Carbon Offshoring and Manufacturing Clean-up

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Abstract

In many developed countries, pollution stemming from manufacturing has decreased, despite a significant rise in output. I study how carbon offshoring – import of carbon intensive inputs, own-produced goods and concentration of manufacturing plants in countries with laxer environmental policies – have contributed to the manufacturing cleanup. First, I exploit detailed product-level data on production, trade, and emissions of Swedish manufacturing firms to examine how firms adjust their production decisions in response to supply shocks in trading partner markets. Next, using a shift-share instrument and difference-in-difference estimation strategy, I show that carbon offshoring activities lead to a substantial composition effect – where multi-product firms change their product mix towards low emission-intensive products. Paradoxically, I find that carbon offshoring also result in increased transport pollution in the short run. This suggest that carbon offshoring can mask firms overall environmental performance. Latter results show that the role of environmental policy arbitrage in this effect is nontrivial, and clean-ups are highly unevenly distributed among sectors. My study recommends that *efficient* carbon border adjustment mechanism could serve as an effective strategy to tackling carbon leakage.

Keywords: Offshoring, Swedish Firms, Emissions, Trade

JEL: Q56, Q58, F18, F14.

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1 Introduction

A significant portion of carbon emissions arises from the production of goods and the burning of fossil fuels. However, the emission intensity in the manufacturing sector of many developed countries has significantly decreased in recent decades. For instance, between 2007 and 2014, air pollution emissions from Swedish manufacturing firms fell by 29 percent, despite a substantial increase in manufacturing output. Similar trends have been observed in the United States (Levinson, 2010) and Europe (Brunel, 2017). What drives these manufacturing cleanups in the industrialized world?

There are two possibilities here: *technology* –where firms use the same mix of goods but employ production processes that pollute less, and *composition* – where multi-product firms in developed countries can adjust their product mix towards low-energy-intensive and low-marginal-cost products. Previous research shows that an increase in climate policy stringency in these jurisdictions can drive the use of energy-efficient equipment and better end-of-pipe controls, a phenomenon dubbed the 'technique effect' (Levinson, 2023; Najjar and Cherniwchan, 2021; Brunel, 2017; Agostini et al., 1992; Andersson, 2019; Ponce and Khan, 2021; Marin and Vona, 2021). However, we know little about the underlying mechanism for the composition effect and how it contributes to the cleanups of manufacturing firms.

In this paper, I ask whether carbon offshoring, driven by comparative advantage and environmental policy arbitrage, causally changes the emission profile of firms. It is possible that, thanks to free trade, firms can import polluting goods that they once produced domestically, and concentrate domestic manufacturing on less environmentally penalized goods.[1] While the concept of carbon offshoring intuitively compelling, the causal evidence supporting the relationship between firm-level emissions and the intricate dynamics of offshoring and environmental policy arbitrage remains notably deficient and poorly understood within the current state of economic research.[2] The

[1]Take for example, a multi-product firm i who produces final goods $p = 1 \dots n$ (e.g. iWatch, iPhone, Macbook, iPad etc.) and uses intermediate inputs $j = 1 \dots n$, where $p \neq j$ (e.g. Tin, gold, aluminium, beryllium, mercury, phthalates). Firm i has the option to source these intermediate goods either locally or by importing them from abroad. When an intermediate input j is both energy-intensive and locally produced, it becomes an integral part of firm i's production process, contributing to higher emissions. If these emissions surpass a predetermined regulatory threshold, firm i can expect to incur environmental penalties, such as higher carbon taxes (Cole et al., 2014). In order to circumvent such environmental penalties, firms may choose to import these energy-intensive intermediate goods from foreign markets, provided that the cost of importing is more economical than the cost of implementing emission-reduction measures. Thus the decision of offshoring hinges on the fact that importing these goods from countries with a comparative advantage in energy-intensive production and a more lenient environmental regulatory framework can offer a cost-effective solution.

[2]Research in this area has yielded mixed results. Some studies indicate that offshoring can lead to lower emissions by enabling firms to capitalize on lower energy costs and more advanced environmental regulations in other countries, while others have suggested that offshoring may not explain cleanup of firms but rather trade and import which makes firms productive can lead to lower emission intensity (Cristea et al., 2013; Dussaux et al., 2023; Li and Zhou, 2017; Akerman et al., 2021; Shapiro, 2021).

difficulty arises from the challenge of isolating a firm's offshoring incentives amid other contributing factors affecting emissions. Even when exogenous shocks in offshoring can be isolated, data on emissions are often not readily available at the product $\times$ firm $\times$ sector $\times$ destination country level, which is necessary for a rigorous firm-level analysis. Consequently, empirical research on environmental offshoring generally relies on the standard approach of testing related hypotheses, such as pollution havens and the race to the bottom [3], using country and industry-level data (Brunel, 2017; Copeland et al., 2022; Levinson, 2010, 2023). However, this approach does not allow for refined identification, may introduces potential biases stemming from data aggregation, and obscures many of the micro-level dynamics related to how firms adjust their production decisions.

In this paper, I present the first comprehensive study of the impact of carbon offshoring on firm emission intensity, using a panel of 3,348 Swedish manufacturing firms spanning the period from 2007 to 2014. I demonstrate that trade exposure can offer firms the opportunity to engage in internal input and output reallocation, resulting in the enhancement of their production processes and subsequently leading to improved environmental performance. To achieve this, I combine unique and detailed product-level information on production, trade, and emissions sourced from several databases with three objectives. First, I decompose the overall emission intensity within the Swedish manufacturing sector into scale[4], technique and composition effects.[5] Second, show that compositional effects of offshoring manifest both at *extensive* and *intensive* margin.[6] Thus, for my empirical purpose, I begin by asking whether there is a significant difference in emission intensity of offshoring and non-offshoring firms[7] using propensity score matching (PSM). The preliminary

[3]Pollution haven hypothesis (PHH) is where a reduction in trade costs results in production of pollution-intensive goods shifting towards countries with lower environmental standards (Copeland and Taylor, 2004; Copeland et al., 2022). Relatedly, race-to-bottom (RTB) thesis is when different countries or regions compete with each other in environmental regulations, or taxes – they may reduce these standards and regulations to attract businesses and investment (Konisky, 2007; Porter, 1999). Both PHH and RTB are independently necessary but not sufficient condition for carbon offshoring to hold (Copeland and Taylor, 2004)

[4]Changes in emission due to changes in the size of manufacturing sector.

[5]It is worth noting that similar decomposition analyses have predominantly been conducted at the industry or product level in previous studies such as Shapiro and Walker (2018) and Copeland et al. (2022) with the technique effect typically found to be the more prominent factor. However, using detailed firm-level data, I find that the composition effect is comparable to the technique effect.

[6]The *extensive* margin reflects the between-firm component of emission intensity as a result of changes in offshoring status while the *intensive* margin reflects within-firm changes in individual firms' emission intensities over time as a result of increase in imports.

[7]I use both production and import data to identify firms that engage in offshoring. I define offshoring firms as those that substitute parts of production with imports, resulting in a decrease in input and/or own-products while simultaneously increasing the import of such input and/or own-products. I measure imported carbon metrics by assigning weights to firm-level imports, taking into account the carbon intensity (both direct and indirect) specific to each sector-country pairing. Theoretically, this will mechanically generate a lower average emission for offshoring firms. Thus, I construct a Propensity Score Matching (PSM) to compare the average emissions of similar non-offshoring firms. My matching procedure enables me to create a group of offshoring firms matched with the closest non-offshoring firms based on sector and firm-level characteristics, including firm size, revenue, assets, machine investment, profit, and the number of employees.

empirical correlation suggests that firms engaging in pollution offshoring activities tend to have lower levels of emission intensity compared to firms that do not participate in carbon offshoring.

I then delve deeper and analyze the *within-firm adjustment* of production processes as a result of shocks in carbon offshoring (at the intensive margin). To do this, I first provide a comprehensive view of all possible channels through which offshoring could occur: (1) as the import of carbon-intensive inputs, (2) as the import of carbon content of similarly produced goods, and (3) the concentration of Foreign Direct Investment (FDI) by Swedish multinationals in countries with less environmental stringency. My ability to observe actual imports (both quantities and values) at the product level, the number of plants, employment size in affiliate countries, as well as energy consumption by firms, enables me to assess how changes in the import of energy-intensive goods and FDI affect a firm's emission intensity.[8] I proceed by estimating the effect carbon offshoring on firm-level emissions per value of output. However, identifying the causal effect is challenging because, in principle, unobserved supply shocks that leads to an adoption energy-efficient technologies represent an alternative approach to carbon offshoring. Therefore, technological shocks can reduce emission intensity, as well as carbon import, leading to downward bias of the OLS estimate. To address these endogeneity concerns, I take advantage of product-level global supply shocks outside of Sweden and its EU neighbors to isolate the carbon offshoring shocks. Using bilateral trade flows at the product level from the COMTRADE database, defined at the 6-digit level of the Harmonized System (HS), I can trace the shocks in the export supply of carbon inputs and the emission content of goods that are similar to the ones produced domestically by firms.[9]

In the same spirit as Hummels et al. (2014), I generate two instruments that exploits shocks to the Swedish trading environment that change over time and are specific to each trading partner $\times$ the type of product being traded. My first firm-specific shift-share instruments uses world-wide shocks of intermediate inputs and firms' own-produced goods which contains rich variations across countries and products. Given that firms often source inputs from various countries, the impact of these shocks may vary from one firm to another. My second instrument investigate the role that differences in environmental policies between Sweden and its trading partners play in pollution offshoring. The assumption is that differences in environmental polices may well be

[8]To calculate the emission content of imports, I initially used emission and production data for each sector and destination country pairs obtained from the Eora Global Supply Chain Database to calculate industry-level carbon intensities. Subsequently, I weight firm-level imports by their carbon intensity, both direct and indirect. By incorporating foreign emission intensity as a weighting factor for imports, I am able to effectively capture the environmental incentive behind firms' relocation toward emerging economies. This approach also allows me to directly quantify the tangible disparities in carbon intensities among the countries from which sourcing occurs. The underlying concept is that firms already engaged in importing energy-intensive goods from overseas may respond to increasing environmental policy requirements by shifting additional environmentally unfriendly tasks offshore, and this shift may not be evenly distributed across the various sourcing countries (Dussaux et al., 2023).

[9]I use the 3-digit 5th revision of the Classification by Broad and Economic Categories (BEC-3digits) to identify all inputs and own-produced goods crossing the border of Sweden.

tied to the type of imports and pollution intensity of production. Therefore, firms may indulge in policy arbitrage by increasing dirty imports, thereby leading to reduced emissions in the home country (Cole and Elliott, 2005; Esty and Porter, 2002). For this, I employ a novel measurement of environmental policy arbitrage based on the OECD's Environmental Policy Stringency (EPS) index to compare Swedish firms' imports from countries with laxer environmental policies with those from countries with stricter policies[10]. I then construct a novel, firm-specific instrument based on the desirability of importing the energy intensive goods from countries with laxer environmental policies by exploiting changes in these countries comparative advantage. Any supply-based policies by these group of countries will lead to large shifts in the composition of their exports which allow for a strong first stage in predicting changes in intermediate and produced-good imports. An uptick in the export share of "laxer" countries to the rest of the world (excluding Sweden) indicates a growing comparative advantage and policy arbitrage. The identifying variation are in two parts: (i) exogeneity of firm-specific product shares and (ii) the aggregate supply shock (Barrows and Ollivier, 2021; Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). With the assumption that there is stability of offshoring patterns over time, I use pre-sample information about firms' purchase of inputs and their own-produced goods. This removes any contemporaneous shocks due to technology that can affect both the types of product used and firm-level emissions. The exclusion restriction requirement is that the instrument will be valid if the world export shocks are uncorrelated with the average firm-level characteristics that determine emissions (Borusyak et al., 2022). As a robustness to this assumption, I use a difference-in-difference strategy using current-year-weighted foreign supply shocks as instrumental variables, while controlling for arbitrary industry-by-year trends.

The results of the study are in threefolds. First, I find that the impact of globalization on the environment varies depending on the nature of the trade involved and type of pollution. I estimate that in a year where carbon content of input import are 1% higher than it typically is for that firm, then we would expect CO_2 emission intensity (a global pollutant) and LED intensity (a local pollutant) to fall by 0.35% and 0.45% respectively. However, import of own-produced goods have only short run impact of emission intensity reduction. Also, it's important to note that offshoring may not necessarily lead to a reduction in overall firm-level emissions, when we account for emissions from transportation. Similar to Cristea et al. (2013), I find that that emissions from transport can account for as much as one-third of the total emissions associated with producing and transporting goods. Consequently, the results show that offshoring leads to a short-run increase in transport pollution. My second set of results show that environmental policy arbitrage has a visible hand in this effect. Offshoring to countries with laxer environmental policies reduced emissions intensities marginally compared to countries with strict environmental polices – the effect being even more striking when offshoring takes place in low-income countries. Thirdly, I find

[10]In comparison to the traditional approach of using income groups to proxy for policy arbitrage, the EPS is more reliable and an internationally comparable measure of environmental policy stringency which is directly based on a wide range of indicators (see Botta and Koźluk 2014, Koziuk et al. 2019).

that cleanups are highly unevenly distributed across single and multi-product firms, dirty and cleaner industries and multinationals who over-allocate their affiliates in foreign countries. Notably, emission reductions are more pronounced among multi-product firms, cleaner industries (upstream firms), and multinational corporations via FDI concentrations. Interestingly, I find no carbon offshoring effect for firms regulated under European Union Emission Trading Scheme (EU-ETS) which is in tandem with many ex-post studies evaluating EU-ETS (Verde, 2020; Venmans et al., 2020; Neary, 2006).

As a last exercise, I conducted series of tests to identify the mechanisms at play and find that carbon offshoring necessitates productivity growth, reduces overall operational costs, and improves sales performance. However, it is surprising to note that despite the increase in sales and profitability, carbon offshoring does not significantly incentivize firms to invest in abatement technologies designed to mitigate environmental impact. Thus, offshoring typically results from domestic firms seeking efficiency and cost savings by relocating production processes to foreign suppliers who can produce inputs more energy efficiently. This suggest that carbon offshoring maybe a substitute to investment in energy-saving technologies for large, multi-product firms (due to its cost efficiency).

The paper makes three main contributions on the burgeoning studies on manufacturing cleanups (Brunel, 2017; Dussaux et al., 2023; Levinson, 2010; Linaa et al., 2023; Li and Zhou, 2017; Shapiro and Walker, 2018). First, I demonstrate that the overall trend documented in prior studies in France (Dussaux et al., 2023), and U.S (Najjar and Cherniwchan, 2021; Levinson, 2010; Li and Zhou, 2017), extends to Sweden. However, it is important to note that these prior studies do not explicitly consider the impact of transport emissions. This paper is the first to causally estimate the significant role of transport emissions. It conclusively demonstrates that carbon offshoring leads to a contemporaneous increase in transport emissions, suggesting that offshoring can obscure the overall environmental performance of firms.

Second, in relation to papers micro-level papers on globalization and environment (Dussaux et al., 2020; Akerman et al., 2021; Linaa et al., 2023), this paper provides a more comprehensive perspective of carbon offshoring activities. In contrast to a closely related paper by Dussaux et al. (2023), this paper examines whether the elasticity of CO_2 intensity to offshoring varies with the type of good imported – drawing a distinction between a good that is produced by the firm vs an intermediate good used in the production of final goods. While prior research has primarily focused on imported inputs, theoretical studies on offshoring predict that tasks that are offshored may no longer be performed within the firm. Thus, offshoring may primarily involve the import of domestically produced goods, rather than imported inputs (Bernard et al., 2020). This paper highlights the heterogeneous responses of trade shocks on these offshoring strategies and demonstrates that the type of goods imported matters for manufacturing cleanup. Specifically, I find that carbon offshoring through input reallocation leads to a larger reduction in emissions compared to offshoring through the substitution of a firm's own-produced goods, which are typically semi-finished products with lower carbon content. Additionally, the richness of my data allows me to concretize the idea of the migration of environmentally unfriendly firms abroad by examining the concentration of multinationals' Foreign Direct Investments (FDI) overseas. In a broader sense, offshoring encompasses both international outsourcing, when the firm keeps at arm's length from its foreign supplier, and vertical FDI, when the domestic firm is supplied by a foreign affiliate (see e.g El-Sahli et al. 2022; Hummels et al. 2018 for discussion of measurements and definitions). My result suggest that the complete migration of dirty firms leads to a more substantial reduction in firms' carbon footprints as compared to carbon imports.

Another novel contribution of this study is that I explore the role of environmental policy arbitrage. The study shows that where these dirty imports are coming from or where dirty firms migrate to is crucial in firm carbon offshoring activities and magnitude of manufacturing clean-up. In particular, I used a recently introduced OECD environmental policy stringency index to show that firms' importing or migration to countries with lax environmental polices – where environmental arbitrage is high (Cole and Elliott, 2005; Cole et al., 2014) can have a substantial impact on their emission intensity. Though previous studies rely on country income groups to detect policy arbitrage (with the assumption that there exists a high correlation between economic development and environmental policy) (Stavropoulos et al., 2018), I show that such proxy can be problematic, especially when the correlation between economic development and environmental policy stringency becomes weak over time. Income groups do not capture the changes in environmental policies by countries over time. To the best of my knowledge, this is the first paper to provide rigorous comparative analysis between various aspects of offshoring to/from countries with laxer environmental policies using a more direct and composite index of environmental policy stringency which is more reliable and internationally comparable (see Koziuk et al. 2019).

My findings also relates to the studies on productivity, abatement and firm-level emissions (Bernard et al., 2007; Bustos, 2011; Cui et al., 2016, 2012; Forslid et al., 2018; Holladay, 2016; Rodrigue et al., 2020; Tybout, 2001). Mostly, this body of literature finds no evidence of a pollution-haven effect. For instance, Forslid et al. (2018) using Swedish data finds an anti-pollution haven effect for exporting firms. In this study, I find that a pollution haven at firm-level is possible for multinationals and that the productivity level needed to incentivise firms to offshore may be higher than the average exporter productivity cut-off[11]. That is, at each level of productivity, outsourcing firms are more productive (Cole et al., 2014). As such a larger firm that faces a higher cost of abatement, will find it cost-effective to offshore some of its dirty tasks or products.

[11]For instance, multinationals are more likely to offshore compared to exporters, since there is a strong correlation between outsourcing and productivity (Egger and Egger, 2006; Schwörer, 2013; Sturgeon et al., 2013)

The remainder of this paper is as follows. Section 2 presents the data and measurement issues. Section 3 documents some basic facts and outsourcing pattern in the manufacturing sector. Section 4 focuses on the empirical strategy and shows the the source of exogenous variation in offshoring. I provide the main results along with robustness checks in section 5. I then examine the role of environmental policy arbitrage in Section 6, while focusing the major heterogeneity responses in section 7. In section 8, I examine mechanism underlying offshoring on emissions intensity. Section 9 then concludes.

2 Data

A major constraint in studying the effects of firm-level offshoring activities and manufacturing clean-up is the lack of data on emissions disaggregated at the firm level, combined with the availability of detailed offshoring activities data. To explore the effect of offshoring activities on emissions over time, I constructed a rich dataset that combines firm emissions information with detailed product and firm-level characteristics and trade flow data sourced from Statistics Sweden. This dataset was then merged with firm-product-time exports using bilateral trade flows at the product level from the COMTRADE database, defined at the 6-digit level of the Harmonized System (HS). I also obtained industry-year-level emissions and output data from all Swedish firms' source countries from the Eora Global Supply Chain Database, which helped me calculate the emission content of imports. The computation and derivation of variables are as follows.

2.1 Firm-level emissions

Statistics Sweden collects information on the energy consumption of all manufacturing plants with 10 or more employees. Therefore, I consider relatively large firms, although not all large manufacturing firms are necessarily large polluters. Nevertheless, the information provided for smaller firms is likely to be less reliable. I focus on the years from 2005 to 2014, during which energy data is available. It's worth noting that the majority of firms do not report their environmental emissions, leading to many missing observations (see B.1). However, firms report detailed information of annual consumption (with units) of different energy-use (e.g. Litres of diesel, MWh of electricity, $100m^3$ of natural gas, etc.). I use the energy data to calculate pollution in two ways. First, I calculate firms' build-up of global pollutant (CO_2 emissions (kg)) using a fuel-specific CO_2 coefficient as :

$$E_i = e_f\left(x_1, x_2, \ldots, x_n, \alpha_j\right), \quad \sum_j f_{ij}\left(\alpha_j\right) x_j \tag{1}$$

Where e_f represents the emissions of pollutant f, x_j stands for the quantity of fuel type j, and α_j denotes the fuel-specific CO_2 coefficient. Each emission of pollutant is then aggregated at the firm level as E_i for each year (for a similar measurement, see studies by Forslid (2018) and Barrows (2018)[12]. Note that SCB does not use exactly the same naming convention for fuel-types in the emission-factor dataset and energy-use dataset. So I mapped these energy types by hand. I then use the maximum mode of the emission coefficients within each energy ID and replace all missing values due to variations in spellings. However, for some observations, I am unable to standardise units across the two datasets. For this reason, I use another means of gauging emissions, namely, local environmental damage (LED). The LED metric uses the heat value (calorific value) released by fuel during its combustion, which are readily available for all energy type. The LED is distinct from CO_2 , as it has no cross-border impact, primarily affecting local environment.[13] CO_2 emission on the other hand, is a global pollutant since CO_2 emissions has a transboundary effect – it can remain in the atmosphere sufficiently long to spread across national borders. Thus, the two measures offer an interesting comparison of how foreign demand for toxic products can influence the use of energy at firm level and its eventual effect on both local and global pollutants.

Two important issues arise with these pollution measures. First, when computing emissions, it is assumed that the carbon content in the energy sources is fixed, and it disregards the technology used. This assumption appears reasonable in Sweden, given that end-of-pipe carbon capture technology was not available during the study period. However, firm emissions from energy use may reflect changes in the scale of production by firms, firm size, the role of imperfect market competition, and other forces that can lead to varying fuel prices across industries. Thus, observed emission reductions could be interpreted as reductions in production, for example. To address these challenges, I adopt emission intensities measured as emissions per unit of the value of output (similar to Holladay 2016, Rodrigue et al. 2020 and Barrows and Ollivier 2021). I also adopt output-based emission intensity for robustness checks. The difference between these two measures is that, while output-based emission intensity is based on quantities, sales-based emission intensity uses a value measure. Both measures have their advantages and disadvantages. Output-based emission intensity is unaffected by price effects but may have lower statistical power due to the need to standardize units across products and over time. Sales-based emission intensity, however, does not require such restrictions for comparison. Nevertheless, changes in prices can endogenously affect the changes in emissions per sale, even though the denominator is expressed as a value with no direct environmental implication(see Barrows and Ollivier 2021) [14].

[12]Since I have access to energy data on firms' self-produced quantities of fuel (fuel production processes) and fuel used for transportation, I similarly generate values for emissions due to fuel production processes and transportation.

[13]the LED is more localized and vary substantially with the use of dirty sources of energy such as coal, oil, shale gas (fracking) and natural gas (Parry et al., 2014).

[14]For example a $\frac{\text{high quality shoe}}{\text{price(SEK)}}$ with the same unit of emission requirements has no significant impact on

2.2 Production, Trade data and measures of offshoring

I merged the energy and pollution data to the manufacturing surveys and customs data which covers the population of Swedish manufacturing firms (2-digit NACE Rev. 2 codes 10–37). The manufacturing surveys and customs data contain annual observations of product-source level import quantities and values, information of firm characteristics such as size, capital-stock, firm labour, machine investment and total factor productivity and outward FDI measured as the employment and sales in affiliate countries. I have restricted my sample to only manufacturing industries because they are relatively dirtier and manufacturing goods are more often traded, compared to the service sector (see e.g Copeland et al. 2022) [15]. For the study sample, I retained only active firms who have positive sales and imports in the sample period. About 3,348 firms remained after the matching exercise.

I then proceed to capture the idea of firm offshoring. The definition of offshoring in the literature is broad and blurry at best. One point of departure in the literature is to include all imports of products by firms. However, the pitfall of this definition is that it encompasses both inputs in production, final goods and goods that may never be produced domestically (El-Sahli et al., 2022). I overcome this aggregation bias by concentrating on imports of intermediates inputs using the 3-digit 5th revision of the Classification by Broad and Economic Categories (BEC – 3digits). The BEC classification system groups transportable goods according to their main end use: capital goods, consumer goods and intermediate goods. A main challenge for offshoring research based on the BEC system is that revisions imply that unique products might be classified differently over time. To account for the re-classification, I apply the algorithm suggested by Pierce and Schott (2012) and further developed by Van Beveren et al. (2012) for concording trade and production data over time, and consider an imported product as offshored if it is classified as an intermediate good (using codes 121, 220, 420, 521, and 530). I refer to this type of offshoring as `reallocation of input`.

Perhaps, what is important for this paper's objective is the emissions embodied in these imports. This is because pollution offshoring can lead to the composition of production to shift towards a cleaner production by driving a significant increase of imports of dirty goods that are not produced in-house. Studies have shown that about 22 to 35 percent of global emissions are embodied in the entire value chain of traded goods (Copeland et al., 2022) and the share of global pollution embodied in international trade has been on the rise (Eaton et al., 2016). It is therefore important to account for the intensive margin of the toxic content of each type of import. I obtained source countries emissions per output is obtained from Eora Global Supply Chain Database, which comprises a

environment relative to a $\frac{\text{low quality shoe}}{\text{price(SEK)}}$

[15] Studies such as Shapiro (2021) find that dirty manufacturing industries are more trade-exposed as they tend to have lower tariffs and non-tariff barriers.

Multi-Region Input-Output (MRIO) table model of industry emissions and production. I then calculate the emissions embodied in imported inputs and firms' own-produced goods as the weighted sum of each firm's import and industry emissions [16].

Environmental policy arbitrage

As a second objective, this paper explores the interaction between offshoring and environmental policy arbitrage. I consider imports originating from countries with laxer environmental policies and juxtapose this with imports from countries with stricter environmental policies compared to Sweden. To this end, I rely on the OECD's environmental policy stringency (EPS) index which is based on a composite set of indicators of about 15 market based and non-market environmental policy stringency variables. I use EPS data spanning the period 2004 to 2014 to categorise countries into lax if a country's EPS index is less than the Swedish EPS index over the study period (For more details on the stringency index and the construction of the laxity variable, refer to Appendix D).

3 Basic Facts and Outsourcing Patterns

Emissions. Table 1 displays the descriptive statistics for emissions, firm size, and intermediate import (both quantities and values) of my sample. On average, firms emit approximately 1401(tons/GJ) of CO_2 emissions and contributes to around 26.21(tons/GJ) of local pollution emissions (LED). The average transportation CO_2 and LED is 1.46 (tons/GJ) and 0.26(tons/GJ) respectively. All the median values on emission are lower than the average suggesting that emissions are rightly skewed and are highly concentrated among few firms. By tracking the evolution of emissions over the sample period, I observe that between 2007 and 2014, there was a notable decrease of approximately 38% in fuel-use emissions. Conversely, transportation emissions experienced fluctuations, with a decline in 2009 followed by a subsequent increase (see Figure B.2).

Aggregate Emission Decomposition. To understand the role, trade plans in manufacturing green transitioning, I decompose the manufacturing emission into three potential channels: (i) changes in the size of the manufacturing sector – scale effect, (ii) changes in emissions due to technology used in production within industries – technique effect, and (iii) changes in the mix of

[16] Note: ideally, one requires product × firm × industry × country pollution intensity to generate the emission content of each imported input from source countries. However, I do not have access to this source countries pollution intensity at product and firm level. As a standard practice in the literature, I use industry-based emission intensity as proxy for emission intensity of these imported goods (Levinson, 2010; Li and Zhou, 2017).

Table 1: Summary Statistics

	N	**Mean**	Std. dev	Min	10th perc.	**Median**	75th perc.	Max
CO_2(tons/GJ)	26,092	1401.72	10489.98	0	10.96	73.47	252.48	467420.4
LED(tons/GJ)	26,092	26.21	226.83	0	0.19	1.24	4.29	13284.57
Transport CO_2(tons/GJ)	26,092	1.46	8.61	0	0	0	0.47	422.35
Trasnsport LED (tons/GJ)	26,092	0.26	1.54	0	0	0	0.08	77.53
CO_2(tons/GJ) per sale(SEK)	26,092	0.003	0.024	0	0.0002	0.001	0.002	1.65
LED(tons/GJ) per sales(SEK)	26,092	4.94e-05	.0004	0	4.34e-06	1.87e-05	3.72e-05	0.04
Firm Sales(millions)	26,092	435.21	3371.86	0.11	16.98	68.66	188.16	120555
Employment	26,092	121.24	600.23	5	12	36	81	20492
Import ('000kg)	26,092	109.81	1268.53	1.00e-06	0.017	5.61	28.95	53922.02
Import(million SEK)	26,092	79.20	718.79	1.00e-06	0.02	5.17	26.22	36666.57

Note: The sample is unbalanced and covers the years 2006-2014. CO2 intensity is calculated as total CO2 emissions over sales. All nominal variables are in SEK and 2006 prices

sectors towards less pollution-intensive industries – composition effect. [17] More formally, the CO_2 emissions from manufacturing sector in year t, E_t can be written as

$$E_t = \sum_j E_{i,t} = \sum_j \nu_{i,t} z_{j,t} = V_t \sum_i \theta_{j,t} z_{j,t} \tag{2}$$

where $j = 1, \ldots, n$ indexes manufacturing industries (defined at SIC 4-digits). V_t is the manufacturing output and $\theta_{j,t}$ is each industry's share in total output ($\theta_i = v_{j,t}/V_t$), and $z_{j,t}$ is each industry's emissions coefficient measured as the amount of pollution per monetary value of output in industry j ($z_{j,t} = p_{j,t}/v_{j,t}$). Thus, the total CO2 emissions in a particular year is the scale of the sector times weighted emission per output ($V_t \sum_i \theta_{j,t} z_{i,t}$). Equation 1 can be rewritten in a vector notation form as $E = V\boldsymbol{\theta}' z$ – where θ and z are $n \times 1$ vectors containing the output shares of each of n industries and their emissions intensities, respectively. By applying a total differentiation on the vector notation, I obtain:

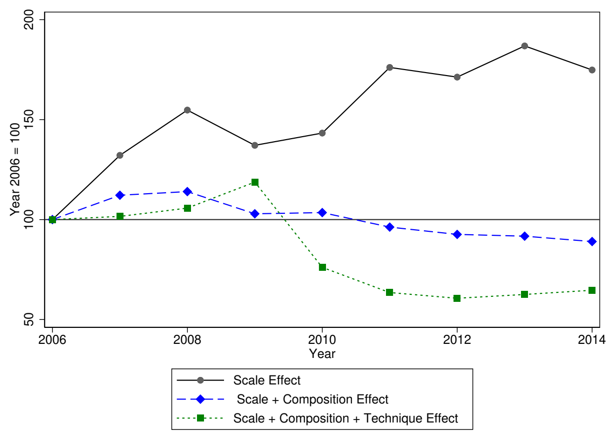
$$dE = \boldsymbol{\theta}' z dV + V z' d\boldsymbol{\theta} + V\boldsymbol{\theta}' dz \tag{3}$$

The three terms on the right-hand side in equation 3 can be interpreted as three primary channels or effects that explain the change in total pollution over time, namely, the scale effect, the composition effect, and the technique effect. Figure 1 illustrates the results of decomposition, tracking changes in total manufacturing emissions of CO_2 relative to the year 2006. I observe that the aggregate

[17] I follow the decomposition exercise of Copeland et al. (2022); Shapiro and Walker (2018); Ustyuzhanina (2022).

decline in CO2 emissions from manufacturing firms is driven by within-industry adjustments and technologies. The black line isolates the change attributed to the scale factor, while blue line incorporates the composition factor in addition to the scale effect. The combined impact of these two channels makes huge contributions to the observed downward trend in CO_2 emissions. The gap between the The gap between the black line (scale) green line (composition), suggest a huge impact of composition effect on emissions over time. Without the composition, emission would have trended upwards. Lastly, the green line, which represents the aggregate change in emission , shows a declining trend in total manufacturing emissions of CO_2 emissions over time. Thus the residual effect represent the contribution of the technique effect, which also accounts for substantial effect of the decline in CO_2 emissions over time.

Figure 1: Decomposition of Aggregate Manufacturing Emissions



Note: The graph illustrates changes in the aggregate manufacturing CO2 Emissions using equations 3. The black line shows the magnitude of the scale effect. The distances between the black line and blue line shows the magnitude of composition effect and the the distance between all three lines, shows the magnitude of the composition and technique effect, respectively. All emission values are normalised to 1 in 2006.

Overall, I observe that despite a substantial increase in manufacturing output, air pollution emissions from Sweden manufacturing firms fell by 29 percent despite a substantial increase in manufacturing output (see Figure B.3) This crucial contribution of technique effect on the emission reduction is unsurprising. This is because, in comparison with most other countries, and despite its limited size, Sweden has a long tradition of strict environmental policies. In 1991 a carbon tax was introduced in Sweden as a complement to the existing system of energy taxes (Johansson, 2000; Jonsson et al., 2020). Since then the carbon tax system has changed several times but a common feature is higher taxes for large carbon emitting industries. Currently, the country levies the highest carbon tax rate in the world, at SEK 1,409 (US$129.89) per metric tonne of CO_2[18]. As such these regulations have historically been important for the possibility of reducing emissions from both stationary and mobile sources. Although these policies may have incentivised some businesses

[18]see https://carbonpricingdashboard.worldbank.org/

to lower their emissions through the use of cleaner technologies, the reduction in emissions also reflect composition of net trade flows across industries. The impact of stringent carbon tax, among other environmental policies, on the energy and resource efficiency of Swedish manufacturing can, therefore, be limited, once offshoring becomes an escape route to avoiding strict environmental policies.[19]

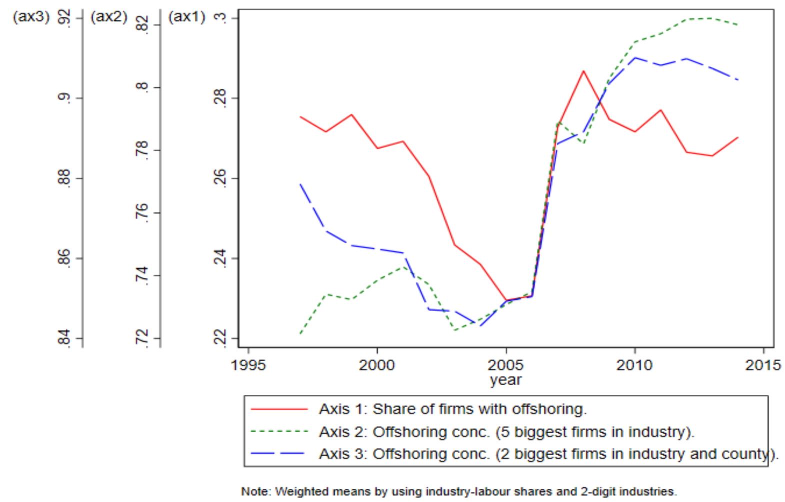
Carbon Offshoring Trends. Trade openness may offer an opportunity for very large polluters with little room for innovation to resort to pollution offshoring to reduce their emissions to the home regulation level. At the national level, Sweden as compared to other countries is the highest importer of CO_2 emissions (see Figure D.5). Also, over the sample period, I observed a substantial increase in carbon offshoring in countries with laxer environmental policies (see Figure D.6). Dirty firms may also relocate to countries with laxer environmental policies. Data from SCB shows that significant parts of Swedish firms' supply chains are located in countries with relatively laxer environmental policies such as China, Indonesia, Turkey and Japan. As such Swedish firms are increasingly dependent on energy imports and intermediate goods from these countries. Overall, an average manufacturing firm imported about 40.93kg carbon content of inputs. About 46.4% of total toxic import comes from EPS lax countries while the share of emissions imported from low-income countries is about 12% (Table A.2).

Within Sector Allocation. I also observe a significant concentration of carbon offshoring within 2-digit industries. Figure 2 illustrates that the share of all firms engaged in offshoring (weighted by labor shares and sectors' labor weights) declined from approximately 25% to 22% between 1997 and 2005. However, this share gradually increased from 2007 (the beginning of my sample period) and reached around 30% by 2015. Interestingly, offshoring tends to be concentrated among a select few firms. On average, the five largest offshoring firms within each industry account for approximately 80% of the total offshoring volume. Moreover, the concentration becomes even more pronounced when considering local markets. Specifically, the two largest offshoring firms within each industry and county contribute, on average, around 90% of the total offshoring volume. These descriptive findings highlight the dynamic relationship between offshoring activities, firm emissions, and the importance of properly controlling for firm characteristics in the regression analysis, as firms may self-select into offshoring.

Correlation between carbon offshoring and emission intensity. As a descriptive evidence,

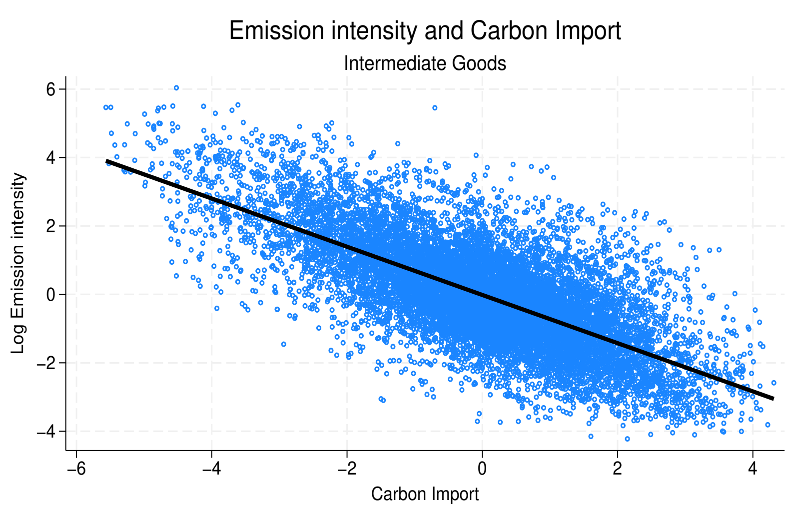
[19] It is important to note that offshoring strategy does not necessarily imply that Swedish firms are deliberately breaking any domestic or foreign environmental laws. Most African countries are energy-intensive economies and largely depend on carbon-based fuels for economic growth (International Energy Agency, 2015; OECD, 2016). Therefore dirty firms may find that it is cost-effective to import from them. Also, since low-income countries have low-cost energy input, they may attract "dirty" firms leading to migration of dirty firms. Hence, firms are making strategic cost-benefit decisions about production and profit. It is also possible that offshoring leads to technological transfer to low-income countries and hence improve their carbon-efficiency. This analysis is, however outside the scope of this paper due to data limitation.

Figure 2: Within Sector Allocation



Note: This figure provides insights into the pollution offshoring patterns at the sector level by illustrating the concentration of offshoring within 2-digit industries. The concentration is measured in terms of the offshoring share represented by: (i) The offshoring activities of all firms engaged in offshoring within each industry. (ii) The total offshoring conducted by the five largest offshoring firms within each industry. (iii) The total offshoring conducted by the two largest firms within each industry and county.

Figure 3: Carbon offshoring and Firm Cleanups– Correlation



Note: This figure illustrates the correlation between carbon offshoring and firm-level emission intensity. For each firm, I calculate the growth rate of emissions The Apparent downward sloping curve suggest that carbon offshoring is related to lower firm emission intensities.

I show the correlation between carbon content of intermediate import and emission per sales (all in logs). I relate the the initial trade carbon import to changes in CO2 emissions. Figure 3 depicts a clear negative correlation between carbon import and CO2 emission intensity with a firm. The subsequent session, detail how I isolate the carbon offshoring effect on the manufacturing firm cleanups.

4 Empirical Strategy

Extensive Margin and Between Effect. begin with preliminary empirical patterns of the difference in emission intensity between carbon offshoring firms and non-offshoring firms. Hypotheses concerning the effects of offshoring are challenging to empirically test. Conducting an experiment where we observe a firm both as an offshoring and a non-offshoring entity at different points in time is practically unfeasible. Consequently, I create a control group consisting of firms that did not engage in offshoring using propensity score matching. This control group closely resembles the sample of offshoring firms, except for the fact that the firms in this group did not relocate their production activities abroad during the period 2007-2014. Subsequently, I estimate the following regression

$$\ln(EI_{it}) = \alpha_1 off_{it} + \theta_i + \theta_{kt} + \epsilon_{it} \tag{4}$$

Where $\ln(EI)$ is the logarithmic transformation of the emission per output (and SEK value of output) of firm i at time t. The primary variable of interest off denotes offshoring firms.[20] II first match all firms that engage in offshoring to those that do not using propensity score matching.[21] Thus, insofar as the two firms A and B have the same propensity score, but one offshore and the other does not, and the conditional independence assumption credibly holds, then differences between their observed emissions are attributable to offshoring. The matching needs to satisfy the common support assumption, which requires the existence of both offshoring and non-offshoring firms across the estimated propensity score.

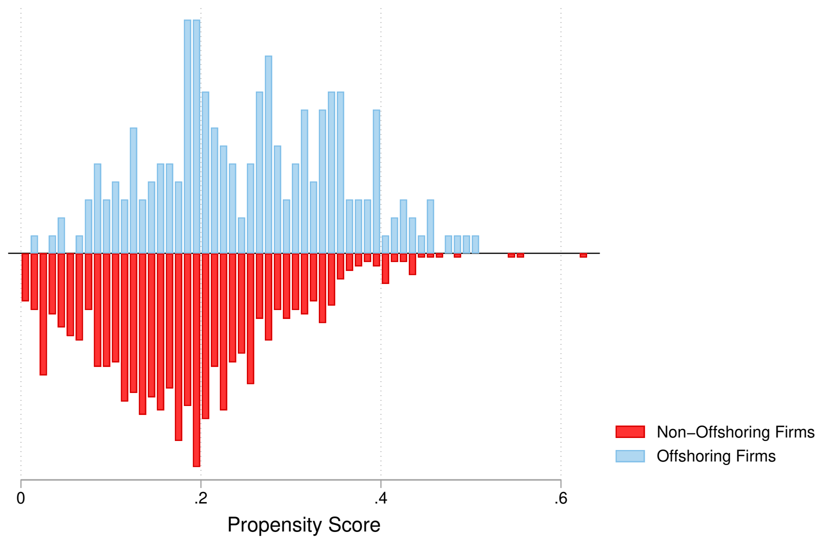
I show the the common support test after matching offshoring and non-offshoring firms in Figure 4. The result is reassuring that the matched firms undergo comparable regulatory environments, and

[20] Offshoring firms are firms that reduce their production of (dirty) input/own-products but at the same time increase the import of such products. Thus, they could appear at different year (t) in my sample. However, I drop firms who changes offshoring status, once they are initially identified as offshoring firm

[21] The assumption is that if, conditional on observable covariates (firm revenue, fixed assets, number of employees, machine investment, productivity, and capital intensities, two firms have the same probability of offshoring, then they have similar propensity scores, and all remaining variation in offshoring is due to chance

are comparable in terms of economic conditions (such as demand conditions and input prices). To ensure higher level of similarity, I use a caliper of 0.85.[22] This means, I sacrificed a larger sample size for a more focused comparison to draw causal estimates of the impact of offshoring. In other demanding specifications, I include both firm fixed effects (θ_i)and industry-year fixed effects (θ_{kt}) to control for broad changes in demand of different sectors.

Figure 4: Propensity Score Distribution



Note: The figure shows the common support test after matching offshoring and non-offshoring firms

Intensive Margin and Within-Firm Adjustment. Next, I turn my attention to how firm adjust their production processes with an increase in carbon imports. In particular, I estimate the effect of firms quantities of import of carbon-intensive intermediate goods on emission intensity using my primary sample (all active importing firms). I specify the main regression equation as a contemporaneous association between offshoring and emission intensity.

$$\ln(EI_{it}) = \alpha_1 CarbImp_{it} + Z_{it}\beta + \theta_i + \theta_{kt} + \theta_{mt} + \epsilon_{it} \tag{5}$$

Where $\ln(EI) \in$ {global pollutants, local pollutants} is the logarithmic transformation of the emission intensity of firm i at time t. The primary variable of interest $CarbImp$ is the emission content of import of intermediate input – reflecting (dirty) input reallocation.[23] I estimate the model

[22]However, some offshoring companies are excluded from the matched sample because no closely resembling firms can be found.

[23]Import quantities are expressed in logs for easy interpretation (elasticities) and makes the results more robust to extreme values.

pollutant-by-pollutant in order to explore the relationship between offshoring activities and emission intensity among firms emitting the same pollutant and within the same industry – as captured by the parameter of interest α_1.

Endogeneity Concerns. There are several confounding factors to account for in this regression model. Two major potential candidates are domestic environmental policy shocks that affect environmental performance and productivity shocks. Firms may be reducing pollution in Sweden due to stricter environmental regulations. Additionally, there are clear indications that, when disaggregated by firm type, firms that have access to foreign markets experience technological improvements and enhanced productivity (Batrakova and Davies, 2012; Forslid et al., 2018; Holladay, 2016; Melitz, 2003; Rodrigue et al., 2020) and thus, these shocks may lead to changes in the energy efficiency of firms. If offshoring requires the payment of fixed costs, then large productive plants are more likely to offshore dirty intermediate inputs. These domestic supply shocks can impact both emission intensity through the adoption of energy-saving technologies. As argued by Dussaux et al. (2023), in theory, adopting energy-saving technologies is an alternative strategy to offshoring dirty tasks, so firms that adopt these technologies should have both lower emission intensity and lower imported emissions. If the coefficient of carbon offshoring, α_1, is negative, we expect the bias to be toward zero, which will be amplified by the standard attenuation bias due to measurement error in imported emissions.[24] Overall, I expect the OLS estimate of α_1 to suggest that the carbon offshoring effect does not exist.

Shift-Share Instruments. To tease out the causal effect of offshoring on emissions, I employ an instrumental variable strategy. In the same spirit as Hummels et al. (2014), I exploit shocks to the Swedish trading environment that change over time and are specific to each trading partner $\times$ the type of product being traded. I use worldwide shocks in import demand for intermediate inputs from countries with laxer environmental policies, which exhibit rich variations across countries and products. In particular, I construct a novel, firm-specific instrument based on the desirability of importing from countries with laxer environmental policies by exploiting changes in these countries' comparative advantage. The idea is that any supply-based policies by this group of countries will lead to significant shifts in the composition of their exports, allowing for a strong first stage in predicting changes in intermediate imports. Also, an increase in the export share by "laxer" countries to the rest of the world (ROW), excluding Sweden, signals an increasing comparative advantage. Since firms may have different inputs coming from different countries, the impact of these shocks may vary across firms. Assuming stability in offshoring patterns over time, I am able to construct the instrument using pre-sample information about firms' purchases of inputs. This eliminates any contemporaneous shocks due to technology that can affect both the types of

[24]Note that carbon offshoring activities may be measured with some degree of error since I do not have a precise proxy for the toxic content of imports at the product level from source countries. These measurement errors can lead to attenuation bias in the point estimates

products used and firm-level emissions.

For expositional purposes, I start by calculating the world export supply of each product j net of the supply to Sweden and neighboring countries (Denmark, Norway, Finland, and Germany).[25] That is,

$$Shock_{it} = \underbrace{\sum_{p \in i} \bar{E}_{jc,t<t_0} \bar{M}_{ip,t<t_0}}_{\substack{\text{product-year} \\ \text{variation}}} \times \underbrace{WX_{pct}}_{\substack{\text{destination} \\ \text{variation}}} \tag{6}$$

where WX_{pct} is world export of product p by country c in year t. This is the shift component containing export shocks to all countries except Sweden and countries close to Sweden (Denmark, Norway, Finland, Germany). I then multiply the world export supply of p by the pre-sample share of product p in total imports by the importing firm i ($\bar{M}_{ip,t<t_0}$). I use pre-sample shares to make sure that the input use of the importing firm is not driven by current technology shocks. Variation in world export supply of j should be positively correlated with the imports of Swedish firms, as it reflects changes in the relative price and quality of the supplied good in the exporting countries. Subsequently, for the IV approach, I further re-weight the pre-sample shares of the imports by pre-sample emission $\bar{E}_{jc,t<t_0}$ to account for the toxic content of imports. When turning my attention to the role of environmental policy arbitrage, I restrict the export shock to only those coming from countries with laxer environmental policies relative to ROW. That is;

$$Shock^{Lax}_{it} = \sum_{p \in i} \bar{E}_{jc,t<t_0} \bar{M}_{ip,t<t_0} \times \underbrace{\frac{\text{Exports}^{Lax}_{pt}}{\text{Exports}^{World}_{pt}}}_{\text{Lax comparative advantage}} \tag{7}$$

The major question of validity is whether the instrument is relevant, the exclusion restriction holds and any errors in offshoring activities are independent.[26] The instrument assumes that changes in the export supply of intermediate inputs and produced-goods in other countries, is a good predictor of firm's offshoring activities in destination countries. For instance, an increase in the export supply of input p from country c could signify a change in the cost or quality of that input. In either case, firms that utilize input p from country c will benefit from this change and may respond by increasing

[25] I exclude these countries to mitigate the possibility of picking up local or regional demand shocks instead of supply shocks. Note that I use both a firm-product-time export with the help of bilateral trade flows at the product level from the COMTRADE database defined at the 6-digit level of the Harmonized System (HS)

[26] If errors are independent, then I expect that the IVs will eliminate attenuation bias due to measurement error. If not, then the IV estimates may be biased towards the OLS.

their imports of that input. However, firms that do not use input p should not be impacted by this change in cost or quality. In Table 2, I formally test whether the instrument is a good predictor of imports. As would be expected, imports of inputs with the export shock and initial mix of imports (i.e. the share component of the instrument). The strength of the instrument is consistent with two well known facts of the Sweden Custom data; that the set of imported product is very stable over time and there is little overlapping of product-specific shocks across firms (see Akerman et al. 2021).

Table 2: First Stage Regression

	Input Import				PG Import			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input export shock	0.421***	0.378***	0.364***	0.387***				
	(0.025)	(0.018)	(0.013)	(0.032)				
PG export shock					0.455***	0.429***	0.421***	0.428***
					(0.004)	(0.008)	(0.001)	(0.002)
F-stats	79.89	191.21	72.626	172.95	52.301	179.89	72.626	179.95
Control	×	√	√	√	×	√	√	√
Year Fixed Effect	×	×	√	×	×	×	√	×
Firm Fixed Effect	×	×	√	√	×	×	√	√
Industry-year Effect	×	×	×	√	×	×	×	√

Note: PG Import is import of energy content of similar goods produced by a particular firm. Export shocks are quantities of export shocks to all countries except Sweden and countries close to Sweden (Denmark, Norway, Finland, Germany. The instruments uses pre-sample share of product to make sure that the input use of the importing firm is not driven by current technology shocks. I also include firm fixed effect year fixed effect. Controls include machine investment and capital intensity of firms. Standard errors clustered at firm level in parentheses. *,**,***denotes significant at the 10% , 5% and 1% level respectively.

The exclusion restriction requires that the components of export shocks are independent of shocks in the Swedish economy, as well as on forward-looking behaviour of firms. A potential threat to the validity of the instrument is that the world's export supply of product j and firm i's environmental performance may be influenced by a worldwide shock (e.g. through changes in demand, transport costs, or technology) facing all manufacturers of product j. Using pre-sample shares in building the instrument mitigates but not fully solves this concern. I address this issue in two different ways. My benchmark solution is to include firm, industry-year and municipal-year fixed effect. As the import shares are fixed in a pre-sample year and add up to one for each firm, incorporating fixed effects for both the firm and the year suggests that it is satisfactory to presume that variations in the global export supply, particular to each country-input, are practically randomly allocated to Swedish firms Borusyak et al. (2022). My second approach is to condition offshoring on a number of factors including an energy prices domestic (a proxy for domestic environmental policy).[27] I show

[27] I adopt a similar shift-share-style instrument for the energy prices of firms. This approach involves using the initial share of different types of fuel (e.g. electricity, gas, oil) in a firm's energy mix and the median price of these fuels in the industry in which the firm operates, as a means of measuring the impact of energy price changes on the firm (see recent discussion by Dussaux et al. (2020), Marin and Vona (2021) Sato et al.

that offshoring and energy price are quite independent in explaining variation in firm emission.[28] Lastly, in some specifications I account for the possibility of this pre-trends by including lagged information about firms' productivity, capital-labour ratio (proxy for capital intensity) and machine investment (Z_{it}).

5 Results

Between Effect. What is the relationship between offshoring (at the extensive margin) and emissions observed during the sample period? Figure 5 reveals a preliminary pattern suggesting that firms engaging in offshoring activities tend to have lower levels of CO_2 emissions and LED per unit of sales compared to firms that do not participate in offshoring. However, it is worth noting that when I measure emission intensity by calculating emissions per unit of output, the relationship remains negative but lacks statistical significance. One of the primary reasons for the insignificant estimates in the emissions per output analysis is the need to ensure consistent units of measurement across different products and over time (see also Barrows and Ollivier (2021)). This requirement, although necessary for robust analysis, reduces the statistical power of the results. In addition, note that in my matching approach, I sacrificed a larger sample size for a more focused comparison to draw relationship between offshoring firms and emission intensity, thus exacerbating the issue of low statistical power. Despite this limitation, both measures of emission intensity indicate tangible emission savings resulting from offshoring activities.

Within-Firm Adjustment. I now present the main results – the intensive margin of carbon offshoring activities on emissions in Table 3. First of all, notice that the coefficients for both OLS and IV estimates are negative, suggesting that firms environmental performance improves with an increase in carbon offshoring activities. This is in line with the preliminary evidence above. The results hold true after including firm-fixed effect, industry-year and municipal-year fixed effect to purge the residual from all time-invariant factors and aggregate shocks affecting emission intensity.[29]

(2019) and Goldsmith-Pinkham et al. (2020)). Specifically:

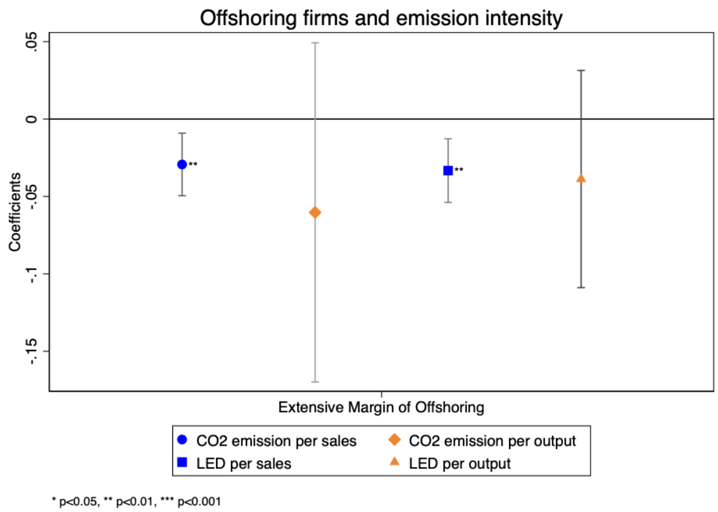
$$EP_{it}^{IV} = \sum_{j=1}^{n} \omega_{i,t=t_0}^{j} p_{st}^{j}.$$

For each firm, industry price variations are constructed net of firm prices and thus are uncorrelated with firm-specific shocks. The idea is that a sharp rise in prices of energy will lead to a sharp rise in production cost and impact firms emissions. Again, by using pre-sample weights ($\omega_{i,t=t_0}^{j}$), I block the energy-mix before the entry of firms in the estimation sample and hence help to mitigate concerns about reverse causality and simultaneity biases due to adoption of technologies.

[28]In tandem with the literature, the energy price in the model reflects the role of inducement effect of climate policies on emission intensity relative to the role of offshoring (Dussaux et al., 2020)

[29]The results are also robust to the inclusion of firm-specific covariates such as past firm productivity and machine investment and capital intensity. All control variables were consistent to theoretical expectation.

Figure 5: Offshoring Firms and Emissions



Note: The figure illustrates the estimated coefficients obtained from regressing the offshoring dummy variable against CO2 emission intensity and LED emission intensity. Offshoring firms are firms that increase in the import of pollution-intensive inputs while simultaneously decreasing the production of such inputs. The emission intensity is computed by dividing emissions by the value of sales (represented by blue points) and by physical units of outputs (represented by orange points). All regressions incorporate firm fixed effects and industry-year fixed effects to account for potential confounding factors.

Table 3: Carbon Offshoring and Firms Environmental Performance

	CO_2 emission intensity				LED intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Carbon Import	-0.297***	-0.614**	-0.518**	-0.533***	-0.290***	-0.629***	-0.529**	-0.576***
	(0.037)	(0.259)	(0.262)	(0.188)	(0.032)	(0.217)	(0.225)	(0.191)
Energy Price				-0.429***				-0.442***
				(0.027)				(0.027)
Control	√	×	√	×	√	×	√	×
Firm FE	√	√	√	√	√	√	√	√
Sector-Year FE	√	√	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√	√	√
Estimation	**OLS**	**IV**	**IV**	**IV**	**OLS**	**IV**	**IV**	**IV**
KP		137.09	91.39	92.04		137.21	92.67	93.34

Note: The table presents a series of regression coefficients for different specification of equation 5. Emission intensity is log of emission per sale. All specifications include firm, industry-year and municipal-year fixed effects and lagged (up to three lags) information of firms' productivity, machine investment and capital intensity of firms. Standard errors clustered at firm level in parentheses. First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics. *,**,*** denotes significant at the 10% , 5% and 1% level respectively.

However, I find a stark contrast between the estimated coefficients using OLS and IV. After properly instrumenting for carbon imports, I find that the effect of carbon offshoring activities on emissions tends to be larger compared to the OLS estimates. Though the IV computes the average effect of all compliers or firms who decide to offshore as a result of the low cost of offshoring[30], the difference in coefficients suggests that OLS is downward-biased. Following the discussion in section 4, I interpret this bias as the result of unobservable technological choices correlated with both emission intensity and offshoring. Overall, I estimate that emission intensity falls by about 5-6% with a 10% increase in carbon offshoring. The finding that carbon offshoring leads to reduction in CO_2 emission intensity is in line with the findings by Li and Zhou (2017) and Dussaux et al. (2023) who use data on the US and French manufacturing industry respectively.

In Columns 4 and 8 of Table 3, I include energy prices to capture role of inducement effect via domestic environmental policy (see Dussaux et al. (2020); Levinson (2010); Shapiro and Walker (2018)). The results show that for a given firm, in a year where carbon content of input import are 1% higher than it typically is for that firm, then we would expect CO_2 emission and LED intensity to fall by 0.53% and 0.56% respectively. However, inducement effect via energy prices will lead to about 0.43% and 0.44% reduction in CO_2 emission and LED intensity. These findings suggest two key implications. First, offshoring has a greater impact on local pollutants compared to global pollutants – thus carbon leakage will be high for local emission. Second, energy prices play a comparable role in the reduction in emission intensity. This result is perhaps unsurprising. Energy price is a direct cost to energy consumption. The higher the energy cost, the more difficult it is for firms to increase their energy demand, hence leading to a reduction in fuel-based emissions. What is interesting is that, the carbon import coefficients does not change significantly with the inclusion of energy price, suggesting an independent effect of offshoring and energy price on emissions. In contrast to the findings of Dussaux et al. (2023), who reported that energy prices have a more substantial impact compared to the carbon offshoring effect, I find that the effects are comparable.

To reduce clutter, I do not present results for the control variables.I find that more productive firms are generally cleaner (emits less pollution intensity). This is because more productive firms require fewer inputs to produce a given output (Copeland et al., 2022) and hence the amount of fossil fuel needed is less. This result echoes the findings in the productivity and emissions literature (Bernard et al., 2007; Bustos, 2011; Cui et al., 2016, 2012; Forslid et al., 2018; Holladay, 2016; Rodrigue et al., 2020; Tybout, 2001). In sync with theoretical intuition, I also find that machine investment reduces emission per sale while capital intensity makes firms dirtier. This finding is very stable across all specifications and hence, to save space, I will not show these results again. In examining column 2 and 3, I find that without these controls, the estimates of offshoring effect will be slightly larger, suggesting upward bias.

[30] The IV estimates capture what is termed the local average treatment effect (LATE) and do not capture a global effect (Angrist and Pischke, 2008).

5.1 Robustness

In this subsection, I provide several robustness checks for the main findings. First, I assess the presence of pre-trends and test the stability of selection bias before and after the export shock occurred. Next, I explore alternative definitions of offshoring to investigate their potential impact on firms. I then address the possibility of conflating offshoring with import competition and examine how carbon offshoring can lead to distinct implications for fuel-based emissions, emissions from production processes, and emissions from transportation.

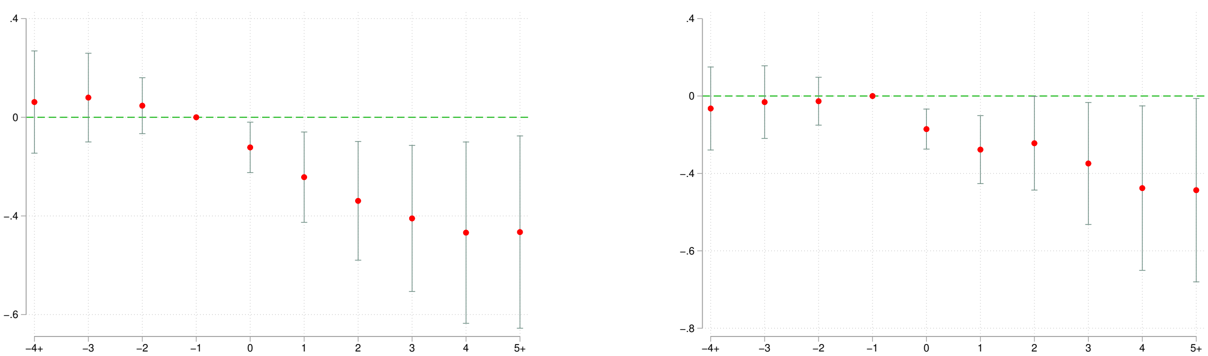
Pre-Existing Trends and Dynamic Treatment Effects. Given the quasi-random assignment of shocks, the primary concern regarding identification is the possibility of unobservable firm characteristics influencing the trend of firm-level outcomes and being correlated with the shocks. For instance, firms with more robust market research departments may be better equipped to identify and capitalize on growing foreign markets with laxer environmental policies, leading to independent reasons for their accelerated growth in dirty imports. Also, large multinational firms could also influence exporting policies of emerging markets which could mechanically correlate with positive foreign supply shocks. If omitted variables are linking expanding firms to growing foreign markets, we would expect to observe distinct trends among firms that are projected to experience larger dirty imports in the future, even prior to the the shocks. To overcome this empirical issue, I employ a standard difference-in-differences using current-year-weighted foreign supply shocks as instrumental variables, while controlling for arbitrary industry-by-year trends. Additionally, I instrument these shocks with base-year-weighted shocks and inspect how the pre-trends changes prior and after the export shocks. In particular, I run the following regression:

$$EI_{it} = \alpha_i + \gamma_{st} + \sum_{m=-G}^{M} \beta_m CarbImp_{i,t-m} + Z'_{it}\psi + \varepsilon_{it} \tag{8}$$

Where the outcome variable EI_{it} represents the firm-level emission intensity. I instrument each $CarbImp_{i,t-m}$ using $Shock_{i,t-m}$. I normalize $\beta_{-1} = 0$ so β_m is in normalized differences. To account for industry-specific trends like labor regulations, income shocks, and general technological progress, I include an industry indicator interacted with year interval fixed effects α_{st}. I also include, firm-fixed effect to obtain within-firm responses devoid of unobserved firm-heterogeneity. This specification has the advantage of assessing the pre-trends and estimating cumulative long-run impact of carbon offshoring on emissions.

I present the results in Figure 6. In both Panel A and B, the results show a significant and immediate response in emission intensity to export shocks, as well as a delayed response. In Panel A, the estimated effects indicate that a 1% increase in export shocks related to dirty inputs leads to a decline of approximately 0.15% in emission intensity in period 0, 0.22% in period 1, and a substantial decline of 0.43% in period 5. All of these effects are statistically significant at a 5% level. Regarding the impact of offshoring on LED intensity (Panel B), the findings indicate that dirty imports have a consistent short-term and long-term impact. Both Panels show that the influence of future shocks (β_m = -1 ... -4) on current emissions is negligible and statistically indistinguishable from zero. This result contradicts the existence of divergent pre-trends, thereby reinforcing the credibility of the specification's identification assumption.

Figure 6: **Dynamic Effect:** Carbon offshoring and Firms' Environmental Performance



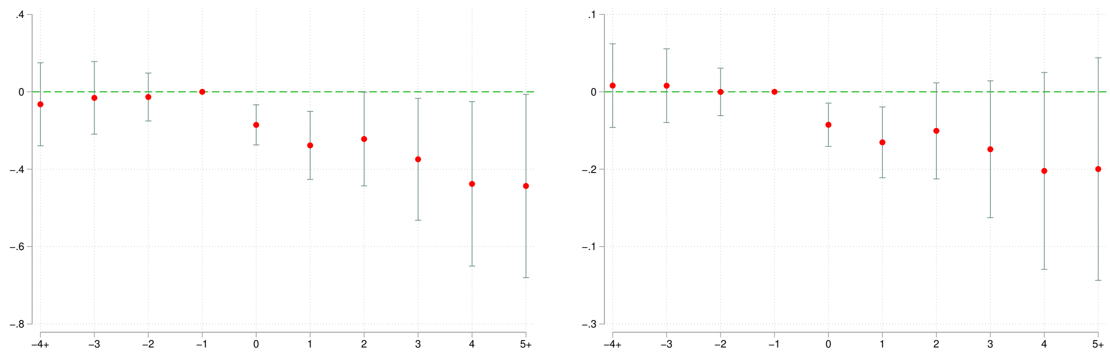
A. Carbon Import and CO_2 intensity B. Carbon Import and LED intensity

Note: Estimates of coefficients β_m for $m = -4, \ldots, 5$ from equation 8 are reported graphically. I normalize $\beta_{-1} = 0$ so β_m is in normalized differences. Panel A. reports these coefficients for Input Import and CO_2 emissions intensity, and panel C. for Input Import and LED intensity. The x-axis represent the value of m, the dots the point estimates of β_m, the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous carbon offshoring are instrumented by export supply shocks weighted by pre-sample shares of imports and energy mix. Standard errors are clustered at firm-level. Kleibergen-Paap rk LM statistics range from 50.25 to 74.34.

Own-Produced Goods. Theoretical works on offshoring predict that offshored tasks may cease to be performed domestically and offshoring is predominantly correlated with the import of domestically produced goods rather than import of inputs (see Bernard et al. 2020). Thus, taking advantage of the production data and BEC codes provided by Statistics Sweden, I track all products that used to be produced in-house by firms but are substituted for foreign products over time. That is if the BEC of the primary product of production at firm-level and industry-level is rather imported by firms, I refer to this as `own good substitution`. Figure B.4 suggests the reallocation of intermediate inputs and substitution of firms' own-produced goods are descriptively evident among Swedish manufacturing firms though the import of inputs tends to dominate.

The point estimates for carbon offshoring through firm imports of own-produced goods consistently show a similar impact on CO_2 intensity but are relatively smaller concerning LED intensity. In contrast to the import of toxic inputs, the import of own-produced goods only exerts a short-term effect. It is evident from the findings that while there is a significant reduction in emissions in the short run, the effect becomes noisier after the third year (Panel B of Figure 7). This result suggests that firms engaging in importing similar goods they produce do not offshore much of local pollution abroad. Perhaps this is not entirely surprising; there may be little room for dirty firms to alter their technology related to the production of pollution-intensive inputs compared to innovating (own-produced goods) in the context of semi-finished goods. Consequently, firms are more likely to achieve greater environmental benefits through the reallocation of dirty inputs rather than importing their own-produced goods.

Figure 7: **Dynamic Effect:** In-house offshoring and Firms' Environmental Performance



A. In-house offshoring and CO_2 intensity B. In-house offshoring and LED intensity

Note: Estimates of coefficients β_m for $m = -4, \ldots, 5$ from equation 8 are reported graphically. I normalize $\beta_{-1} = 0$ so β_m is in normalized differences. Panel A. reports these coefficients for Own Produced Goods Import and CO_2 emissions intensity, and B. Own Produced Goods and LED intensity. The x-axis represent the value of m, the dots the point estimates of β_m, the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous carbon offshoring are instrumented by export supply shocks weighted by pre-sample shares of imports and energy mix. Standard errors are clustered at firm-level. Kleibergen-Paap rk LM statistics range from 50.25 to 74.34.

Import Competition. An important caveat when interpreting the results is that there could have been a massive shift in imports of final and consumer goods from emerging economies that occurred over the same time span, automatically generating pollution offshoring (Linaa et al., 2023; Akerman et al., 2021; Dussaux et al., 2023). For example, including all imports may not capture the idea of offshoring because it considers a broad range of products that local firms would not consider producing themselves. Due to the symbiotic relationship between imports of final goods and emissions, the results here may, therefore, capture the combined effects of offshoring and import competition on emissions through various channels. To test whether import competition may be driving these effects, I replace emissions embedded in imports with the quantities of all types of imports (excluding inputs) in Table **??**, Panel A. I also run the same regression, but this time using only the quantities and values of imports (without adjusting for carbon content) in Table C.1, Panel B and C, respectively. In line with Akerman et al. (2021), I find that the import of intermediate goods leads to a reduction in emission intensity for Swedish manufacturing firms. Overall, the results suggest that importing may conflate with carbon offshoring motives, albeit with a smaller effect. Distinguishing between these factors will require another source of variation related to the comparative advantage in pollution-intensive production in the source countries. I elaborate on this in detail in section 6.

Narrow Offshoring. I also differentiate between imports that are more likely to replace in-house production and those that are less likely to do so. I consider a narrow definition of offshoring as defined by Feenstra and Hanson (1999), which allows us to use imports of products belonging to the same industry to capture the possibility of firms switching domestic production of these goods to international offshoring. By focusing on the specific production activities in certain sectors that are being offshored, I am able to better understand the contribution of offshoring to overall emissions and contextualize different measures of offshoring on emissions. To this end, I use imports of products (excluding raw materials and finished machines) from firms belonging to the same 3-digit manufacturing industry. The results in Table C.2 show that limiting the analysis to import flows within the same industry leads to a smaller and less statistically significant point estimate. However, I find that the estimate of emissions intensity is always negative and significant across different specifications, which provides reassuring evidence that offshoring results in lower firm emissions intensity.

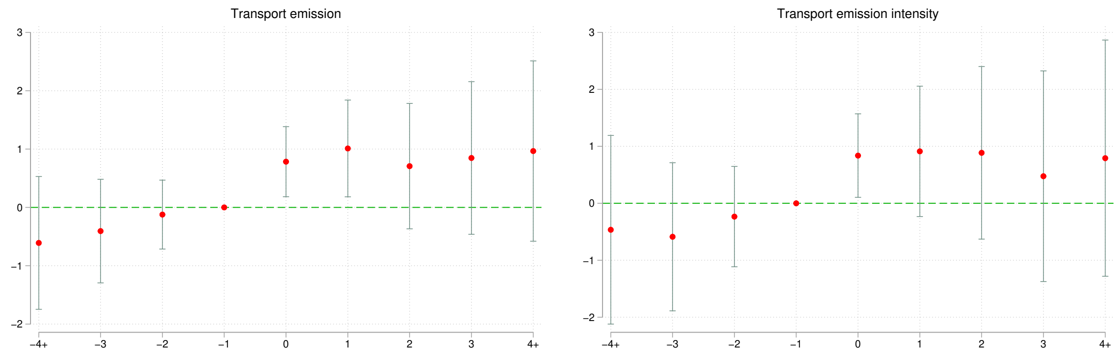
Overall, the results suggest that carbon offshoring has a significant effect on the environmental performance of firms. Firms exposed to trade respond to foreign supply shocks by adjusting production decisions that subsequently lead to lower emissions intensity. This aligns with the notion that trade can yield environmental benefits as it tends to weed out less productive and more polluting firms (Forslid et al., 2018; Akerman et al., 2021). Notably, the analysis in section 8 highlights the pivotal role of productivity as a mechanism driving the influence of carbon offshoring on emissions

5.2 Carbon offshoring and Transport Emissions

Until relatively recently, the literature on trade and the environment had predominantly focused on emissions stemming from production. Pollution originating from transportation received little attention (Copeland et al., 2022). This emphasis is somewhat surprising, given that policymakers also care about the environmental damage caused by trade-related transport. In what follows, I analyze firms' demand for fuel for transportation purposes and calculate the emissions released into the atmosphere that are solely related to transportation. I then test the effect of carbon offshoring on transport emissions.

Overall, I find that transport emissions increased as a result of increased demand for energy-intensive inputs; however, the estimates are very small and mostly insignificantly different from zero in the long run (see Figure 8). Though it appears that the long-run effect of offshoring on transport emissions is minimal, I find that it changes the emission profile of firms as well as the classification of clean and dirty goods. In line with Cristea et al. (2013), who found that emissions from transport can account for as much as one-third of the total emissions associated with producing and transporting goods, I rationalize the results by the complex and uncertain

Figure 8: **Dynamic Effect:** Carbon offshoring and Transport Emissions



C. Transport emissions B. Transport emission intensity

Note: Estimates of coefficients β_m for $m = -4, \ldots, 4$ from equation 8 are reported graphically. I normalize $\beta_{-1} = 0$ so β_m is in normalized differences- . Panel A. reports these coefficients for carbon import and Transport CO_2 emissions , and B. carbon import and Transport CO_2 emissions intensity. The x-axis represent the value of m, the dots the point estimates of β_m, the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous carbon offshoring are instrumented by export supply shocks weighted by pre-sample shares of imports and energy mix. Standard errors are clustered at firm-level.

relationship between production and transportation. For example, clean production of goods such as textiles and leather can be very dirty in transportation (e.g., air transport). In contrast, the production of natural resource commodities, which tends to be very energy-intensive (dirty), can have a transportation mode that is exclusively very fuel-efficient (e.g., maritime). Depending on the type of goods firms import, the transportation mode may be environmentally unfriendly in the short run but become relatively fuel-efficient in the long run.

6 Role of Environmental Policy Arbitrage

A second contributing aspect of this paper is to demonstrate that differences in environmental policies can provide a potential source of comparative advantage in pollution-intensive production and, consequently, pollution offshoring. In a simple Heckscher-Ohlin model, relatively more stringent environmental policies in a capital-abundant country can potentially increase imports (reduce net exports) from countries with laxer regulations. Thus, changes in emissions can occur because firms shift their dirtiest production to parts of the world with weaker environmental standards. Since environmental policy arbitrage may well be tied to the type of imports and the pollution intensity of production, it is important to account for such differences in policies between Sweden and the country of origin of imports. For example, firms in Sweden will have easier access to carbon-intensive inputs in India because such inputs are less expensive in such an environmentally lax country.

To examine whether firms respond differently depending on the environmental policy stringency of the origin of imports, I use Environmental Policy Stringency (EPS) Index data from the OECD to define a laxity variable for country groups with lower EPS relative to Sweden. Given Sweden's high environmental standards, approximately 70% of the countries in the sample fall into the lax category. Therefore, I further rank countries into four different categories of laxity to ensure richness in variation.[31].

I approach the analysis and interpretation of the role of environmental policy arbitrage through three distinct methods. Firstly, I examine the interaction between carbon offshoring and the variable representing policy laxity, comparing it to the effects of offshoring to low-income countries. I find a slight reduction in emissions when offshoring occurs in countries with relatively lenient environmental policies. However, a limitation arises as firms do not make rapid decisions to switch their imports from one country to another, and it is challenging to easily detect the comparative advantages of these so-called 'laxer countries.

To address this issue, I construct two additional measures for carbon offshoring: one based on import shares from countries with more lenient environmental policies and the other adjusting for the fact that Sweden operates an open economy in Scandinavia, with a significant portion of goods entering Sweden subsequently re-exported to other nations. For each input import and own-produced (OPG) import, I construct a measure based on net imports by firms, encompassing those that are eventually re-exported. Let M_{ijt} represent the quantity of imports by firm i for product j at time t, and let $M_{jt} = \sum_{\text{Importers}} M_{ijt}$ be the total quantity of imports for product j at the 8-digit level. Let Q_{jt} denote the overall domestic quantity sold for product j.

For expositional purposes I start with import shares from laxer countries, given as :

$$IMP_{1jt}^{share} = \frac{M_{jt}^{Lax}}{Q_{jt} + M_{jt}}.$$

Continuing to work in quantity units, I define net imports at the firm level as $\text{Max}\left\{M_{ijt} - E_{ijt}, 0\right\}$ where E_{ijt} is the physical quantity of exports of good j from firm i at time t. This export-corrected import share measure is then given as:

$$IMP_{2jt}^{share} = \frac{\sum_{i \in \text{ Importers}} \text{Max}\left\{M_{ijt} - E_{ijt}, 0\right\}^{Lax}}{Q_{jt} + \sum_{i \in \text{ Importers}} \text{Max}\left\{M_{ijt} - E_{ijt}, 0\right\}}.$$

Table 4 and Table D.3 show the results for using IMP_{2jt}^{share} and IMP_{1jt}^{share} respectively. I estimate

[31]Please see Appendix D for the construction of the laxity variable and country ranks. The rank takes values from 0 to 3, where 0 represents countries with strict environmental policies, and 3 indicates the highest level of environmental policy laxity (or countries with extremely lax environmental policies)

Table 4: Share of Export-corrected Carbon Offshoring by Country Groups

	1	2	3	4	5	6	7	8
Dependent Variable:	CO_2 emission intensity				*LED* intensity			
EPS Lax/Income Group:	QL	VL	EL	LIC	QL	VL	EL	LIC
			Panel A: Dirty Input Reallocation					
Share of Input import$_{it}$	-0.105*	-0.092**	-0.477***	-0.156***	-0.190	-0.122*	-0.102	-0.249***
	(0.057)	(0.038)	(0.007)	(0.020)	(0.203)	(0.069)	(0.254)	(0.006)
Observations	8,393	7,132	7,650	15,914	8,393	7,132	7,650	15,914
KP	18.33	79.9	29.0	43.7	18.33	79.9	29.0	43.7
			Panel B: Dirty Own-produced goods					
Share of PG import$_{it}$	-0.090***	0.141	-0.124**	-0.347***	-0.095**	-0.110	-0.123**	-0.125***
	(0.003)	(0.101)	(0.051)	(0.003)	(0.010)	(0.099)	(0.059)	(0.003)
Observations	3,902	2,132	2,132	4,772	3,902	2,132	2,132	4,772
KP	16.9	27.3	9.01	23.7	16.9	27.3	9.01	23.7
Controls	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√
Industry-Year FE	√	√	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√	√	√

Note: Offshoring is measured as the export-corrected import share of import input and firm own-produced goods coming from countries with laxer environmental policies (and low income countries) respectively. All specifications includes inputs imports and PG imports. *,**,*** denotes significant at the 10% , 5% and 1% level respectively.

that a 10% increase in the share of net imports from countries with laxer environmental policies reduces emissions by about 0.5%. However, emission intensity reduction is strikingly large with an increase in net imports from low-income countries, with an estimated reduction of about 20% to 30%, suggesting that offshoring to LICs is a potent source of reduction in manufacturing CO_2 emissions. The result is robust with the import of own-produced goods though the estimated coefficient is relatively smaller. [32] A plausible interpretation for the significance and difference in estimated magnitude is that low-income countries present themselves as countries with high environmental policy arbitrage. That is the environmental policy stringency gap between Sweden and low income countries is wide enough to offer opportunities for pollution offshoring as compared to countries in the OECD (see Figure D.4). Also, according to the International Energy Agency (2015), low-income countries have low-cost energy inputs, and as such may offer an attractive destination for "dirty" firms leading to pollution offshoring. Import from EPS lax countries such as Belgium, Greece, Portugal and China etc., may be due to other factors such as low trade cost,

[32]Comparatively, offshoring measured by firm own-produced goods results in a relatively smaller reduction in emissions relative to the import of inputs. I rationalise the findings to be an indication that inputs are dirtier compared to the import of own-produced products – which may be at a cleaner level of production. Put differently, changing the technology of production of dirty inputs is more difficult relative to innovating semi-finished goods with cleaner technology. Thus, reallocation of inputs will lead to higher positive environmental impact compared to the import of almost finished products

distance, and friendly business environment, other than environmental differences and energy input. As such the offshoring effect is relatively smaller, as firms may not necessarily be relocating their dirtiest part of production to these countries based on differences in environmental policies.

Similar to the analysis in section 5.1, I check whether the effect is not purely due to import competition from these country groups in Table D.4. While I find no significant effect for import competition from low-income countries, I find that the estimated coefficient of import penetration from laxer countries is still negative and significant but smaller in magnitude. This indicates that the carbon offshoring effect may not necessarily detect a pollution haven effect of countries with less stringent environmental policies but rather may reflect differences in labor costs and market conditions (Arlinghaus, 2015). On the other hand, since the import competition effect from low-income countries is not easily detectable, it suggests that toxic imports from low-income countries are a by-product of relocation to these countries to a large extent. Thus, firms may have pollution haven motives to offshore dirty processes to low-income countries compared to other factors such as market conditions, institutional quality, and the quality of the local workforce. The result that the carbon offshoring effect may not detect the pollution haven effect of countries with less stringent environmental policies is somewhat in line with Dussaux et al. (2023), but in contrast with the study's findings when considering the case of low-income countries.

Overall, the results in this section suggest that the environmental policy arbitrage between Sweden and foreign countries can drive offshoring and manufacturing clean-up. The carbon offshoring effect on emission intensity is higher when dirty imports originate from countries with laxer environmental policies. However, the effect is dampened when firms offshore from countries with relatively similar environmental policies, and energy prices become a larger contributory factor to emission intensity. This finding is in line with Shapiro and Walker (2018), who shows that the implicit pollution tax facing manufacturers accounts for most of the emission reductions compared to changes in trade and productivity (assuming no offshoring effect).

7 Allowing for Heterogeneity

Since differences in environmental performance across tables may reflect response heterogeneity across industry and firm type, I conduct additional analyses to examine potential heterogeneity across firms that may affect the relationship between imports from countries with weaker environmental regulations and domestic pollution.

Single Product vs Multi-product Firms. Firms that offer multiple products have the ability to modify their average emission intensity by adjusting their product mix. If each product within a firm generates a specific amount of CO2 emissions per unit of output, altering the mix of products can impact the firm's emission intensity without requiring any investments at the firm-product level. However, it is important to recognize that multi-product firms may possess inherent differences compared to single-product firms. Multi-product firms are often larger, more productive, and less likely to encounter liquidity constraints. To address this distinction, I define single-product firms as those that exclusively produce a single product throughout the entire analysis period. To examine potential variations in responses to foreign supply shocks between single-product and multi-product firms, I conduct separate analyses by running equations 5 for each sub-sample.

Table 5: Heterogenous Effect: Single-Product vs Multi-Product Firms

	Single-Product		Multi-Product	
	CO_2	LED	CO_2	LED
	Panel A: Dirty Input reallocation			
Carbon Import	-0.158	-0.061	-0.618**	-0.707**
	(0.595)	(0.494)	(0.286)	(0.276)
Observations	6,412	6,410	14,548	14,557
KP	13.81	13.62	35.78	35.45
	Panel B: Dirty own-produced goods substitution			
PG Import	-0.153	-0.059	-0.549**	-0.628**
	(0.571)	(0.477)	(0.266)	(0.257)
Observations	1,761	1,761	3,779	3,779
KP	11.72	11.42	37.40	37.09
Control	√	√	√	√
Firm FE	√	√	√	√
Sector-Year FE	√	√	√	√
Municipal-Year FE	√	√	√	√

Note: The table presents a series of regression coefficients for different specification of equation 5. Panel A shows estimates of the imported inputs while Panel B shows estimates for import of own produced goods. Emission intensity is emission per sale. All specifications include firm, industry-year and municipal-year fixed effects and lagged (up to three lags) information of machine investment and capital intensity of firms. Standard errors clustered at firm level in parentheses. First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics. *,**,***denotes significant at the 10% , 5% and 1% level respectively.

The results in Table 5 suggest that multi-product firms behave differently from single-product firms. While single-product response in emission intensity is negative, the coefficient is smaller whereas the multi-product firm response is negative and larger with 5% level of significance. This suggest that the results are driven by multi-product firms as they have relatively more room to change their product mix to favor low-energy intensive products compared to single-product firms.

Dirty vs Cleaner Industries. Dirty industries may respond differently to offshoring compared to cleaner industries. In fact, I observe that the top 5 largest offshoring sectors are in chemicals, basic metals, coke and refined petroleum, non-metallic minerals, and electrical equipment (see Figure E.1). This suggests that firms that tend to offshore are generally more energy-intensive. To examine the heterogeneity among sectors, I first classify industries into "dirty" (heavy emitters of each criteria pollution) and "clean" (industries with lower emissions compared to the average manufacturing emission). Due to industry heterogeneity in pollution intensity, I obtain the mean value by first normalizing the per unit pollution emission. Using 3-digit SIC codes, each industry is then ranked from high to low emitters based on the distance between their emission intensity and the mean

Table 6: Heterogeneity: Dirty sectors vs Clean sectors

	Dirty Industries		Cleaner Industries	
	CO_2 intensity	LED intensity	CO_2 intensity	LED intensity
Carbon Import	-0.384	-0.492**	-0.720*	-0.599*
	(0.277)	(0.241)	(0.374)	(0.327)
Control	√	√	√	√
Firm FE	√	√	√	√
Sector-Year FE	√	√	√	√
Municipal-Year FE	√	√	√	√
Observations	2,480	2,480	4,760	4,769
KP	67.11	67.11	48.92	48.87

Note: Controls include lagged (up to three lags) information of firms' productivity, machine investment and capital intensity of firms. Standard errors clustered at firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Next, I estimate equation 5 separately for each sub-sample of dirty industries and clean industries. I present the results in Table 6. The heterogeneity analysis demonstrates that both types of industries experience a significant reduction in emissions through carbon offshoring. However, the emissions reduction tends to be slightly larger in cleaner industries compared to dirty firms. Figure E.2 also suggests that these effects may be driven by specific sectors, such as basic and fabricated metals, computers and electrical, and coke, chemicals, and pharmacy. Overall, the results demonstrate that both clean and dirty industries benefit from pollution offshoring.

EU-ETS firms. The introduction of the European Union Emission Trading system has had a profound effect on carbon leakage risk. Introduced in 2005, the EU-ETS initiative employs a two-step approach to address concerns related to carbon leakage. The initial step involves the identification of sectors that may be susceptible to the risk of carbon leakage, necessitating the substitution of domestic mitigation measures. These sectors are often referred to as "carbon-intensive-trade-exposed" (CITE) sectors (Sato et al., 2015). The second phase involves the development of specific provisions or exceptions implemented to address concerns related to carbon leakage. The approach followed in policies such as the EU-ETS is to allocate permits to CITE industries without cost.

Despite efforts to reduce carbon leakage risk, studies using computable general equilibrium modeling frameworks as well as empirical models have provided mixed evidence regarding the impact of the EU-ETS on carbon leakage (Reinaud, 2008; Sato et al., 2015). I contribute to the literature by examining the comparable effects of firms regulated under the EU-ETS and their unregulated counterparts. The results are presented in Table 7. I estimate that carbon imports by ETS-regulated firms have no significant effect on the firms' emission intensity compared to non-EU-ETS firms. Overall, the assessment of the EU-ETS suggests that trade flows and production patterns hardly change for EU-ETS firms, and there is insufficient evidence to conclude that firms regulated under the EU-ETS contribute to carbon leakage. These findings are in line with many previous studies (Verde, 2020; Naegele and Zaklan, 2019; Reinaud, 2008; Martin et al., 2014; Sato et al., 2015).

Table 7: Heterogeneity: EU-ETS Firms

	CO_2 emission intensity		LED intensity	
	(1)	(2)	(3)	(4)
Carbon Import	-0.633**	-0.550***	-0.649***	-0.594***
	(0.273)	(0.198)	(0.230)	(0.202)
Carbon import × ETS_{it}	0.342	0.307	0.352	0.323
	(0.321)	(0.254)	(0.302)	(0.278)
Energy Price		-0.442***		-0.205***
		(0.027)		(0.027)
Observations	16,544	16,498	16,548	16,502
KP	73.32	73.15	73.38	73.22
Control	√	√	√	√
Firm FE	√	√	√	√
Sector-Year FE	√	√	√	√
Municipal-Year FE	√	√	√	√

Note: Controls include lagged (up to three lags) information of firms' productivity, machine investment and capital intensity of firms. Standard errors clustered at firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Swedish multinationals

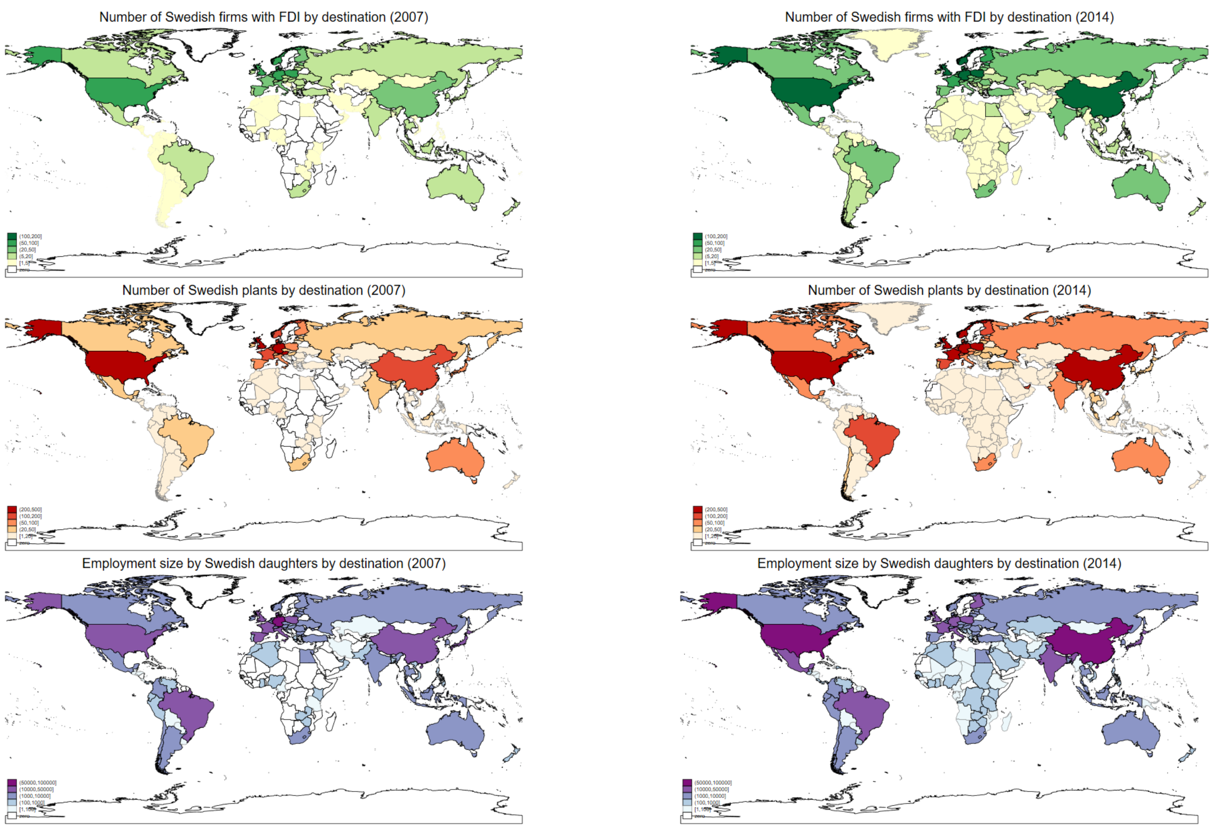
As a last exercise, I operationalize the idea that the migration of firms could occur and potentially lead to another source of pollution haven incentives for firms, particularly multinational corporations (MNCs), as they may over-allocate affiliates in foreign countries. Specifically, Swedish multinationals possess a unique advantage as they can simultaneously import emissions-intensive products while also relocating or outsourcing production to countries with lower emissions standards. This strategic combination enables them to reduce their overall emissions compared to domestic firms operating solely within Sweden. To proxy the decision of MNCs' over-allocation of affiliates in countries with lax environmental policies, I employ the employment size of the firm's affiliate in such countries, reflecting the concentration of Foreign Direct Investment (FDI) in those regions.[33] My working hypothesis is that strict domestic environmental regulations may lead to an

[33]It is crucial to acknowledge that directly observing the "direct" relocation of dirty firms is inherently challenging, and investigating the causation behind environmental regulations and direct relocation is beyond the scope of this paper. This exercise seeks to address a more straightforward question: whether the presence

increase in FDI activities in a laxer environment, all else being equal, especially for firms in "dirty industries" (Cole and Elliott, 2005; Esty and Porter, 2002; Antweiler et al., 2001).

I have access to information of number of swedish firms with FDI, number of plant by the affiliates, sales and employment. However, the percentage of missing observations or zero plants and sales are much higher than that for employment. I therefore choose to focus on employment by the affiliate as a measure of investment size in destination countries. Subsequently, I calculate FDI concentration in lax and low income countries (herein referred to as toxic FDI) is calculated as:

Figure 9: FDI Concentration by destination



Note: Figure 9 plots FDI concentration of Swedish mufacturing firms around the world. The top panel (in shades of green) plots the number of Swedish firms with FDI. The middle panel shows the number of plants of affiliates firms in destination countries, and the bottom panel, shows the employment size by Swedish daughters in destination countries. I show how each measure of concentration has changed in 2007 and 2014. Generally, the concentration of FDI seems to have increased over the years and mostly situated in China, Brazil, India, US and EU countries close to Sweden.

$$\text{Share of employment}^{\text{X}}{}_{it} = \frac{\sum \text{Affiliate employment size}_{it}^{X}}{\text{Global employment size}_{it}}$$

Where $X \in$ lax, low-income country, and Global employment is the sum of employment in the

of the migration of firms with high emissions has implications for emissions.

parent firm and employment abroad. Before delving into the main analysis, I present a descriptive graph in Figure B.5, illustrating that multinationals engaged in direct and indirect activities in countries with laxer environmental regulations tend to exhibit higher productivity levels compared to non-FDI firms. This observation suggests that the productivity threshold required for relocation is above the level of abatement firms, including both domestic and exporting firms. This finding is in line with theoretical insights from Cole et al. (2014), which highlight that outsourcing firms typically demonstrate higher productivity levels. Furthermore, the graph shows that firms with international affiliates generally display lower emission intensity compared to those without such affiliations. Notably, such firms concentrated in countries with more lenient environmental policies tend to exhibit cleaner emission profiles at home than those operating in countries with stricter environmental regulations. This indicates a potential relationship between the presence of multinational corporations in countries with lax environmental policies and improved emission performance domestically.

The results in columns 2 and 4 (Panel A of Table E.2) echo the descriptive evidence. I find that multinational offshoring activities through imports and FDI are complementary in reducing emissions. In column 2, the results show that the concentration of multinational investment in countries with lax environmental policies is associated with lower levels of CO_2 emission intensity after controlling for productivity, capital intensity, and machine investment. I find that a 10% increase in investment share in EPS lax countries leads to a 6.1% reduction in firms' CO_2 emission intensity. Again, the study finds a negative and significant impact of input imports on CO_2 emission intensity. Specifically, a 10% increase in the parent firm's share of input imports from lax countries reduces emissions by about 1.5%. The estimates, however, vary considerably when considering low-income countries. A 10% increase in the investment size of multinationals in low-income countries leads to a 49.6% reduction in CO_2 emission intensity, while about 44.4% to 46.8% reduction in emissions is attributed to the intensification of imports of intermediate inputs from low-income countries.[34]

Yet again, a plausible interpretation for the difference in estimated magnitude is that low-income countries present themselves as countries with high environmental policy arbitrage (see Figure

[34] I provide a robustness check of FDI concentration by using an alternative measure. I adopt a measure of FDI calculated as the share of FDI in lax countries, expressed as a ratio of total employment in lax countries to employment size in the parent firm. The results are presented in Table E.3. I find that though the estimates are relatively smaller, the general pattern of the main results still holds. In an ideal world, data on the production technique and plant size of these affiliates would be more beneficial for our understanding of toxic FDI in these countries. Notwithstanding this, proxying FDI with employment size reflects the size of affiliates in laxer countries over time, and these findings are very provocative and suggestive of the relocation effect of polluting multinationals. Also, in column 3 of Table E.3, I interact the toxic content of general imports with FDI status. The results reveal that CO_2 emissions reduced drastically among FDI firms compared to domestic firms. Overall, the results show that offshoring activities through the import of emissions and direct relocation to lax/low-income countries have a positive concomitant effect on environmental performance.

D.4). As such, setting aside productivity differences and energy prices, offshoring activities in these countries by multinationals provide a potent source of "environmental gain". Also, following the idea of Ederington et al. (2005) and Dussaux et al. (2020), since EPS lax countries are more similar to Sweden, trade within these countries is not primarily associated with asymmetric environmental regulations. For example according to Dussaux et al. (2020), trade between OECD countries is usually more suited to gain technological transfer and create incentives to climb up the learning curve than to save environmental costs (e.g. potential government fine, and abatement costs). Lastly, EPS also reflects some environmental improvements by lax countries over time and hence arbitrage may reduce over the period of study.

To summarise, the results shows that carbon offshoring leads to a reduction in emission intensity, especially when offshoring takes place in countries with less stringent environmental policies. Firms engaging in international outsourcing in these countries are able to tap into the arbitrage created by the differences in polices to reduce their domestic emissions. These findings are robust, even after adjusting linearly for, energy price, capital intensity, and machine investment.

8 Mechanisms at Work

What could be the potential mechanisms for the offshoring effect on firm emission intensity? The literature on trade and productivity argues that offshoring could lead to an exponential increase in firm productivity by providing them with inputs that are more suitable for their requirements or by enabling them to specialize in tasks where they possess a comparative advantage (Bernard et al., 2007; Bustos, 2011; Cui et al., 2016, 2012; Forslid et al., 2018; Holladay, 2016; Rodrigue et al., 2020; Tybout, 2001). An increase in firm productivity will result in fewer inputs needed to produce a given output (Copeland et al., 2022), and hence the amount of fossil fuel needed will be less. In Table 8, column 1, I find that offshoring increases firm productivity (TFP)[35] by about 3%. Therefore, productivity may provide a potential mechanism for the effect of offshoring on emissions.

Secondly, there is a possibility that as firms offshore, their costs decrease (because imported products are cheap), but sales and output increase. The increase in firm sales (denominator of emission intensity) could enable Swedish manufacturing firms to invest more in pollution abatement technologies, leading to a reduction in emission intensities. In columns 2 and 3 of Table 8, I find that both firm sales and costs are positively related to offshoring. However, the sales elasticity is higher than the cost elasticity, which underscores the potential impact of offshoring on firm profits.

I then proceed to test how carbon offshoring affects firms' abatement. To this end, I obtain

[35]Total Factor Productivity (TFP) is calculated using the method outlined by Wooldridge (2009)

Table 8: Carbon Offshoring and Firms' Environmental Performance - Mechanisms

	Productivity		Firm Sales		Firm Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Import	0.266*	0.264*	0.874***	0.877***	0.842***	0.844***
	(0.151)	(0.151)	(0.149)	(0.149)	(0.143)	(0.144)
Control	×	√	×	√	×	√
Firm FE	√	√	√	√	√	√
Sector-Year FE	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√
KP	135.07	134.61	134.73	134.27	134.73	134.27

Note: Standard errors clustered at firm-level are in parentheses.*,**,*** denotes significance at the 10% , 5% and 1% level respectively.

annual abatement data through an extensive survey by SCB, where firms report their abatement investments and expenditures (measured in tSEK) for various purposes, including clean air, water, waste, and research and development (R&D). Specifically, firms are asked to report any investments and expenditures they've made in machinery and equipment aimed at reducing emissions.[36] This abatement data comes from a semi-random sample of manufacturing firms, which includes all manufacturing firms with more than 250 employees, 50% of firms with 100-249 employees, and 20% of firms with 50-99 employees. Thus, I consider relatively large firms. In total, the survey covers approximately 700 manufacturing firms per year between 2006 and 2016.

Table 9 presents the main results for the effect of carbon offshoring on: (1) firm-level investment intensity in environmental protection and (2) firm-level current expenditure intensity for environmental protection, which includes all other costs of environmental protection that are not considered to be investment. First, notice that the OLS estimates (with no controls and fixed effects) in columns 1 and 4 show a positive relationship between carbon imports and both abatement investment and abatement expenditure. However, once I account for firm-fixed effects, industry-year fixed effects, and other firm-level controls, the estimates become becomes large in magnitude but statistically insignificant. However, using the IV I find that a 10% increase in carbon imports leads to about a 5.7% reduction in abatement investment. Also abatement investment falls by 3.5%

However, I note that, the statistical significance is not consistent for both total abatement investment and total abatement expenditure. Though I do not have a direct explanation for the contrasting statistical significance, it can be hypothesized that increasing carbon offshoring implies

[36]Abatement investments are typically long-term in nature and often require significant capital expenditures upfront. Examples of abatement investments include the installation of pollution control equipment in factories, the development of renewable energy projects, or the implementation of waste management systems. Abatement expenditure, on the other hand, refers to the actual costs or expenses incurred in carrying out abatement measures. It represents the financial outlays associated with implementing and maintaining environmental protection initiatives. Abatement expenditures can include a wide range of costs, such as operational expenses, maintenance costs, monitoring and compliance costs, research and development expenses, or fees paid for environmental permits or licenses.

Table 9: Carbon Offshoring and Abatement Intensity

	Abatement Investment per sale			Abatement Expenditure per sale		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Import	0.052**	-0.119	-0.579**	-0.009	0.043	-0.344
	(0.021)	(0.080)	(0.260)	(0.020)	(0.086)	(0.216)
Control	√	√	√	√	√	√
Firm FE	×	√	√	×	√	√
Industry-Year FE	×	√	√	×	√	√
Observations	2,661	1,965	2,660	2,693	1,997	2,692
KP			23.85			24.17

Note: Controls include lag information on firm capital, employment and machine investment and EU-ETS dummies. Standard errors clustered at firm level in parentheses. *,**,***, denotes significant at the 10% , 5% and 1% level respectively.

a decreasing pressure on firms' available cash for new environmentally friendly investment initiatives. These plans often do not receive high priority within firms' investment agendas, thus the reduced allocation of available funds.

Table 10 presents a comprehensive breakdown of the components of abatement investment and expenditure. My primary emphasis is on dissecting the environmental investment and expenditure related to air quality, water management, waste management, and other forms of pollution. By exploring these specific categories, I aim to gain insights into the allocation of resources aimed at mitigating environmental impacts. The results reveal intriguing patterns in the relationship between offshoring and abatement expenditure. While the overall effect of offshoring on abatement expenditure is insignificant, I find that there is a substantial reduction in firms' expenditure on water and waste management.

Table 10: Offshoring and Abatement Intensity

	Abatement Investment per sale				Abatement Expenditure per sale				R&D Cost
	Air	Water	Waste	Other	Air	Water	Waste	Other	
Carbon Import	-0.312*	-0.571***	-0.433***	-0.243	-0.229	-0.467**	-0.343***	-0.324**	-0.467**
	(0.187)	(0.208)	(0.162)	(0.157)	(0.147)	(0.186)	(0.132)	(0.150)	(0.187)
Control	√	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√	√
Industry-Year FE	√	√	√	√	√	√	√	√	√
Observations	2,692	2,692	2,692	2,367	2,692	2,692	2,692	2,367	2,038
KP	24.17	24.17	24.17	22.59	24.17	24.17	24.17	22.59	25.36

Note: Controls include lag information on firm capital, employment, machine investment and amount of emission right purchased. R&D cost is the cost (in SEK) of Research and Development (R&D) geared towards environmental management. Standard errors clustered at firm level in parentheses. *,**,*** denotes significant at the 10% , 5% and 1% level respectively.

Furthermore, I uncovered that with each additional 1% increase in carbon imports, a firm's environmental R&D costs per sale reduce by approximately 4%. This highlights the potential cost-saving advantages linked to carbon offshoring, indicating that firms could optimize their R&D expenses while simultaneously reducing their carbon emissions. Despite the various gains associated with offshoring, such as productivity growth, R&D advancements, and increased sales, it appears that these benefits are not being directed towards increasing investments in abatement technologies. Instead, the results suggest that carbon offshoring may serve as a substitute for abatement investment. In other words, firms may utilize carbon offshoring as a means to enhance their profit margins and reduce costs to remain competitive within their respective industries. This result echoes several findings on the trade-off between economic optimization and environmental sustainability (Cole et al., 2014; Cole and Elliott, 2005; Ferguson and Sanctuary, 2019; Ganapati et al., 2020; Marin and Vona, 2021). I find that while carbon offshoring may yield cost advantages and potentially boost overall business performance, it does not necessarily translate into increased investments in technologies aimed at reducing environmental impacts. In Appendix F, I perform a series of robustness checks to validate these findings

9 Conclusion

We know little about the causal evidence of carbon offshoring on emission via composition effect of firms. The paper analyzes the effect of carbon offshoring on pollution in the context of Swedish manufacturing firms, utilizing a unique and detailed product-level data on production, trade, and emissions maintained by Statistics Sweden (SCB). My identification strategy exploits the exogenous variation in export supply shocks of energy intensive inputs at firm-product-time dimension, leveraging bilateral trade flows at the product level sourced from the COMTRADE database.

The main finding of this paper is that carbon offshoring activities significantly reduce a firm's emission intensity in the importing country, comparable to the impact of local climate policy stringency, particularly through energy price dynamics. I provide new evidence that the type of produced imported and the pollution under study matters. I find that carbon leakage is high in terms of local emission LED intensity when firms import energy-intensive inputs but relatively low when firms engage in importing own-produced goods. On the contrary, carbon input imports lead to a significant reduction in CO_2 emissions compared to own-produced goods. Again, I show that overall environmental performance should also consider transport emissions. Despite the finding that carbon offshoring can lead to a reduction in firms' pollution intensity, the study shows that there will be a disproportionate increase in transport emissions.

I also provide new evidence that environmental policy arbitrage plays a significant role in pollution offshoring. This is the first study to rigorously demonstrate that the greater the arbitrage between the home country and trading countries, the more pronounced the implied offshoring effect on firm-level emissions. I find that the impact of offshoring on emissions is more pronounced when offshoring occurs in countries with relatively lax environmental policies (and low-income countries) compared to countries with similar environmental policy stringency as the home country. The difference in the environmental gains when offshoring occurs in lax and low-income countries suggests that pollution offshoring can contribute to the "clean-up" of production in developed countries. Additionally, I provide evidence that multinational offshoring activities through the import of emissions and direct relocation to lax/low-income countries have a positive concurrent effect on environmental performance

The overall result is driven by productivity gains, increased sales, and profit, but it does not support the hypothesis that Swedish firms will increase abatement investment as a result of carbon offshoring. From a policy perspective, these findings suggest that uniform environmental policies are the first and best approach to curb the rise in global and local emissions, consequently helping to combat the looming danger of climate change. However, since this is mostly impracticable, an efficient carbon border adjustment mechanism could serve as an effective strategy for tackling carbon leakage. This would ensure that firms innovate more to keep their total emissions lower than the home country's regulatory threshold, thus helping to mitigate the need to pay abatement costs and high environmental penalties

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Appendix

A Variable Definitions and Summary Statistics

Table A.1: Variable Definitions

Variable	Measurement/Definition
Environmental Performance	
$C02$ Emission (kg)	Fuel-specific CO2 emission coefficients by fuel type
$C02$ Emission Intensity (kg/SEK)	CO2/firm sales
Environmental Damage	Heat (calorific) value by fuel type
LED Intensity	Environmental damage/firm sales
Offshoring Activities and Firm Relocation	
Offshoring (Lax)	Import (intermediate / firms' own produced goods) from EPS lax countries
Offshoring (LIC)	Import (intermediate / firms' own produced goods) from low income countries
FDI Concentration (Lax)	Total employment (investment size) in affiliates located in EPS lax countries per Global firm's employment size
FDI Concentration (LICs)	Total employment in affiliates in low-income countries per Global firm's total employment
Other Variables	
Productivity	Total factor productivity using Wooldridge (2009)
K/L	Capital labour ratio
Machine Investment (SEK millions)	Firm investment in machinery (Adjusted due to unrecorded increase in assets)
Sales (SEK millions)	Firm-specific sales measured in million SEK
Output	Firm-specific value of output measured in physical quantities
Lax/Arbitrage	Dummy = 1 if Swedish EPS - EPSc > 0 otherwise, 0
Low Income	Dummy =1, if classified by by CEPII as a low income country, otherwise, 0

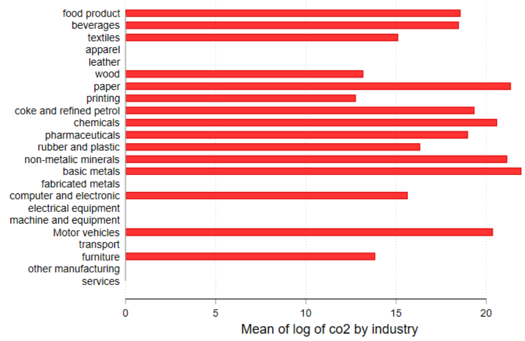
Table A.2: Summary Statistics

	N	Mean	SD	Min	Max
Sourcing Patterns					
Toxic content of input import	26,092	40.93	4.947	0	50.48
Toxic content of PG import	26,092	13.72	18.29	0	47.92
Share of toxic content of import^{lax}	24,392	0.464	0.288	0	1
Share of toxic content of import^{LICs}	26,092	0.114	0.556	0	1
Import share of OECD	26092	0.881	0.520	0	1
Import share of top 2 country-inputs	26,092	0.642	0.761	0	1
Import share of top 5 country-inputs	26,092	0.891	0.491	0	1
Number of source country-inputs	26,092	43	10	2	1890
Number of years with source country	26,092	6	8	3	10
Stringency Index (OECD EPS)					
EPS lax	24,392	0.663	0.425	0	1
→ Strict	24,392	0.337	0.425	0	1
→ Quite lax	24,392	0.425	0.284	0	1
→ Very Lax	24,392	0.147	0.112	0	1
→ Extremely Lax	24,392	0.191	0.182	0	1
LICs	26,092	0.121	0.109	0	1

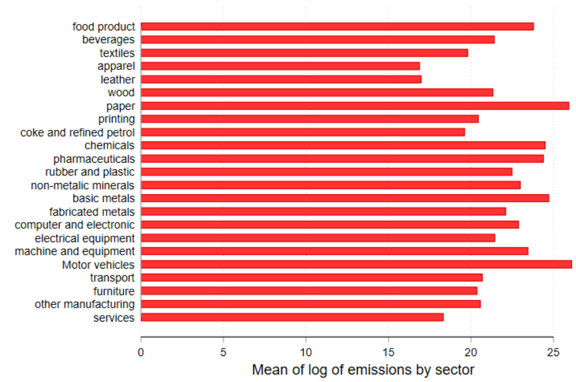
Note: LED and LIC denotes Local pollution emissions and Low Income Countries respectively.

B Figures

Figure B.1: Emissions by Sector



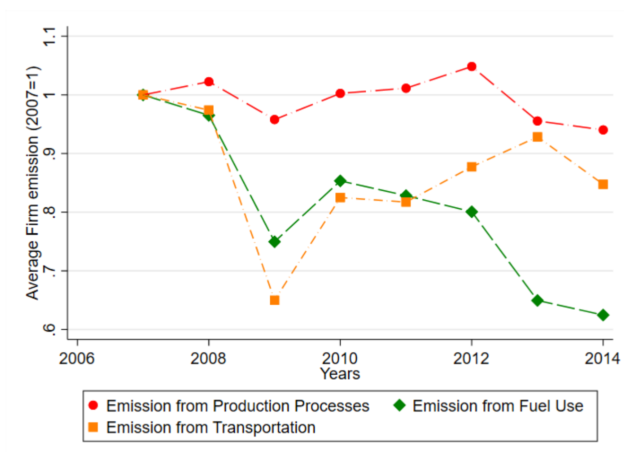
B.1A.Self-reported emissions



B.1B. fuel-based emissions

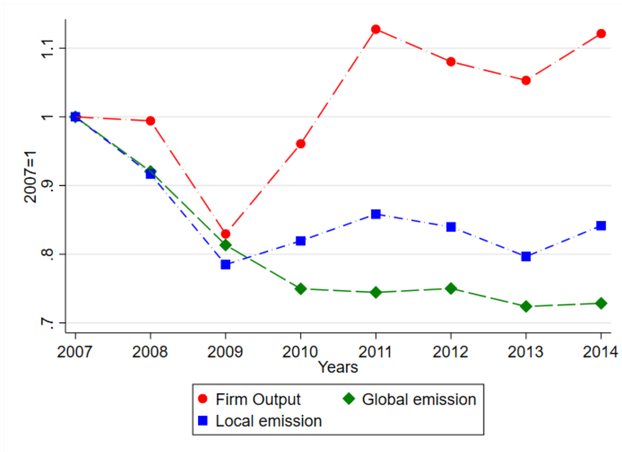
Note: Figure in Panel A plots sectorial emissions reported by firms. Although some firm-level emission data are available, the firms in the sample do not provide sufficient industry coverage to provide industry-level observations and comparison in results. Panel B plots the computed fuel-based emissions by each sector using emission factors conditional on the assumption that CO2 emissions are directly proportional to the quantity of an energy source consumed.

Figure B.2: Trend of Firms Pollution Emissions Between 2007 - 2014



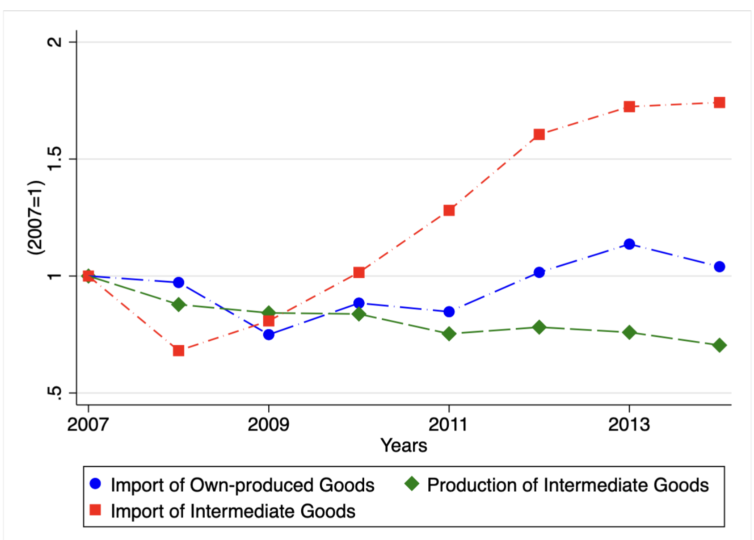
Note: Figure 3 plots the evolution of average emissions from Swedish firms. The dashed red line plots emission from production processes which appears to have declined marginally between 2012 and 2014. The dashed green line plots emissions from fuel use/combustion. The trend shows a substantial fall in emission from fuel-use compared to 2007 average. The last plot is emission from transportation which is represented by a dashed orange line which interestingly shows an upward trend after 2009 but still lower than 2007 average. All emission values are normalized to 1 in 2007.

Figure B.3: Trend of Firms' Pollution Emissions and Output



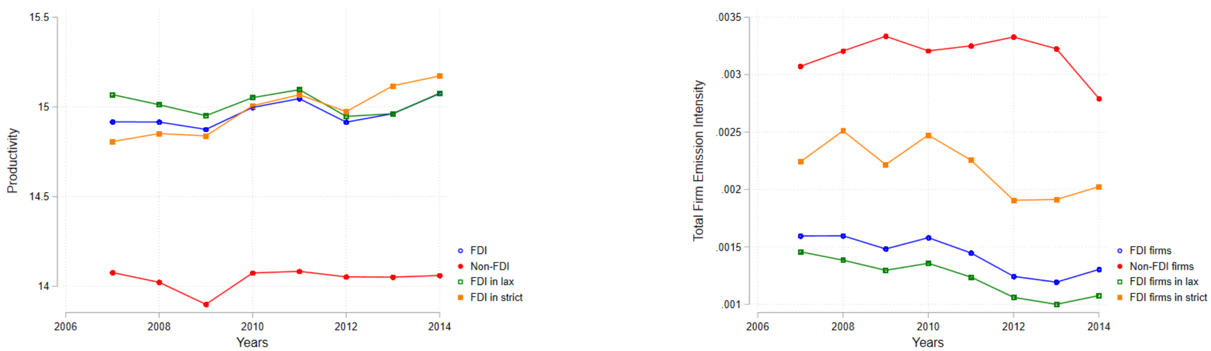
Note: Figure 1 plots the evolution of average emissions from Swedish firms. The dashed red line plots firm output between 2007 and 2014. The dashed green line plots total global emissions from fuel use/combustion, transportation and production processes. The dashed blue line plots total local emissions (damage) from fuel use/combustion, transportation and production processes. All emission values are normalised to 1 in 2007.

Figure B.4: Firm-level Import of Intermediate products and Own-produced goods



Note: The figure plots the trend of average import of processed intermediate imports (red line) and firms' own-produced goods (blue line) as well as Swedish firms' production of intermediate products. All import values are normalised to 1 in 2007. While the import of intermediate goods increased after 2008, production of these products declined compared to 2007 values

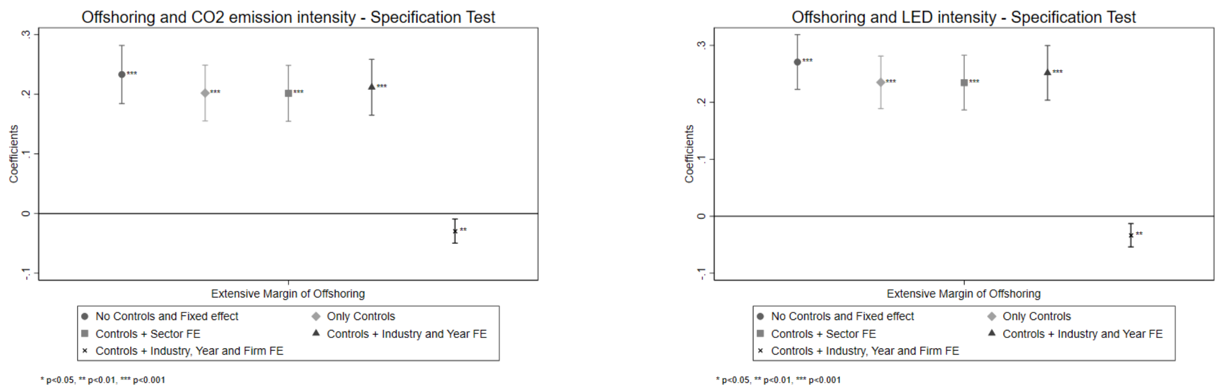
Figure B.5: Firm-level Emissions and Productivity by Firm-type and Destination



Note: The figure plots the trend of productivity (Panel A) and total firm emissions (Panel B) categorized by firm type, specifically whether a firm is a multinational or not, and whether it operates in countries with laxer environmental policies or countries with stricter environmental policies

C Robustness Results

Figure C.1: Coefficient Plot of Offshoring Dummy and Emissions



Note: The figure plots the coefficients of extensive margin of offshoring on CO_2 emission intensity and LED emission intensity using several specification. Recall that offshoring firms are those that increase the demand of dirty inputs but decrease the production of dirty inputs.

Table C.1: Import and Firms Environmental Performance

	CO_2 emission intensity				LED intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Total import (excluding inputs)							
Total import	-0.038***	-0.054***	-0.043	-0.027	-0.039***	-0.049***	-0.036	-0.029
	(0.006)	(0.018)	(0.028)	(0.019)	(0.005)	(0.015)	(0.023)	(0.020)
Energy Price				-0.307***				-0.406***
				(0.033)				(0.036)
KP		218.45	527.74	534.43		214.66	526.23	532.92
	Panel B: Inputs Import in Quantities							
Input Import	-0.040***	-0.045**	-0.060*	-0.040*	-0.044***	-0.046***	-0.061**	-0.051**
	(0.007)	(0.020)	(0.032)	(0.022)	(0.007)	(0.017)	(0.028)	(0.024)
Energy Price				-0.329***				-0.432***
				(0.045)				(0.048)
KP		52.02	374.87	380.047		50.27	374.90	379.95
	Panel C: Inputs Import in Values							
Input Import	-0.039***	-0.047**	-0.062*	-0.042*	-0.044***	-0.048***	-0.064**	-0.053**
	(0.008)	(0.020)	(0.033)	(0.023)	(0.007)	(0.017)	(0.029)	(0.025)
Energy Price				-0.329***				-0.432***
				(0.045)				(0.048)
KP		37.2	364.24	369.79		35.59	364.52	369.93
Control	√	×	√	√	√	×	√	√
Firm FE	√	√	√	√	√	√	√	√
Sector-Year FE	√	√	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√	√	√
Estimation	**OLS**	**IV**	**IV**	**IV**	**OLS**	**IV**	**IV**	**IV**

Note: The table presents a series of regression coefficients for different specification of equation 5. Emission intensity is log of emission per sale. All specifications include firm, industry-year and municipal-year fixed effects and lagged (up to three lags) information of firms' productivity, machine investment and capital intensity of firms. Standard errors clustered at firm level in parentheses. First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics. *,**,*** denotes significant at the 10% , 5% and 1% level respectively.

Table C.2: Narrow definiton of offshoring and firm emissions

	CO_2 emission intensity		LED emission intensity	
	1	2	3	4
Narrow offshoring (Quantities)	-0.104**		-0.106**	
	(0.049)		(0.043)	
Narrow Offshoring (Values)		-0.168**		-0.172**
		(0.082)		(0.074)
Observations	16,544	16,544	16,548	16,548
KP	34.07	19.99	33.68	19.83
Control	√	√	√	√
Firm FE	√	√	√	√
Sector-Year FE	√	√	√	√
Municipal-Year FE	√	√	√	√

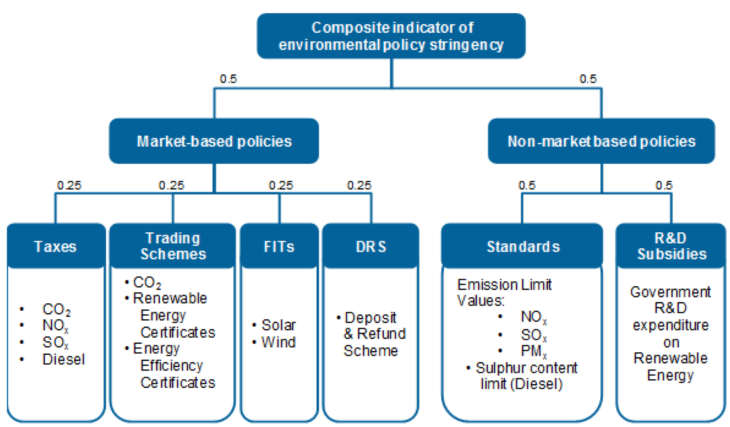
Note: Offshoring is measured as imports of products (excluding raw materials and finished machines) belonging to the 3-digit industry. *,**,*** denotes significant at the 10% , 5% and 1% level respectively.

D Environmental Policy Arbitrage

Environmental Policy Stringency Index

A few papers have shown that offshoring dirty tasks abroad can have an important influence on firm emissions. However, we know little about the interaction of offshoring and environmental policy arbitrage; often because measuring the strictness of environmental standards between countries can be challenging. Some regulations may be strict but not enforced, while others are lax but tightly enforced and ranking such multidimensional regulations is difficult if not impossible. Previous studies have used income groups of countries as a proxy for environmental arbitrage with the assumption that there is a positive correlation between environmental stringency and economic development (Li and Zhou, 2017; Stavropoulos et al., 2018). However, using income group as a proxy for environmental stringency can be rather crude and unlikely to allow confident identification – using GDP or income groups becomes problematic when the correlation between economic development and environmental policy stringency becomes weaker over time. It is likely the case that policy changes may reveal an environmental arbitrage even among developed countries [37]. Therefore, examining the effect of environmental policies in a meaningful way requires adequate proxy for environmental stringency (Koziuk et al., 2019).

Figure D.1: Environmental Policy Stringency (EPS) Indicator



Note: This figure shows the structure of EPS indicator where individual policies are aggregated with equal weight at each level and category. Source: Koziuk et al. (2019)

Unlike previous studies, this paper adopts the OECDs Environmental Policy Stringency (EPS)

[37] In fact the data from the environmental policy stringency index shows instances where countries classified as low and middle-income countries by the World Development Index (WDI) can surprisingly be relatively stricter in terms of environmental policies (for example South Korea) or are very much comparable to Swedish environmental policy stringency. Likewise, some high-income countries are relatively laxer when compared to Sweden's environmental stringency.

index spanning the period 1991 to 2014 to categorise countries into lax or strict in terms of environmental policies. Recently introduced by Koziuk et al. (2019), the EPS appears to be more reliable and internatonally comparable. The EPS is a composite index based on a wide set of indicators (see Botta and Koźluk, 2014; Koziuk et al., 2019) of about 15 market-based and non-market environmental policy instruments[38] covering 28 countries(including 4 non-OECD countries). According to the OECD the EPS index incorporates the evolution of both local and national environmental policies undetarken by countries to encourage broad-based action to reducing environmental damage, climate change and other efficiency gains such as green innovations. While such measure is a major strength of the EPS, it also poses an important pitfall in measuring environmental policy arbitrage. That is, EPS is highly aggregated. The EPS index equally weights all the environmental regulations within each category of policy instruments and then aggregates them into a single indicator. The indicator ranges from 0 to 6, where 0 is associated with lax and 6 is associated with more stringent policies (see Figure D.1). While I acknowledge that firms operating in the same source country may be subjected to different levels of environmental tax, studies find that EPS is highly correlated with firm environmental activities in source country and which are likely to be correlated with firm's abatement investment (Cole et al., 2014). Thus offshoring firms' environmental cost in destination country, if available , is positively correlated with the destination country's environmental policy index.

Given, the EPS index, I proceed to classify how lax a country is compared to Sweden. First, due to country heterogeneity in I normalize the EPS index to take the value of 0 to 1. I then calculate the average index from the normalised EPS index and categorized countries as lax if their normalized EPS index is less than the mean value. Not surprisingly, I find that countries change from lax to more stricter in terms of environmental policies over time. This variable of laxity can be used to interact with offshoring to detect how changes in changes in countries where firms import inputs and goods affect emissions. However, firms do not make instantaneous decisions to change dirty imports from one country to another in a short period of time. To take advantage of environmental policy arbitrage, firms might have considered the environment policy stringency of a country over a long period of time. That is, countries have to be well-known as lax in terms of environmental policies to offshore to them if and only if firms care about where to offshore dirty products. Also Swedish firms internalise Swedish environmental stringency relative to other trading partners' environmental policies. As such what is important is how the average Swedish environmental policy stringency differs from average foreign policy. Therefore the laxity variable used in this paper is calculated as:

[38] While market-based instruments define price for the inputs or the goods that, during production or consumption, emit negative externalities, the non market-based instruments are the command-and-control regulations on emissions by governments.

$$Lax = \begin{cases} 1 & EPS_{\text{Sweden}} - EPS_{\text{Trading Country}} > 0 \\ 0 & EPS_{\text{Sweden}} - EPS_{\text{Trading Country}} < 0 \end{cases}$$

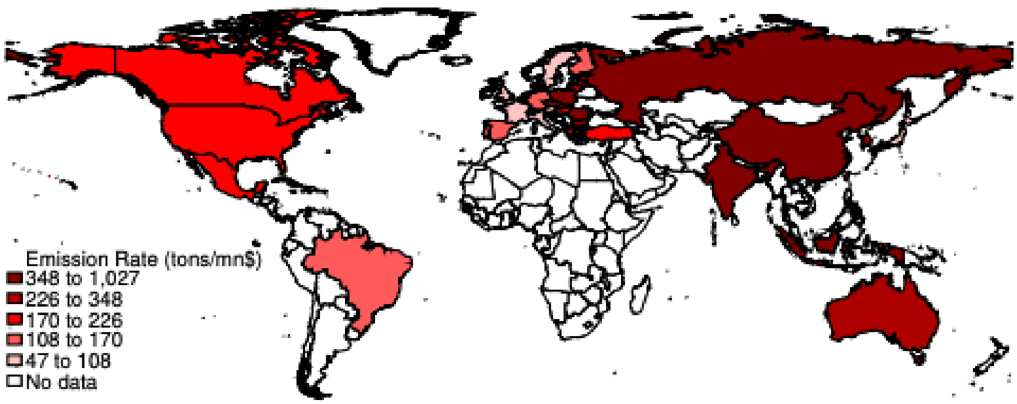
Where EPS_{Sweden} is Sweden's average environmental policy stringency index between 2005 and 2014. $EPS_{\text{Trading Country}}$ is the average environmental policy stringency of trading countries over the same period. First, notice that this indicator contains little variation since about 80% of countries fall in the lax categories (Sweden is one of the few stricter countries over the period). For this reason, I further disaggregate the index into "strict", "quite lax", "very lax" and "extremely lax", given some thresholds or gaps in the stringency index. In particular, all countries with an index of about 0.5 mean deviation away from Sweden's index are categorised as "quite lax", between 0.51 and 1.5 is classified as "very lax" and above 1.5 is classified as "extremely lax". Thus I create a variable called Rank $\in \{0, 1, 2, 3\} = \{$Strict, Quite Lax, Very Lax, Extremely Lax$\}$ which indicates a country group classified according to the stringency index. Table D.1 shows the countries in each group of classification.

Table D.1: Classification of Countries based on EPS Index

Rank =0/Strict	Rank =1/ Quite Lax	Rank =2/ Very Lax	Rank =3/ Extremely Lax
Austria	Canada	Australia	Brazil
Denmark	France	Belgium	China
Finland	Greece	Czech Republic	India
Germany	Italy	Hungary	Indonesia
Switzerland	Japan	Ireland	Russia
Netherlands	Korea	Poland	South Africa
	Norway	Slovak Republic	Turkey
	Portugal	Slovenia	
	Spain	United Sates of America	
	United Kingdom		

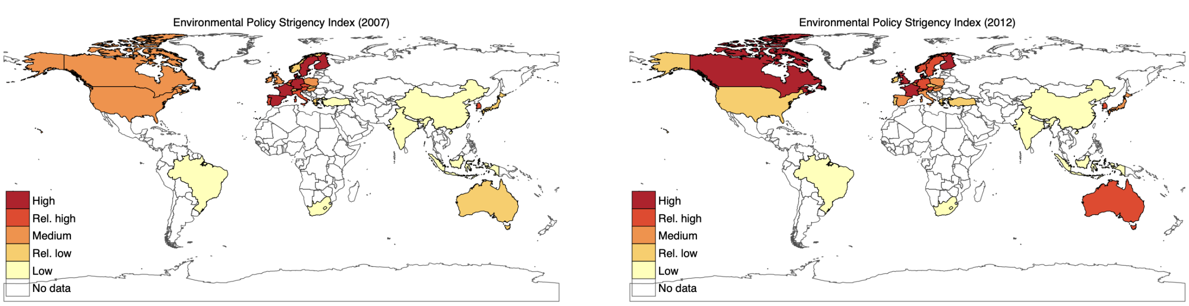
This classification supports the empirical patterns of pollution emission rates across country and over time. We expect that countries with more stricter environmental policies to be relatively cleaner. Figure D.2 maps CO_2 emission intensity of all industries in about 43 countries in the World Input Output Dataset in 2009. By visual inspection, we see that lowest emission intensities are in Europe. Also, Canada and US has slightly higher emission compared to Europe while Latin America countries, Asia and Oceania pollute more. The emission rate appears to be highly skewed. According to Copeland et al. (2022), the dirtiest countries have 20 or more times emission intensity of the cleanest countries. Also countries in a the same income group can show a systematically different emission rate (example Japan and Australia). These large differences in emissions across countries (and country groups) as a result of different environmental policies seems to be consistent over time (see Panel B of Figure D.4) which suggests that outsourcing of production of dirty industries could have detrimental consequences on global emissions. Consistent with the pollution haven hypothesis, I expect an increase in firms' (toxic) import that originates from lax and low income countries reflecting the outsourcing of domestic production (Cole et al., 2014). Figure D.4 indicates that environmental arbitrage between in EPS lax countries is smaller than low-income countries on average. A simple descriptive statistics in table A.2 in appendix B show that while importing firms sources about 66.3% from EPS lax countries, about 12.1% of toxic import comes from low-income countries.

Figure D.2: Emission rate of all industries per country (2009)



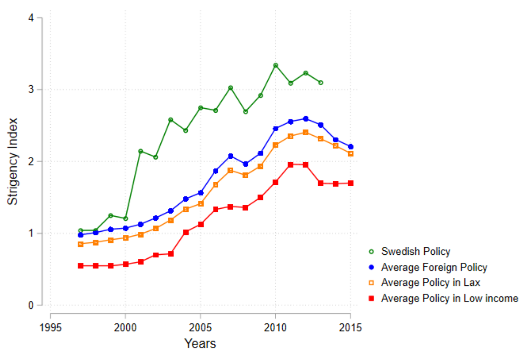
Note: The graph shows a direct CO_2 emission rate of all industries in a particular country in 2009, using data from the World Input Output Dataset. Source: Copeland et al. (2022)

Figure D.3: Environmental Policy Stringency of countries in 2007 and 2012

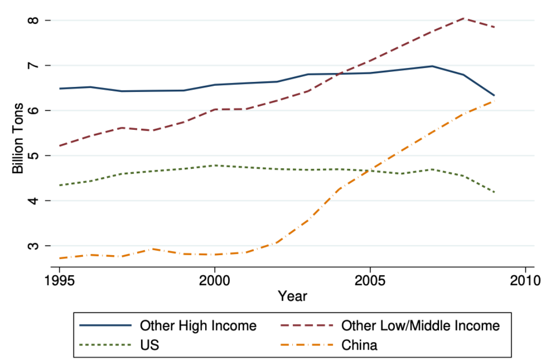


Note:This figure plots Environmental Policy Stringency in 2009 and 2012 by country. Countries for which I have no observation are left blank. Data is sourced from OECD Environmental Policy Stringency Index.

Figure D.4: Trends in Environmental Policy Stringency and CO_2 Emission Rate by Income Group



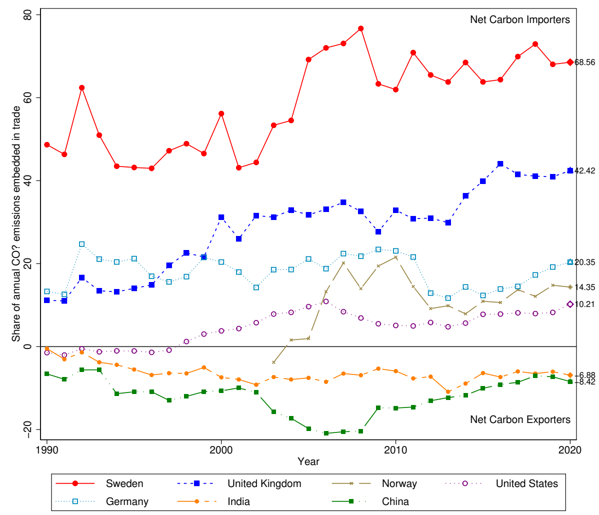
D.4A.Environmental Policy Stringency Index



D.4B. CO_2 emission rate by group of country

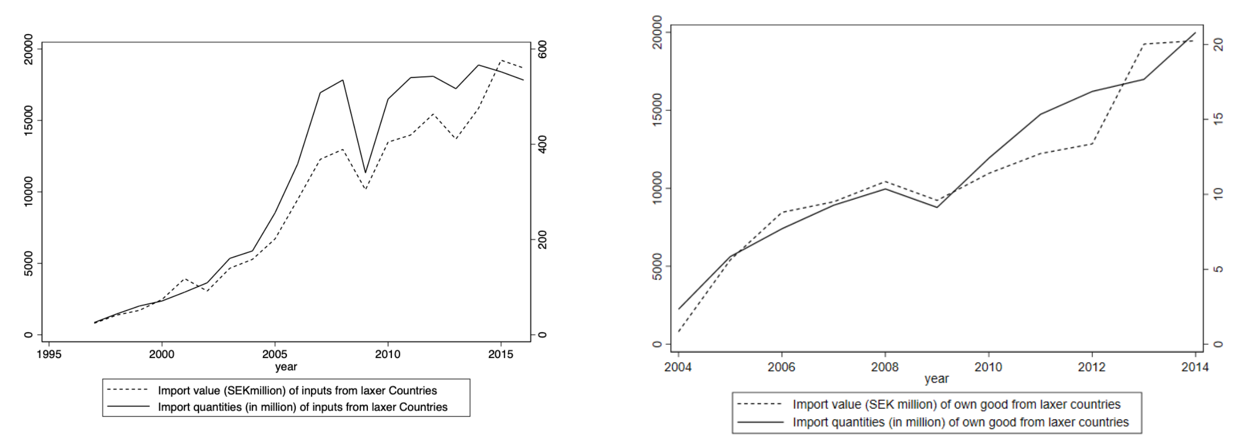
Note: Figure D.4A plots plots the average EPS index of Sweden (green line), the rest of the world (blue line), countries with laxer EPS compared to Sweden (orange line) and low-income countries (red line). Panel B shows CO_2 emission rate by group of country and Year, as shown in Copeland et al. (2022) using data from the World Input Output Dataset.

Figure D.5: Carbon content of Trade in Selected Countries



Note: The figure plots emissions exported or imported as a percentage of domestic production emissions. Positive values represent net importers of CO_2. Negative values represent net exporters of CO_2. Annual CO_2 emissions – is sourced from the Global Carbon Project and Our World in Data.

Figure D.6: Manufacturing Offshoring Activities to Laxer Countries



D.5A. Trend of Input demand

D.5B. Trend of in-house offshoring

Note: Figure D.6A and D.6B plots the trend of offshoring activities measured as total import of processed intermediate import and trend of import of firms' own-produced goods respectively. Imports in values (SEK million) are depicted by a dashed line and import in quantities are shown by solid lines. Laxer countries are classified based on OECD's Environmental Policy Stringency (EPS) index.

Table D.2: Interaction Effect of Carbon offshoring, Laxity index and and LIC Countries

	FE			FE+ IV			FE+ IV		
	CO_2 emission intensity			CO_2 emission intensity			*LED* intensity		
	1	2	3	4	5	6	7	8	9
				Panel A: Dirty Input Reallocation					
Input import	-0.007**	-0.012*	-0.011**	-0.097**	-0.101**	-0.104**	-0.053*	-0.062*	-0.062*
	(0.003)	(0.006)	(0.006)	(0.044)	(0.046)	(0.031)	(0.031)	(0.032)	(0.032)
Input import × Lax	-0.001***			-0.041***			-0.013**		
	(0.000)			(0.007)			(0.006)		
Input import × Rank		-0.003***			-0.092***			-0.018**	
		(0.000)			(0.050)			(0.007)	
Input import × LIC			-0.009**			-0.253***			-0.276***
			(0.011)			(0.159)			(0.176)
Observations	15,792	15,313	15,914	15,792	15,313	15,914	15,792	15,313	15,914
KP				19.7	32.21	95.87	11.43	32.21	95.87
				Panel B: In-House offshoring					
PG import	-0.004**	-0.006***	-0.005**	-0.053***	-0.059***	-0.064***	-0.037***	-0.049***	-0.044***
	(0.001)	(0.001)	(0.020)	(0.003)	(0.003)	(0.005)	(0.012)	(0.001)	(0.002)
PG import× Lax	-0.000**			-0.045			-0.012		
	(0.004)			(0.101)			(0.036)		
PG import× Rank		-0.002***			-0.086*			-0.013*	
		(0.005)			(0.048)			(0.007)	
PG import× LIC			-0.007**			-0.196*			-0.207**
			(0.008)			(0.003)			(0.099)
Observations	4,745	4,628	4,772	4,745	4,628	4,772	4,745	4,628	4,772
KP				40.3	73.10	20.7	40.3	73.10	20.7
Control	×	√	√	√	×	√	√	√	√
Firm Fixed Effect	√	√	√	√	√	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√	√	√	√	√	√
Municipal-Year Fixed Effect	√	√	√	√	√	√	√	√	√

Note: The table presents a series of regression coefficients for offshoring given the role of environmental policy differences between countries. Panel A shows estimates of the imported inputs while Panel B shows estimates for import of own-produced goods. *Lax* is a dummy of 1 for countries with "laxer environmental policies" compared to Sweden and 0, otherwise. *Rank* takes the value of 0 to 3, in which 0 means countries with strict environmental policies, and 3 indicates the highest environmental policy laxity. *LIC* denotes "Low income countries". FE estimates for *LED* intensity is omitted to reduce clutter. All specifications include firm, industry-year and municipal-year fixed effects. Controls include lagged (up to three lags) information of firms' productivity, machine investment and capital intensity of firms. Standard errors clustered at firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table D.3: Share of Carbon Import by Country Groups

	1	2	3	4	5	6	7	8
Dependent Variable:	CO_2 emission intensity				LED emission intensity			
EPS Lax/Income Group:	QL	VL	EL	LIC	QL	VL	EL	LIC
			Panel A: Dirty Input Reallocation					
Share of Input import$_{it}$	-0.043	-0.053**	-0.058**	-0.322***	-0.020	-0.026*	-0.026**	-0.245***
	(0.032)	(0.019)	(0.021)	(0.159)	(0.023)	(0.010)	(0.002)	(0.076)
Observations	8,393	7,132	7,650	15,914	8,393	7,132	7,650	15,914
KP	22.7	32.1	20.5	56.8	22.7	32.1	20.5	56.8
			Panel B: In-House Offshoring					
Share of PG import$_{it}$	-0.022*	-0.028**	-0.029	-0.248***	-0.024	-0.030	-0.036*	-0.218***
	(0.008)	(0.005)	(0.014)	(0.048)	(0.027)	(0.021)	(0.016)	(0.014)
Observations	3,902	2,132	2,132	4,772	3,902	2,132	2,132	4,772
KP	61.4	38.36	73.0	86.97	60.2	37.52	73.0	86.97
Controls	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√
Industry-Year FE	√	√	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√	√	√

Note: Offshoring is measured as the share of import input and firm own-produced goods coming from countries with laxer environmental policies (and low income countries) respectively. All specifications includes inputs imports and PG imports. *,**,***denotes significance at the 10% , 5% and 1% level respectively. Standard errors clustered at firm level are in parentheses.

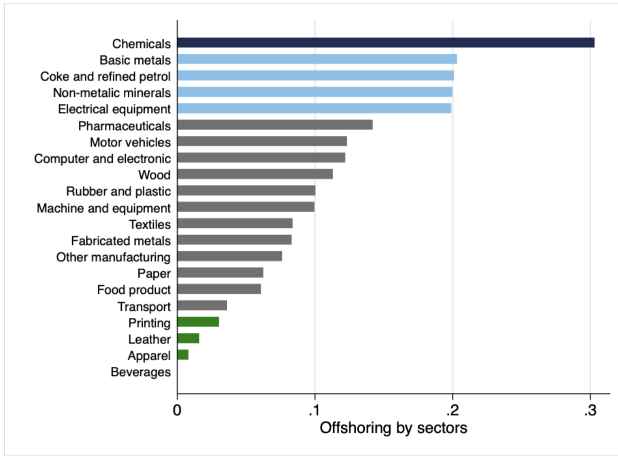
Table D.4: Emissions and Import Competition

	FE+ IV		FE+ IV	
	CO_2 emission intensity		LED intensity	
	1	2	3	4
Import^{Pen} (from EPS Lax)	-0.065**		-0.032***	
	(0.028)		(0.009)	
Import^{Pen} (from low-income)		-0.031		-0.047
		(0.022)		(0.023)
Controls	√	√	√	√
Firm FE	√	√	√	√
Industry-Year FE	√	√	√	√
Municipal-Year FE	√	√	√	√
KP	100.1	54.2	112.0	35.3

Note: Import^{Pen} denotes import penetration which is measured as all import from EPS lax and low-income countries. Standard errors are clustered at firm level. *,**,*** denotes significant at the 10% , 5% and 1% level respectively.

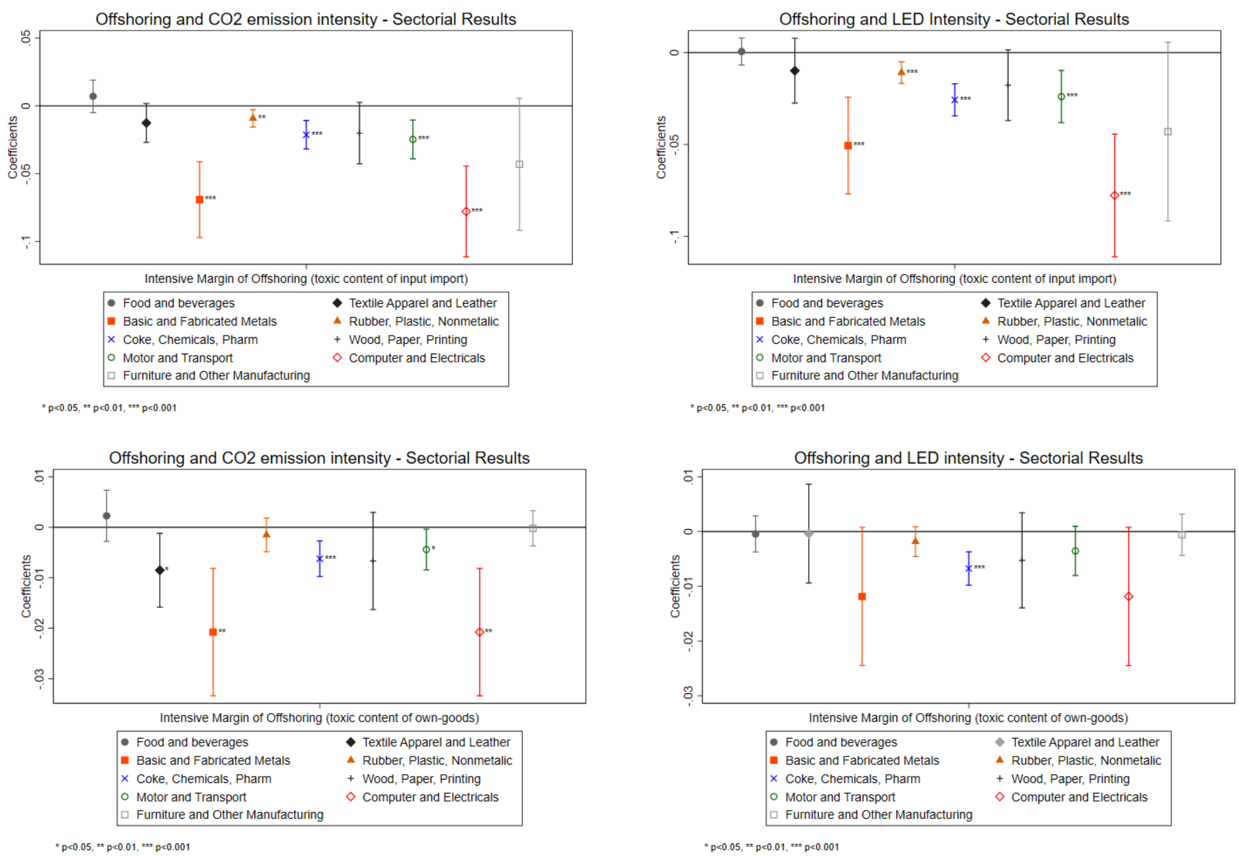
E Heterogenous Effect

Figure E.1: Sectorial Distribution of Offshoring Firms



Note: The figure shows how offshoring firms are distributed across sectors. The majority of offshoring firms are heavily-energy intensive, in particular, in chemicals, basic metals, coke and refined petrol, non-metallic minerals and electrical equipment sectors.

Figure E.2: Allowing for heterogeneity across sectors



CO_2 emission intensity $\qquad\qquad$ LED intensity.

Note: This figure plots the sector-specific coefficients of the extensive margin of offshoring on CO2 emission intensity (left panel) and LED intensity (right panel). The figure shows the fixed effect estimate of offshoring measured as toxic content of imported inputs goods. I report only Fixed Effect estimates because I lose a lot of statistical power with the shift-share instrument. So the result here should be interpreted with caution. In the worst case, the results indicate a downward bias of the estimated coefficients. All controls are properly included

Multinationals and Emissions

Table E.1: Multinationals, Productivity and CO_2 Emissions

	CO_2 intensity			LED intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
Multinationals	-0.206**	-0.190***	-0.163**	-0.248**	-0.233***	-0.203**
	(0.090)	(0.063)	(0.073)	(0.100)	(0.075)	(0.083)
Productivity		-0.265***	-0.337***		-0.265***	-0.343***
		(0.020)	(0.019)		(0.021)	(0.019)
Observations	5,742	4,822	4,822	5,760	4,836	4,813
Controls	×	×	√	×	×	√
Firm Fixed Effect	√	√	√	√	√	√
Year Fixed Effect	√	√	√	√	√	√

Note: I test the hypothesis that multinationals are cleaner given productivity and other covariates. Table E.1 shows how CO_2 emission intensity vary with productivity and with being a multinational. Standard errors clustered at firm level are in parentheses. *,**,*** denotes significance at the 10% , 5% and 1% level respectively.

Table E.2: Multinational Environmental Performance, Imports and Outward FDI

	Lax		LIC		Lax		LIC	
	CO_2 emission intensity				*LED* emission intensity			
	Panel A: Input Reallocation and FDI concentration							
Input import	-0.096***	-0.146**	-0.444*	-0.468**	-0.136	-0.146	-0.590	-0.468
	(0.000)	(0.058)	(0.156)	(0.068)	(0.153)	(0.094)	(0.392)	(0.076)
FDI Concentration		-0.061***		-0.496***		-0.135*		-0.452***
		(0.003)		(0.032)		(0.094)		(0.087)
Energy Price	-0.249***	-0.245***	-0.259**	-0.177***	-0.241***	-0.320**	-0.165*	-0.258***
	(0.036)	(0.043)	(0.099)	(0.000)	(0.066)	(0.109)	(0.018)	(0.070)
Observations	1,260	1,260	1,014	1,014	1,260	1,260	1,014	1,014
KP	16.9	16.9	16.7	16.7	37.8	46.8	36.4	46.4
	Panel B: Own-Produced Goods and FDI Concentration							
PG import	-0.116	-0.128**	-0.324**	-0.147***	-0.105	-0.120	-0.302	-0.325
	(0.075)	(0.045)	(0.099)	(0.003)	(0.050)	(0.068)	(0.291)	(0.153)
FDI Concentration		-0.155*		-0.452***		-0.135*		0.151**
		(0.071)		(0.020)		(0.094)		(0.060)
Energy Price	-0.276***	-0.257***	-0.322***	-0.286***	0.258***	-0.235***	-0.316***	-0.359***
	(0.041)	(0.050)	(0.057)	(0.039)	(0.076)	(0.312)	(0.066)	(0.115)
Observations	958	958	872	872	958	958	872	872
KP	16.9	27.3	9.01	23.7	16.9	27.3	9.01	23.7
Controls	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√
Industry-Year FE	√	√	√	√	√	√	√	√
Municipal-Year FE	√	√	√	√	√	√	√	√

Note: Panel A shows estimates of the imported inputs while Panel B shows estimates for import of own produced goods. *Lax* and *LIC* denotes "environmentally laxer countries", and "Low income countries" respectively. Standard errors clustered at firm level are in parentheses.*,**,***denotes significance at the 10% , 5% and 1% level respectively.

Table E.3: Emission, Toxic Import and FDI Concentration (Alternative Measure)

	(1) CO_2 intensity	(2) CO_2 intensity	(3) CO_2 intensity
FDI concentration in EPS Lax	-0.141***		-0.103***
	(0.009)		(0.009)
FDI concentration in Low-income		-0.265***	
		(0.022)	
Carbon Import			-0.003
			(0.002)
Carbon Import × FDI dummy			-0.867***
			(0.043)
Observations	1,274	1,274	1,274
Controls	√	√	√
Firm FE	√	√	√
Year FE	√	√	√

Note: This estimate uses a multinational sample. The FDI concentration here is measured as the ratio of investment in EPS lax to the parent company's investment size in Sweden. In column 3, the toxic content of general imports is interacted with the FDI dummy. The result shows that CO2 emissions reduced drastically among FDI firms as compared to domestic firms. Standard errors clustered at firm level are in parentheses *,**,***denotes significance at the 10% , 5% and 1% level respectively.

Table E.4: Firm Environmental Performance and FDI (`relocation effect`)

	CO_2 Intensity				LED Intensity			
	Total	Fuel-use	Own-Prod.	Transp.	**Total**	Fuel-use	Own-Prod	Transp.
FDI Concentration^{Lax}	-0.040**	-0.048***	-0.009	0.021	-0.020***	-0.015***	-0.001	0.010
	(0.012)	(0.009)	(0.074)	(0.049)	(0.001)	(0.001)	(0.023)	(0.019)
Energy Price	-0.262***	-0.262***	-0.242	0.145	-0.2408***	-0.2547***	-0.1553	0.0203
	(0.063)	(0.061)	(0.185)	(0.349)	(0.0658)	(0.0675)	(0.1971)	(0.2570)
Controls	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√

Note: Standard errors clustered at firm level are in parentheses. *,**,*** denotes significant at the 10% , 5% and 1% level respectively.

F Carbon Offshoring and Abatement– Robustness

Sampling issue. Key econometric issue using the abatement data is that firms have the option to invest in technologies that reduce carbon emissions, which determines whether I can observe their abatement in our data. If firms made this decision randomly, I could disregard the fact that I do not observe all instances of carbon abatement and utilize ordinary regression to establish an abatement model. However, it is unlikely that this assumption of random participation holds true. For example firms with lower profit margins are less likely to choose to engage in abatement, which leads to an downward bias in the sample of observed abatement. Additionally, some firms may not report their environmental expenditure/investment because of their small amounts relative to their total investment scale. Thus, there is potential sample selection bias arising from the dependent variable (i.e., the level of environmental expenditure/investment). To tackle these problems, I adopt Heckman selection strategy in line with the recommendation by Wooldridge (2010). Specifically, we first estimate the predicted probability of being selected into the sample using rich set of firm-level variables such as firm sales, cost, firm size, employment, capital, productivity, energy cost and amount of emission right purchased. I then calculate the inverse mills ratio (IMR), or the correction term from the selection equation. By augmenting our main regression equation with the IMR, I am able to correct for the sampling bias and the extent to which offshoring effect firms abatement. The results in Table F.1 points to a strong positive selection bias in the OLS estimates but a robust effect of our IV estimate. I find total abatement intensity falls by about 5.4% as compared to our baseline estimate of 5.8% and an insignificant carbon offshoring effect on total abatement expenditure.

Table F.1: Carbon Offshoring and Abatement – Correcting for Sampling Bias

	Abatement per sale		**Abatement**	
	Total Investment	Total Expenditure	Total Investment	Total Expenditure
	(1)	(2)	(3)	(4)
Carbon Import	-0.538*	-0.212	-0.518	-0.185
	(0.324)	(0.263)	(0.319)	(0.256)
Control	√	√	√	√
Firm FE	√	√	√	√
Year FE	√	√	√	√
Observations	2,636	2,668	2,636	2,668
KP	16.47	16.52	16.472	16.52

Note: The table presents regression coefficients of augmented specification of equation **??**. Controls include inverse mills ration (IMR) and lag information on firm capital, employment and machine investment. Standard errors clustered at firm level in parentheses. *,**,***denotes significant at the 10% , 5% and 1% level respectively.

Abatement. In principle, carbon offshoring could affect the nominator, i.e., abatement, and the denominator of abatement intensity, i.e., sales. As hypothesized, it is expected that carbon offshoring will prompt firms to search for ways to optimize their margins and reduce costs in order to remain competitive. Therefore, I anticipate that abatement will decrease in response to stronger competition and sales will either increase or remain stable. Thus in Table F.2, I estimate the carbon import on log of abatement and not abatement per sale. Similar to our main result, I find that carbon offshoring leads to reduction in abatement investment but statistically insignificant effect on abatement expenditure. The point estimates are somewhat smaller than the estimated effect on abatement intensity, indicating that import competition has a positive effect on sales.

Table F.2: Carbon Offshoring and Abatement

	Abatement Investment					**Abatement Expenditure**					**R&D Cost**
	Total	Air	Water	Waste	Other	Total	Air	Water	Waste	Other	
Carbon Import	-0.590*	-0.244	-0.520**	-0.279*	-0.054	-0.265	-0.088	-0.381*	-0.136	-0.132	-0.376*
	(0.026)	(0.216)	(0.250)	(0.170)	(0.168)	(0.251)	(0.158)	(0.215)	(0.120)	(0.146)	(0.210)
Control	√	√	√	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√	√	√	√
Industry-Year FE	√	√	√	√	√	√	√	√	√	√	√
Observations	2,692	2,692	2,692	2,692	2,367	2,692	2,692	2,692	2,692	2,367	2,038
KP	17.64	17.64	17.64	17.64	16.43	17.64	17.64	17.64	17.64	16.43	18.78

Note: The table presents a series of regression coefficients for different specification of of equation ??. Controls include lag information on firm capital, employment and machine investment. Standard errors clustered at firm level in parentheses. *,**,***denotes significant at the 10% , 5% and 1% level respectively.

Table F.3: Carbon Offshoring and Theoretical Abatement

	Abatement per sale			
	(1)	(2)	(3)	(4)
Carbon Import	-0.143***	-0.142***	-0.137***	-0.423***
	(0.018)	(0.018)	(0.018)	(0.157)
Control	√	√	√	√
Firm FE	×	√	√	√
Year FE	×	√	×	×
Industry-Year FE	×	×	√	√
Observations	12,853	12,853	12,853	12,853
KP	44.55	44.52	43.93	40.32

Note: The table presents regression coefficients of augmented specification of equation ??. Controls lag information on firm capital, employment and machine investment. Standard errors clustered at firm level in parentheses. *,**,***denotes significant at the 10% , 5% and 1% level respectively.

Theoretical Abatement. Lastly, I measure the energy saving technology by firms by looking at what firm ought to emit per what they actually emit. One advantage of this measurement approach is that it allows us to capture a larger number of firms that report their emissions in our sample. I adopt a theoretically consistent measure of abatement by Rodrigue et al. (2020) as.

$$Abatement_{it} \equiv -\ln(1-\pi_{it}) = \ln\left(\frac{\mathrm{EFP}_{it}}{\mathrm{EFU}_{it}}\right) \tag{9}$$

Where π_{it} theoretically, captures the fraction of labour redirected to reduce firm-level emission. For our empirical purpose, abatement is captured as the log of emission generated from fuel production processes (EFP) per emission emitted from fuel use (EFU). It is worth noting that fuel production processes tend to change minimally, leaving little room for innovation in production methods. As a result, abatement technology primarily varies based on emitted emissions. Intuitively, this means that lower emission will be associated with greater abatement, ceteris paribus. The negative estimates observed in Table F.3 provide reassuring evidence in support of our main results regarding abatement investment, albeit with slightly smaller magnitudes.