta}_i^C\right)+A^D\left(\underline{\Theta}_i^D\right)} > \frac{1+\theta^C-\eta}{\sigma-\eta}$,

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.

Necessary conditions for SDC-C from above. The conditions for the operational profit to exhibit SDC-C from above are:

1. $\sigma > 1$,
2. $\sigma < \eta$ (from the cross derivatives),
3. $\frac{A^C\left(\underline{\Theta}_i^C\right)}{A^C\left(\underline{\Theta}_i^C\right)+A^D\left(\bar{\Theta}_i^D\right)} > \frac{1+\theta^C-\eta}{\sigma-\eta}$,
4. $\frac{A^C\left(\underline{\Theta}_i^D\right)}{A^C\left(\underline{\Theta}_i^D\right)+A^D\left(\bar{\Theta}_i^C\right)} > \frac{1+\theta^D-\eta}{\sigma-\eta}$.

Note that submodularity cannot arise if clean and dirty inputs are complements. Note that the (stringent) sufficient conditions for the problem to be submodular are $\sigma > 1$, $\sigma < \eta$ and $Min(1+\theta^C, 1+\theta^D) > \eta$.

B.1.3 Algorithm

Theorem 1 in Arkolakis et al. (2023) explains how their algorithm solves the profit maximization problem whenever the objective function exhibits either SDC-C from above or from below.

B.2 Other model equations

This section provides additional details on key model equations and terms mentioned in the main text, but included here for brevity.

Firm-level bilateral type-t input purchases $M_{ij}^t(\varphi)$:

$$
\begin{aligned}
M_{ij}^t(\varphi) &= \chi_{ij}^t(\varphi;\mathcal{I}^t(\varphi))\left(\frac{c_i^t(\varphi;\mathcal{I}^t(\varphi))}{c_i(\varphi;\mathcal{I}^D(\varphi),\mathcal{I}^C(\varphi))}\right)^{1-\eta}(\sigma-1)\left(\frac{c_i(\varphi;\mathcal{I}^D(\varphi),\mathcal{I}^C(\varphi))}{\varphi}\right)^{1-\sigma} B_i \\
&= \frac{T_j^t\left(\tau_{ij}^t w_j\right)^{-\theta^t}}{\Theta_i^t(\varphi;\mathcal{I}^t(\varphi))}\left(\frac{(\mathcal{A}^t)^{\frac{1}{1-\rho}}\left(\gamma^t\Theta_i^t(\varphi;\mathcal{I}^t(\varphi))\right)^{-1/\theta^t}}{\left[\left(\mathcal{A}^D\right)^{\frac{1-\eta}{1-\rho}}\left(\gamma^D\Theta_i^D(\varphi;\mathcal{I}^D(\varphi))\right)^{\frac{\eta-1}{\theta^D}}+(1-a^D)^{\frac{1-\eta}{1-\rho}}\left(\gamma^C\Theta_i^C(\varphi;\mathcal{I}^C(\varphi))\right)^{\frac{\eta-1}{\theta^C}}\right]^{\frac{1}{1-\eta}}}\right)^{1-\eta} \\
&\quad (\sigma-1)\varphi^{\sigma-1}\left[\left(\mathcal{A}^D\right)^{\frac{1-\eta}{1-\rho}}\left(\gamma^D\Theta_i^D(\varphi;\mathcal{I}^D(\varphi))\right)^{\frac{\eta-1}{\theta^D}}+(1-a^D)^{\frac{1-\eta}{1-\rho}}\left(\gamma^C\Theta_i^C(\varphi;\mathcal{I}^C(\varphi))\right)^{\frac{\eta-1}{\theta^C}}\right]^{\frac{1-\sigma}{1-\eta}} B_i \\
&= (\sigma-1)B_i\,\gamma^{t\,\frac{\eta-1}{\theta^t}}\,\varphi^{\sigma-1}\left[\left(\mathcal{A}^D\right)^{\frac{1-\eta}{1-\rho}}\left(\gamma^D\Theta_i^D(\varphi;\mathcal{I}^D(\varphi))\right)^{\frac{\eta-1}{\theta^D}}+(1-a^D)^{\frac{1-\eta}{1-\rho}}\left(\gamma^C\Theta_i^C(\varphi;\mathcal{I}^C(\varphi))\right)^{\frac{\eta-1}{\theta^C}}\right]^{\frac{\eta-\sigma}{1-\eta}} \\
&\quad \Theta_i^t(\varphi;\mathcal{I}^t(\varphi))^{\frac{\eta-1-\theta^t}{\theta^t}} T_j^t\left(\tau_{ij}^t w_j\right)^{-\theta^t}\left(\mathcal{A}^t\right)^{\frac{1-\eta}{1-\rho}}.
\end{aligned}
$$

Aggregate bilateral type-t input purchases $M_{ij}^t(\varphi)$: Aggregating $M_{ij}^t(\varphi)$ across firms that are sourcing from j:

$$M_{ij}^t = N_i \int_{\tilde{\varphi}_i}^{\infty} M_{ij}^t(\varphi) \mathbb{1}_{ij}^t(\varphi) dG_i(\varphi). \tag{B.1}$$

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

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

where $\tilde{\varphi}$ 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 B_i, solve for firms optimal sourcing decisions, and then solve for a value of B_i which allows equation (B.2) to hold. We then solve our economy with the updated sourcing potentials and market demand B_i.

Finally, the equilibrium measure Ω_i of entrants in the manufacturing sector is solved for using the above free-entry condition together with the definition of B_i under constant mark-ups:

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

B.3 Construction of the random shocks

To draw the fixed costs shocks, we follow Antràs et al. (2017) closely. We first draw a van der corput sequence sequence of size $S = 100$, i.e., we construct a vector of $\frac{1}{2}, \frac{1}{4}, \frac{3}{4}, \frac{1}{8}, \frac{5}{8}, \frac{3}{8}, \frac{7}{8}, \frac{1}{16}, \frac{9}{16}, \cdots \frac{5}{32}$, a low-discrepancy sequence of 100 elements over the unit interval.

Then, for each country $\times$ input, we compute a random permutation of the von der corput sequence above. We then calculate a vector of 100 shocks for each country *times* input, where each row of the vector of shocks is computed using an inverse standard normal distribution (mean 0 and variance 1) evaluated at the corresponding row in the permuted von der corput sequence.

For example, if the permuted sequence is such that the first element is $\frac{1}{4}$, the new vector of shocks will take a value of -0.6745 in the first position. If the second element is $\frac{1}{2}$, the new vector of shock will take a value of 0 in the second position, etc. This yields, for each country $\times$ input, a vector of 100 identical shocks, randomly permuted. Given the length of the van der corput sequence and the fact that we use a standard normal, the maximum shock for each country vector is 1.8627, and the minimum -2.4176.

Finally, we interact the productivity draws (we make 360 such draws) with this vector of shocks of size 100. In particular, for each productivity value φ we drew from the Pareto distribution, we duplicate it 100 times and assign a vector of random shocks of size equal to the number of country times the number of input types. The first duplication of each φ gets assigned the first elements of the country $\times$ input vector. Hence, in total, the interaction of those 100 random shocks per country and the 360 different productivity draws yields 36,000 firms.

Note the slight abuse of notation when we introduce heterogeneous fixed costs. While in the model with homogeneous fixed costs φ designated both a firm and its productivity parameter, a firm in the SMM with heterogeneous fixed costs is defined as the interaction of its productivity φ and its vectors of fixed costs $f_{ij}^t(\varphi)$, $t = C, D$.

B.4 Calibration of μ_i

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

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

where $CO_{2,baseline}$ is the baseline level of emissions, equating the total amount of emissions embedded in France's inputs purchases at the baseline. This is calculated using WIOD's data. As explained in the main text, this specification is designed to measure damages from changes in emissions only, and we thus abstract from baseline climate damages.

Indirect utility is given by

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

We calibrate the value of μ_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 μ_i accordingly. As explained in the main text, we assume that one extra ton of carbon has a global net damage of €40 (in the main counterfactual). However, countries are affected differently, and we will assume that France's share of the global net damage is about 6.6% of that €40. To get this value, we proceed as in Shapiro (2021) and compute $\frac{d_i Y_i}{\sum_j d_j Y_j}$ for i being France. Y_i is country GDP, and d_i is damage as a share of GDP from Nordhaus and Boyer (2000). In simple terms, $\frac{d_i Y_i}{\sum_j d_j Y_j}$ gives the share of the €40 loss due to an additional ton of carbon that is going to France. 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%. Our calculation yields $\frac{d_i Y_i}{\sum_j d_j Y_j} \approx 0.066$. Finally, we divide the damage value by the baseline price index P_i to express it in real terms. To sum up, we find μ_i that solves $\frac{\partial V_i}{\partial CO_2} = -\frac{40 \times 0.066}{P_i} = -1.03$, using baseline values for P_i, and with $CO_2 = CO_{2,baseline}$ in the baseline scenario.

Given this calibration, as emissions embedded in inputs reduce by about 1.84M tons of CO_2, this increases real income by about 10.58 × 1.84M = €19.47M. The resulting price increase leads to real spending to fall by €836.66M, thus explaining why the price effect dominates the drop in emissions.

C Additional Tables

Table C.1. 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	Organbic 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 C.2. List of HS products covered by the Carbon Border Adjustment Mechanism

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 C.3. Statistics on the prevalence of dirty products, by HS chapter

Code	Description	ETS products Count	ETS products Value Share	CBAM products Count	CBAM products Value Share	Dirty products Count	Dirty products 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 dirty products and their contribution to the value of French imports, by HS chapter. Columns (1)-(2) considers dirty 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 C.4. List of dirty and dirty-intensive NAF sectors

Code	Description	ETS (1)	D-I (2)	CBAM (3)	Code	Description	ETS (4)	D-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 dirty-intensive ('D-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 dirty-producing sectors but not in the set of dirty-intensive manufacturing sectors.

Table C.5. List of dirty and dirty-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 C.4 into ISIC rev.4 sectors in order to use WIOD tables.

Table C.6. 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 C.7. SMM model parameter estimates

	Dirty	Clean
β^t_0	0.081	0.102
β^t_{short}	0.732	1.311
β^t_{long}	1.190	0.001
β^t_{cont}	0.554	0.703
β^t_{corr}	-0.223	0.011
β^t_{EU}	0.710	0.180
β^t_{TAB}	0.003	0.006
$\beta^t_{Climate}$	0.015	
δ^t	1.778	1.593
B_i	8.257	
$\mathcal{A}^D$	0.375	

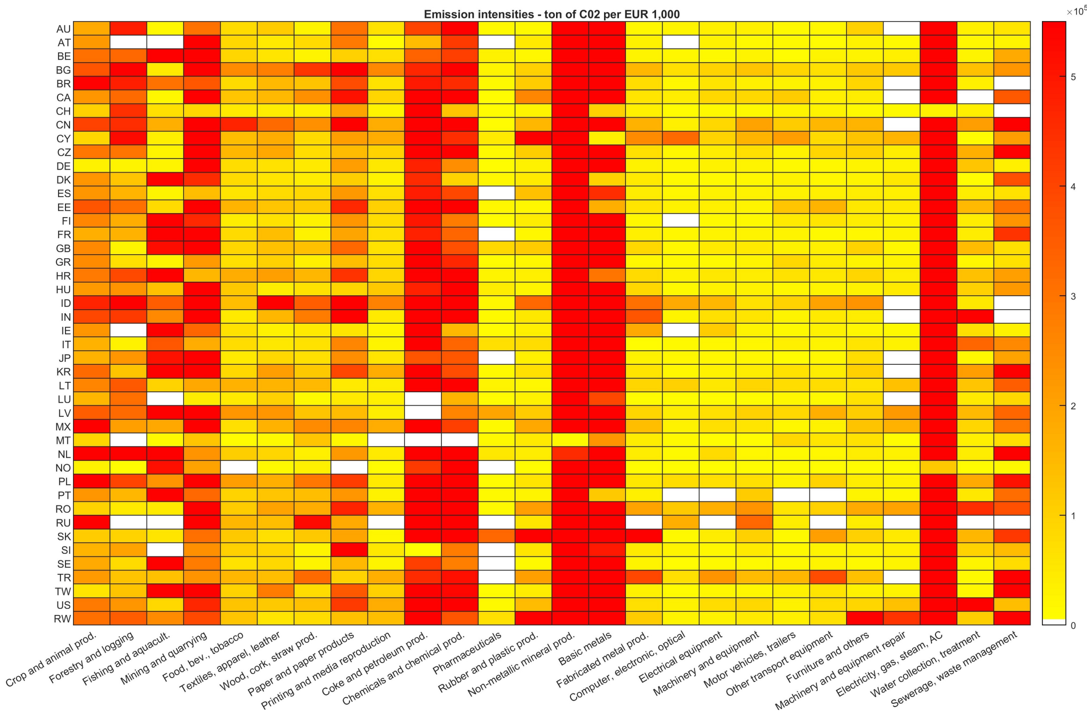
Table C.8. Targeted moments: model and data

Parameter	Moment: Share of	Sector	Model	Data
$\boldsymbol{\beta^t}$	Importers among all firms	Clean	0.309	0.279
		Dirty	0.075	0.193
	Firms importing from each country	Clean	See Figure 5	
		Dirty		
δ^t	Importer from most popular country among importers	Clean	0.476	0.596
		Dirty	0.332	0.541
	Importers among firms with sales below median	Clean	0.070	0.070
		Dirty	0.000	0.022
$\mathcal{A}^D$	Dirty inputs aggregated across firms		0.348	0.367
B_i	Firms with sales below data median value		0.908	0.500

Notes: This table presents the data and model moments that are estimated by GMM, as described in Section 5.3 and Table 2.

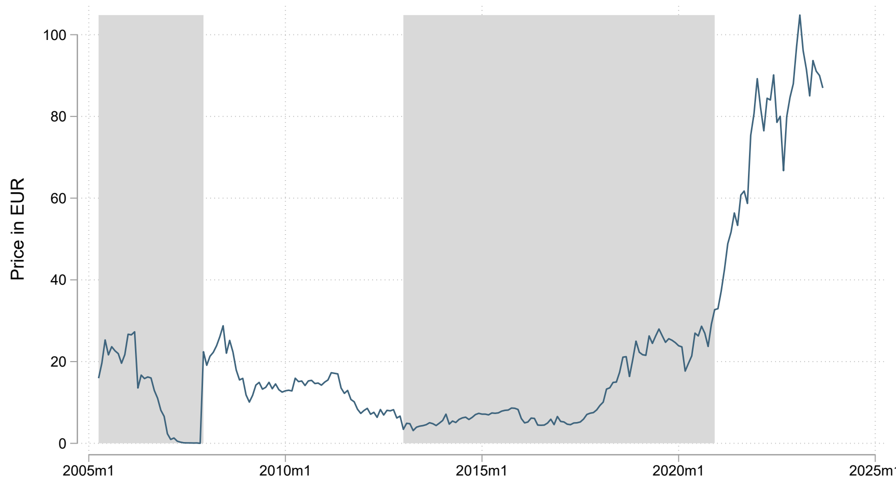
D Additional Figures

Figure D.1. Country-sector variation of CO_2 emissions in production in 2004



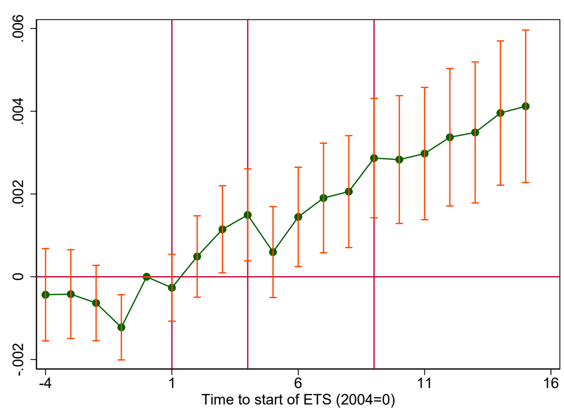
Notes: This figure plots a heat map of sectoral emissions intensities, measured as tons of CO_2 emitted per 1,000 euros of goods produced. The data are sourced from the WIOD's Environmental Acccounts and Input Output table.

Figure D.2. Carbon Prices in the ETS

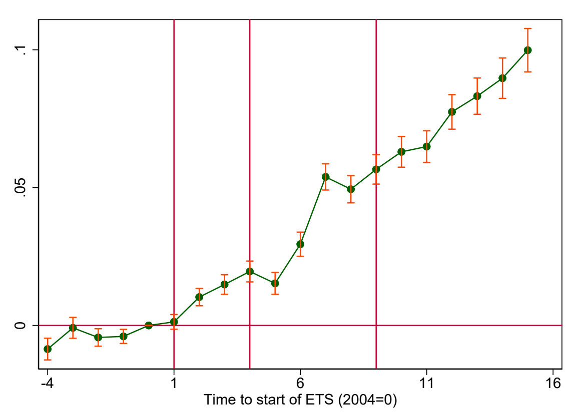


Notes: This figure is constructed using the end of month value of the closest carbon futures contract series sourced from the Intercontinental Exchange, Inc (ICE). Each shaded and non-shaded area represents a phase of the EU ETS.

Figure D.3. Evolution of firm-level imports from non-ETS countries: Dirty vs. Clean inputs. Robustness to heterogeneous treatment effects



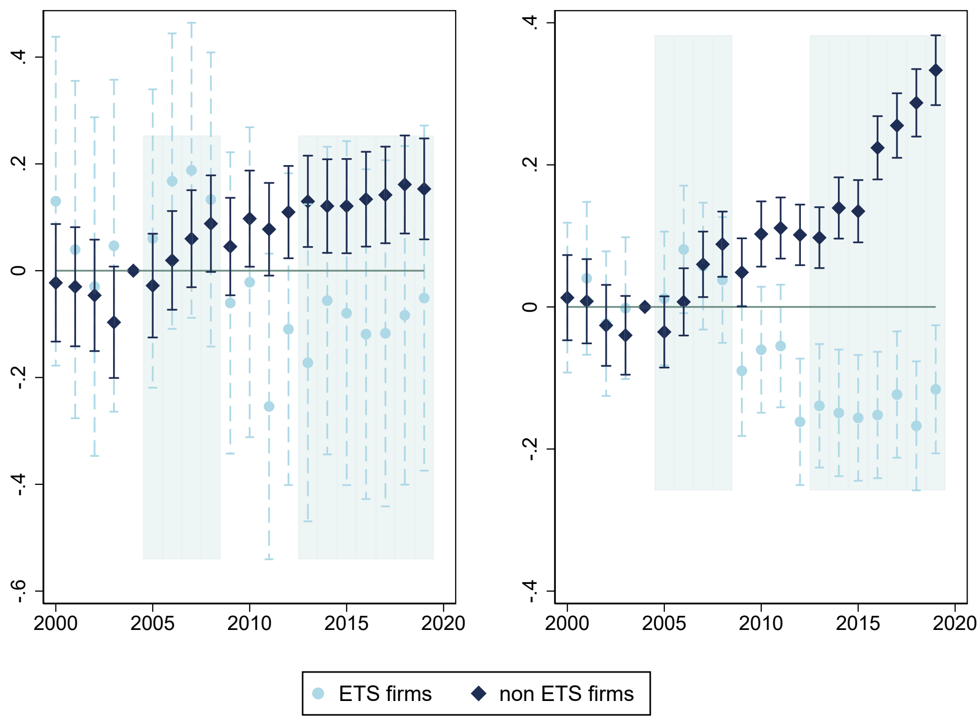
(a) Import share



(b) Import probability

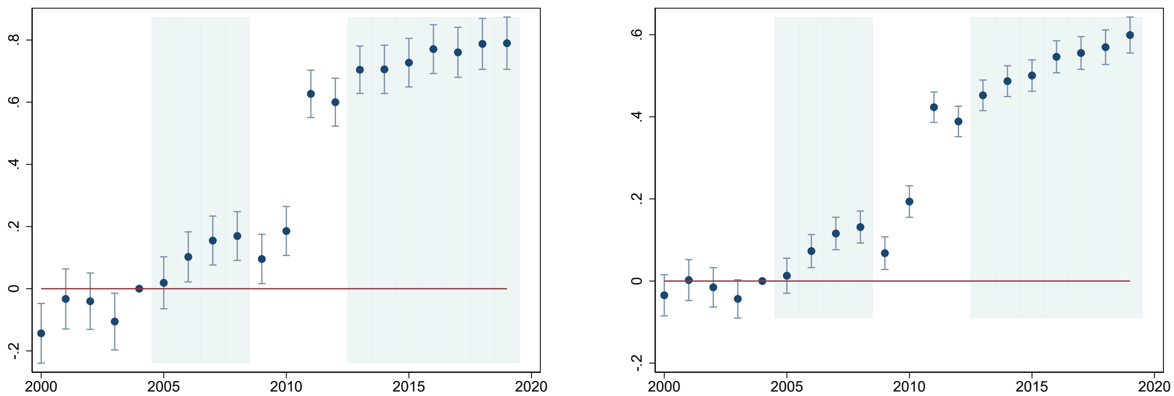
Notes: This figure shows the point estimates recovered from the estimation of a log-linear version of equation (1), using 2005 as the first "treatment" date (1). The model controls for heterogeneous treatment effects using the estimator in de Chaisemartin and D'Haultfœuille (2020). The underlying equation 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.

Figure D.4. Evolution of firm-level imports from non-ETS countries: Dirty vs. Clean 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 dirty inputs sourced in non-ETS countries. The control group covers clean 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.

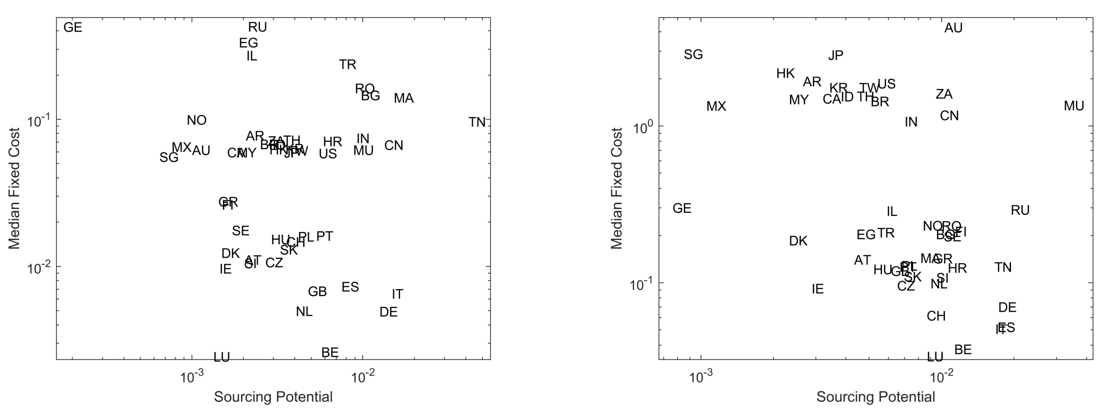
Figure D.5. Evolution of firm-level imports of dirty inputs, non-ETS vs. ETS origin countries



(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 dirty inputs sourced in non-ETS countries, with sourcing of dirty 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.

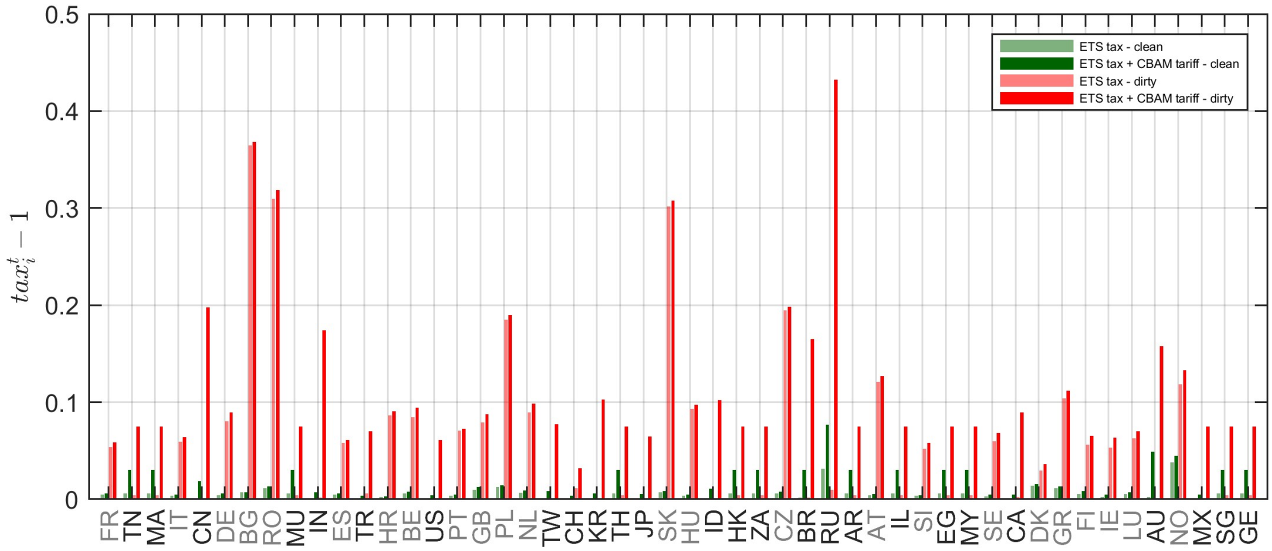
Figure D.6. Fixed costs and Sourcing potential



(a) Clean **(b)** Dirty

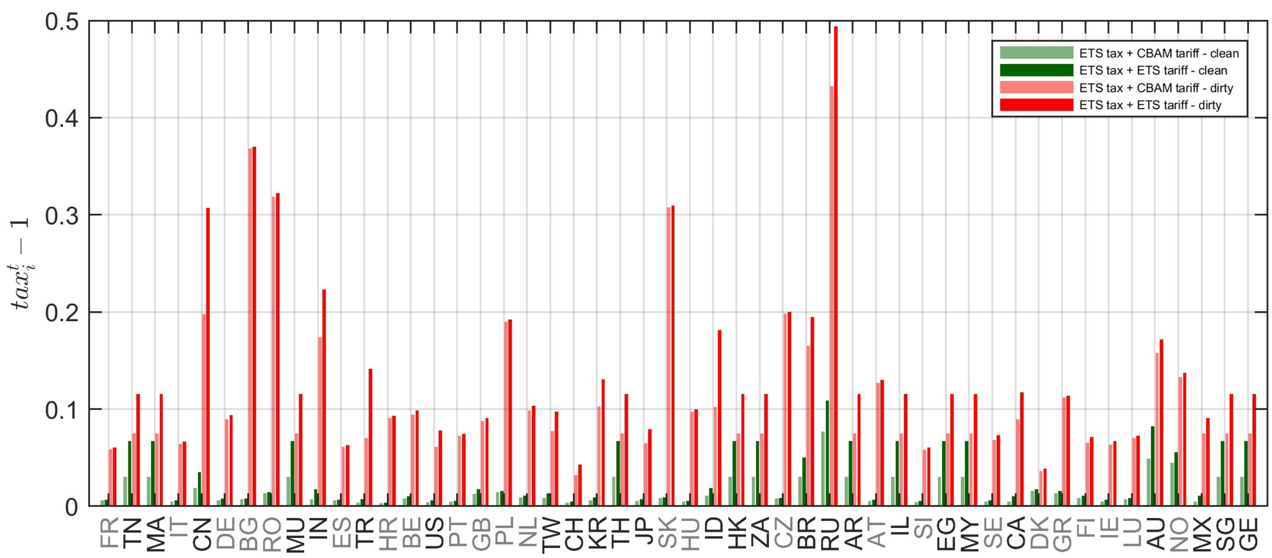
Notes: This figure plots the median fixed cost to source from a given country generated by the model against the source country's estimated sourcing potential for clean inputs in panel (a) and dirty inputs in panel (b). Data used are from 2004.

Figure D.7. Country-level taxes



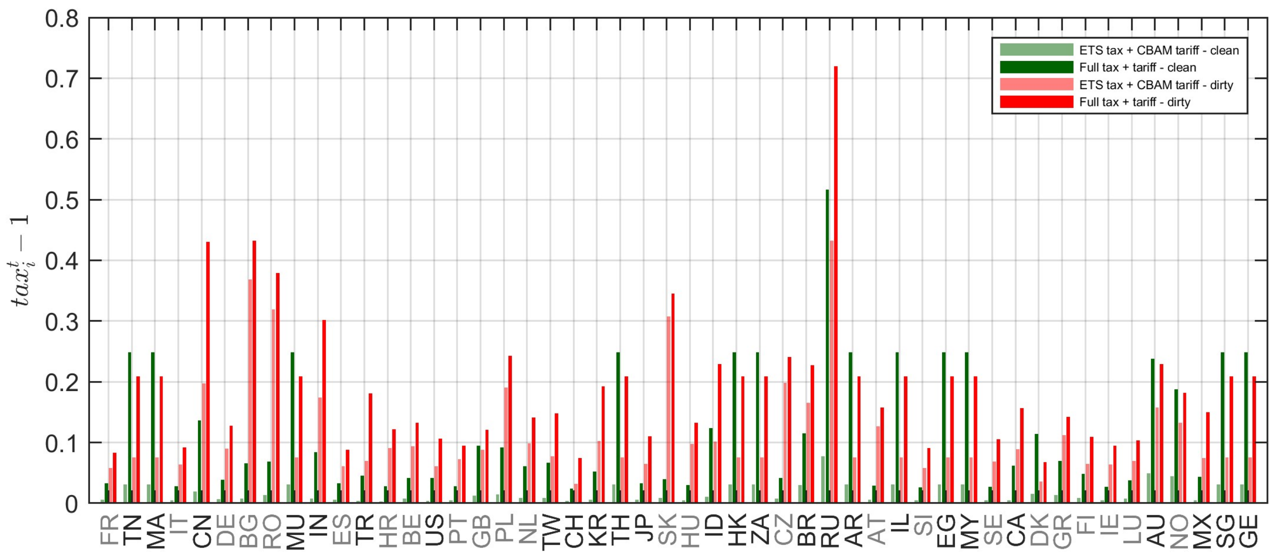
Notes: This figure presents country rates for each input type for ETS (grey labels) and non-ETS countries (black labels), in the ETS tax and ETS tax + CBAM tariff scenarios. Based on authors' calculations using data from WIOD's sector-level emissions + WIOD IO tables.

Figure D.8. Country-level taxes when taxing all dirty inputs using ETS coverage



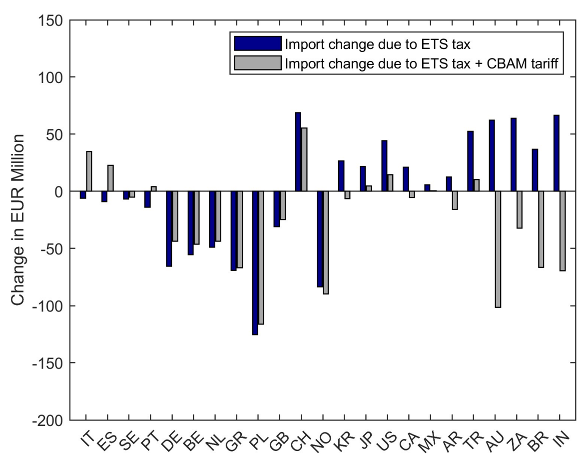
Notes: This figure presents country rates for each input type for ETS (grey labels) and non-ETS countries (black labels), in the ETS tax + CBAM tariff, vs and ETS tax + ETS tariff scenarios. The baseline CBAM tariff scenario uses the CBAM coverage displayed in Table C.2. The ETS tariff scenario applies the same coverage displayed in Table C.1 to both ETS and non-ETS countries. Based on authors' calculations using data from WIOD's sector-level emissions + WIOD IO tables.

Figure D.9. Country-level taxes when taxing all emissions

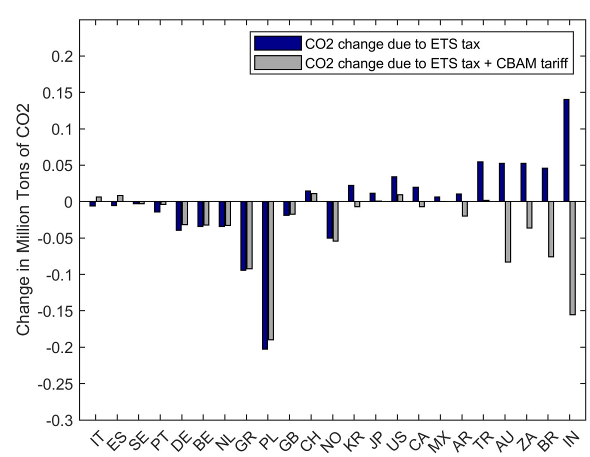


Notes: This figure presents country rates for each input type for ETS (grey labels) and non-ETS countries (black labels), in the ETS tax + CBAM tariff, compared with a scenario in which the sectoral coverage is uniform and all emissions are taxed. Based on authors' calculations using data from WIOD's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

Figure D.10. The geography of leakage: 23 other countries



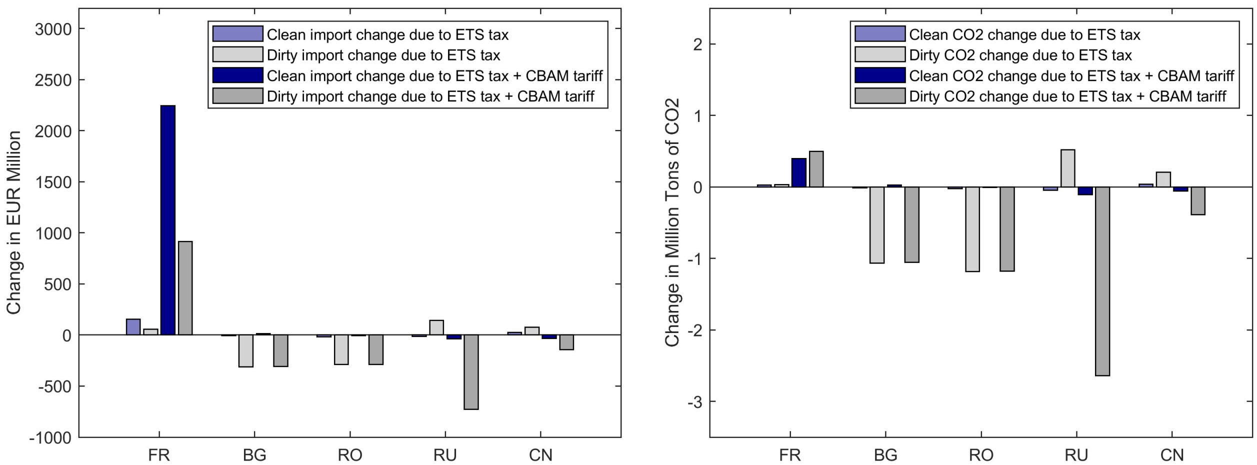
(a) Import leakage



(b) Emissions leakage

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

Figure D.11. The geography of leakage: by input



(a) Import leakage **(b)** Emissions leakage

Notes: This figure plots the change in imports in millions of euros (panel (a)) and in emissions in millions of tons (panel (b)) when imposing the carbon tax, and then both the carbon tax and tariff. We plot a subset of 5 countries for which the change is substantial, and divide the change by input type.