

# Carbon Offshoring and Manufacturing Clean-up

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## Abstract

Manufacturing production in high-income countries is generally becoming cleaner, partly due to the adoption of advanced technologies. However, another contributing factor could be the outsourcing of carbon-intensive production, where dirty production processes are replaced by imports of carbon-intensive products from other countries. If so, this is concerning because it risks undermining climate policies by simply moving emissions to countries with laxer regulations. This is the focus of this paper. Leveraging rich Swedish firm-product level data between 2005-2014 and employing a combination of shift-share instrumental variables and a difference-in-difference estimation approach, I find a compelling paradox: a 10% increase in the import of emission-intensive goods can result in firms' production processes becoming 5% cleaner but increases transport emissions by 2%. This suggests that carbon imports does not only shift emissions elsewhere but also generates new ones (via transportation). Additionally, I show that the type of offshoring matters. For instance, foreign direct investment (FDI), has a much larger emissions-reducing effect than offshoring in the form of imports of inputs not produced in-firm.

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*Keywords:* Offshoring, Swedish Firms, Emissions, Shift-share, difference-in-difference

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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, even as production continues to increase. For instance, between 2007 and 2014, air pollution emissions from Swedish manufacturing firms fell by 29%, despite a substantial increase in the physical quantity of manufacturing output by about 70%. 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 explaining manufacturing cleanups: *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-emission-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 manufacturing firms’ clean-up.

In this paper, I seek to understand how the composition effect via carbon offshoring impacts manufacturing firms’ emissions. It is possible that, thanks to free trade, firms can now import polluting goods that they once produced domestically and concentrate domestic manufacturing on less environmentally penalized goods (Baumert et al., 2019; Jakob et al., 2022; Levinson, 2010; Nielsen et al., 2021). Although the concept of carbon offshoring is 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 within the current state of economic research.<sup>1</sup> The 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,<sup>2</sup> using country and industry-level data (Brunel, 2017; Copeland et al.,

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<sup>1</sup>Research in this area has yielded mixed results. Some studies have indicated that offshoring can lead to lower emissions by enabling firms to capitalize on lower energy costs and more advanced environmental regulations in other countries, whereas others have suggested that offshoring may not explain firms’ cleanup but rather that trade and import can lead to lower emission intensity by making firms productive (Cristea et al., 2013; Dussaux et al., 2023; Li and Zhou, 2017; Akerman et al., 2021; Shapiro, 2021).

<sup>2</sup>The pollution haven hypothesis (PHH) – also related to the concept of environmental policy arbitrage – is where a reduction in trade costs results in the production of pollution-intensive goods shifting towards countries with lower environmental standards (Copeland and Taylor, 2004; Copeland et al., 2022; Li and Zhou, 2017). Relatedly, the race-to-the-bottom (RTB) theory is when different countries or regions compete with each other in environmental regulations, or taxes, where they may reduce these standards and regulations to attract businesses and investments (Konisky, 2007; Porter, 1999). Both PHH and RTB are independently necessary but not sufficient conditions for carbon offshoring to hold (Copeland and Taylor,

2022; Levinson, 2010, 2023). However, this approach does not allow for refined identification, may introduce 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 take an advantage of a unique and detailed product-level information on production, trade, and emissions of approximately 3,300 Swedish manufacturing firms over the period from 2006 to 2014 to analyse how carbon offshoring causally changes firms' emission profiles. I combine several databases from the Statistics Sweden (SCB) and COMTRADE databases with three main objectives. First, I decompose the overall emission intensity within the Swedish manufacturing sector into scale<sup>3</sup>, technique, and composition effects.<sup>4</sup> Second, I show that compositional effects of offshoring manifest both at the *extensive* and the *intensive* margins.<sup>5</sup> Thus, for my empirical purpose, I begin by asking whether a significant difference exists in emission intensity of offshoring and non-offshoring firms using propensity score matching (PSM). The preliminary 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 proceed to my main specification where I analyze the *within-firm adjustment* of production processes due to shocks in carbon offshoring (at the intensive margin).

In practice, offshoring could occur through a variety of ways: (1) the import of carbon-intensive inputs, (2) the import of similarly produced goods with high carbon content, 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 emissions by firms, enables me to assess how changes in the import of emission-intensive goods and FDI affect a firm's emission intensity.<sup>6</sup> In so doing, this paper conducts a rich, heterogeneous analysis of the effects of offshoring on emissions, complementing the study by Akerman et al. (2021), who analyzed the impact of Swedish firms' import of intermediate goods on production-based emissions (CO<sub>2</sub>). Additionally, I estimate the quantitative effect of carbon offshoring on energy intensity and transport-based emissions, which is crucial for understanding the role of globalization in overall firm emissions.

Estimating the causal effect of carbon offshoring on firm-level emissions is, however, challenging because, in principle, unobserved technological shocks that lead to the adoption of energy-efficient technologies represent an alternative explanation to carbon offshoring. There-

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2004).

<sup>3</sup>Changes in emission due to changes in the size of the manufacturing sector.

<sup>4</sup>Contrary to similar decompositions by Shapiro and Walker (2018) and Copeland et al. (2022), which typically reveal a large technique effect, I find that, at the firm level, the composition effect is comparable to the technique effect.

<sup>5</sup>The *extensive* margin reflects the between-firm component of emission intensity due to changes in offshoring status whereas the *intensive* margin reflects within-firm changes in individual firms' emission intensities over time due to imports increases.

<sup>6</sup>By incorporating foreign emission intensity as a weighting factor for imports, I can effectively capture the environmental incentive behind firms' relocations toward emerging economies. This approach also allows me to directly quantify the tangible disparities in carbon intensities among the countries from which sourcing occurs.

fore, technological shocks can reduce emission intensity, as well as carbon import, leading to a 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.<sup>7</sup>

In the same spirit as [Hummels et al. \(2014\)](#), I generate two instruments that 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. My first firm-specific shift-share instrument uses world-wide shocks of intermediate inputs and firms' own-produced goods, which contain 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 investigates the role that differences in environmental policies between Sweden and its trading partners play in pollution offshoring. The assumption is that differences in environmental policies may be 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.<sup>8</sup>

I then construct a novel, firm-specific instrument based on the desirability of importing the emission-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 variations 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 products 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 dynamic difference-in-difference strategy

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<sup>7</sup>I use the 3-digit 5th revision of the Classification by Broad and Economic Categories (BEC-3 digits) to identify all inputs and own-produced goods crossing Sweden's border.

<sup>8</sup>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](#)).

using current-year-weighted foreign supply shocks as instrumental variables, while controlling for arbitrary industry-by-year trends (Barrows and Ollivier, 2021).

The main conclusions of the study are threefold. First, I estimate that in a year where the carbon content of input imports are 10% higher than usual for that firm, we would expect production-based CO<sub>2</sub> emission intensity (a global pollutant) and energy intensity to fall by 5.3% and 5.8% respectively. However, the elasticity is small when the type of good imported is semi-finished which is similar to firms' own-produced goods. Although there is a positive impact on average production-based emissions, my findings indicate that this is somewhat offset by an increased in transportation emissions. Therefore, it remains uncertain what the net effect on emissions will be. 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 policies – the effect being even more striking when offshoring occurs in low-income countries. Thirdly, I find that clean-ups 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, and multinational corporations via FDI concentrations. Interestingly, I find no carbon offshoring effect for firms regulated under the European Union Emission Trading Scheme (EU-ETS) and a shift towards cleaner manufacturing is not primarily driven by dirty firms. The findings that EU-ETS firms may not drive carbon leakage aligns with many ex-post studies evaluating the EU-ETS (Verde, 2020; Venmans et al., 2020; Neary, 2006).

As a last exercise, I conduct a series of tests to identify the mechanisms at play and find that carbon offshoring reduces overall operational costs, improves sales performance and increases firms' productivity growth. 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 impacts. 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 may be a substitute to investment in energy-saving technologies for large, multi-product firms due to its cost efficiency.

**Related Literature and contribution.** The paper makes three main contributions to the burgeoning studies on manufacturing cleanups (Brunel, 2017; Dussaux et al., 2023; Levinson, 2010; Leisner 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 the United States (Najjar and Cherniwchan, 2021; Levinson, 2010; Li and Zhou, 2017), extends to Sweden. Specifically, I add that carbon offshoring plays a role in reducing emissions at the firm level. In addition, I contribute to our understanding of how offshoring impacts both production-based and transport-based emissions. This paper is the first to estimate such elasticities and shows that, although production-based emissions fall as a result of carbon offshoring, this leads to a contemporaneous increase in transport emissions, suggesting that offshoring can mask firms'

overall environmental performance.

Second, this paper relates to micro-level papers on globalization and environment such as [Dussaux et al. \(2023\)](#), [Akerman et al. \(2021\)](#), [Leisner et al. \(2023\)](#), and [Choi et al. \(2023\)](#) who examined how trade openness and imports affect firm-level emissions. Generally, these papers provide a nuanced perspective on how trade shocks affect imports and import competition and how these translate to firms' reduced emissions via productivity gains, improved abatement, and technology. Closely related to [Dussaux et al. \(2023\)](#), this study quantifies the carbon offshoring channel of trade shock on emissions. However, I use a unique empirical setting (Swedish firms) and a rich product-firm-level dataset to examine whether the elasticity of CO<sub>2</sub> 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.<sup>9</sup> Specifically, I find that carbon offshoring through input reallocation leads to a larger reduction in emissions compared to in-house offshoring through the substitution of a firm's own-produced goods, which are typically semi-finished products with lower carbon content. In line with [Akerman et al. \(2021\)](#) and [Kwon et al. \(2023\)](#), the findings also reveal that dirty imports do not entirely account for the improved environmental impact. Instead, the importation of inputs may also contribute to the reduction of emission intensities, suggesting that globalization conflates carbon offshoring, importing, and exports. To concretize the idea of the migration of dirty firms abroad, I examined the concentration of multinationals' FDI in countries with less stringent environmental policies and their import of dirty inputs with foreign affiliates.<sup>10</sup> I find that vertical FDI exists and 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.<sup>11</sup> The study shows that where these dirty imports are coming from or where dirty firms migrate to is crucial in firms' carbon offshoring activities and the 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 policies – 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,

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<sup>9</sup>While prior research has primarily focused on imported inputs, theoretical studies on offshoring predict that offshored tasks 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 clean-up.

<sup>10</sup>See e.g. [El-Sahli et al. \(2022\)](#) and [Hummels et al. \(2018\)](#) for discussions of measurements and definitions of offshoring via FDI.

<sup>11</sup>That is, differences in environmental policies.



this is the first paper to provide a 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 large literature on productivity, abatement and firm-level emissions ([Bernard et al., 2007](#); [Bustos, 2011](#); [Cui et al., 2016, 2012](#); [Forslid et al., 2018](#); [Holladay, 2016](#); [Kwon et al., 2023](#); [Rodrigue et al., 2020](#); [Tybout, 2001](#)). Mostly, this body of literature finds no evidence of a pollution-haven effect. For instance, [Forslid et al. \(2018\)](#) finds an anti-pollution haven effect for exporting firms using Swedish data. 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.<sup>12</sup> 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. This study also extends our understanding of the implications of trade and environmental policies on firms by examining rich heterogeneity across different firms and industries. I demonstrate that carbon offshoring is a concern for multinational firms, non-EU-ETS firms, and multi-product firms.

**Roadmap.** The remainder of this paper is organized as follows. Section 2 presents the data and measurement issues. Section 3 documents some basic facts and the 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 on the major heterogeneity responses in section 7. In section 8, I examine mechanism the underlying offshoring on emissions intensity. Section 9 then concludes the study.

## 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)<sup>13</sup>. 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

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<sup>12</sup>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](#)).

<sup>13</sup>I use this UN COMTRADE data exclusively for my instrumental variable identification which requires yearly data on the world export supply from source countries

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<sup>14</sup> 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<sup>15</sup>, during which energy data are available. However, most firms do not report their environmental emissions, leading to many missing observations (see B.1). Instead, 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<sub>2</sub> emissions (tons)) using a fuel-specific CO<sub>2</sub> coefficient<sup>16</sup> as :

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

where  $e_f$  represents the emissions of pollutant  $f$ ,  $x_j$  stands for the quantity of fuel type  $j$ , and  $\alpha_j$  denotes the fuel-specific CO<sub>2</sub> coefficient. Each emission of pollutant is then aggregated for firm  $i$  as  $E_i$  for each year (for a similar measurement, see studies by Forslid et al. (2018) and Barrows and Ollivier (2021))<sup>17</sup>. 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 environmental performance, namely, energy consumption. The energy consumption metric uses the heat value (calorific value) released by fuel during its combustion, which is readily available for all energy type. The energy consumption is distinct from CO<sub>2</sub>, as it has no cross-border impact, primarily affecting the local environment.<sup>18</sup> CO<sub>2</sub> emission on the other hand, is a global pollutant because CO<sub>2</sub> emissions have a transboundary effect in that CO<sub>2</sub> 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 the firm level and its eventual effect on both local and global pollutants.

<sup>14</sup>The energy consumption includes fuel, electricity, coal, gas, and other energy types

<sup>15</sup>For my empirical analysis I keep the sample from 2006 to 2014. I use 2005 as my pre-sample year.

<sup>16</sup>Note that these factors do not include the life-cycle of emissions.

<sup>17</sup>Since I have access to energy data on firms' fuel used for transportation, I similarly generate values for emissions due to transportation.

<sup>18</sup>Energy consumption is more localized and varies substantially with the use of dirty sources of energy such as coal, oil, shale gas (fracking), and natural gas (Parry et al., 2014).



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 sales (similar to [Holladay 2016](#), [Rodrigue et al. 2020](#) and [Barrows and Ollivier 2021](#)). I also adopt output<sup>19</sup>-based emission intensity for robustness checks. The difference between these two measures is that, although 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](#)).<sup>20</sup>

## 2.2 Production, Trade data, and Measures of Offshoring

I merged the energy and pollution data to three other databases obtained from SCB. Firstly, from the Production of Commodities and Industrial Services (IVP) database, I obtain annual information detailing production quantities and values at the 8-digit product levels of approximately 6,200 Swedish manufacturing firms. These firms are privately owned and employ at least 20 individuals. Secondly, I obtain trade data from the International Trade in Goods (ITG) database, which offers comprehensive country and product trade details for all Swedish firms, covering import and export values and quantities at the 8-digit product level. I combined the trade data with data on outward FDI measured in terms of employment and sales in affiliate countries. The trade data covers the periods from 1997 to 2014. However, due to the starting date of my emission data, I restricted the sample period to run from 2005 to 2014. I also narrowed the sample to NACE (Rev.2) 2-digit manufacturing industries (codes 10 to 33) since the import data primarily stems from manufacturing firms, which are also typically more polluting (see e.g. [Copeland et al. 2022](#)). Studies such as [Shapiro \(2021\)](#) found that dirty manufacturing industries are more trade-exposed as they tend to have lower tariffs and non-tariff barriers. The last database I use for this study stems from the Structural Business Statistics database (FEK), which provides various firm-level variables including number of employees, industry classi-

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<sup>19</sup>In physical quantities.

<sup>20</sup>For example, a  $\frac{\text{high quality shoe}}{\text{price(SEK)}}$  with the same unit of emission requirements has no significant impact on environment relative to a  $\frac{\text{low quality shoe}}{\text{price(SEK)}}$ .

fication, and balance sheet metrics like sales, assets, and investments. For the study sample, I retained only active firms who have positive sales in the sample period. About 3,300 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 intermediate 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 concordance 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% 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 (Dussaux et al., 2023). To do this, I first compute the emission intensity of each sector in foreign country using data on total emissions and production.<sup>21</sup> I compute emission intensity in foreign country as:

$$EI_{cjt} = \frac{E_{cjt}}{Y_{cjt}}.$$

where  $E_{cjt}$  is the total CO<sub>2</sub> emissions from fuel combustion of sector  $j$  in country  $c$  for year  $t$ ,  $Y_{cjt}$  is total real output of sector  $j$  in country  $c$  for year  $t$ . This study departs from the conventional reliance on the World Input-Output Database (WIOD) by utilizing the Eora Global Supply Chain Database (EGSCD), which provides a Multi-Region Input-Output (MRIO) framework to model industry-level emissions and production in source countries. The Eora database offers two significant advantages over WIOD: broader coverage and superior temporal and sectoral

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<sup>21</sup>Note: ideally, one requires product  $\times$  firm  $\times$  industry  $\times$  country pollution intensity to generate the emission content of each imported input from source countries. However, I do not have access to the source countries’ pollution intensity at product and firm level. As a standard practice in the literature, I use industry-based emission intensity as a proxy for emission intensity of these imported goods (Levinson, 2010; Li and Zhou, 2017).

standardization. While WIOD is constrained by its limited country coverage and emissions data spanning only 1995–2009, Eora encompasses comprehensive historical emission and production data for all countries, with detailed sectoral disaggregation, from 1970 to 2023. This extended temporal and geographical scope enables a more precise assessment of the environmental life cycle and carbon footprint of international trade.

Then, I calculate the emissions embodied in imported inputs as the weighted sum of each firm’s import and industry emissions. That is,

$$CarbImp_{it} = \sum_p \sum_c M_{ict,p \in j} EI_{ct,p \in j}$$

where  $EI_{ct,p \in j}$  is the total emissions intensity (i.e., tons of CO<sub>2</sub> per unit of real output) of product  $p$  of sector  $j$  in sourcing country  $c$ , while  $M_{ict,p \in j}$  is the imported quantity of firm  $i$  of products  $p$  of sector  $j$  from sourcing country  $c$ .

### 2.3 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

**Firm 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) of CO<sub>2</sub> emissions and contribute to around 26.21 (tons) of energy-use. The average transportation CO<sub>2</sub> and energy-use is 1.46 (tons) and 0.26(tons), respectively. All the median values on emission are lower than the average suggesting that emissions are rightly skewed and highly concentrated among few firms. By tracking the evolution of emissions over the sample period, I observe 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).

**Emission Intensity Gap.** Figure 1 Panel A highlights a well-documented phenomenon: the emission intensity of high-income countries, such as Sweden, is significantly lower than that of low-income countries. This disparity stems from several factors, including stricter environ-

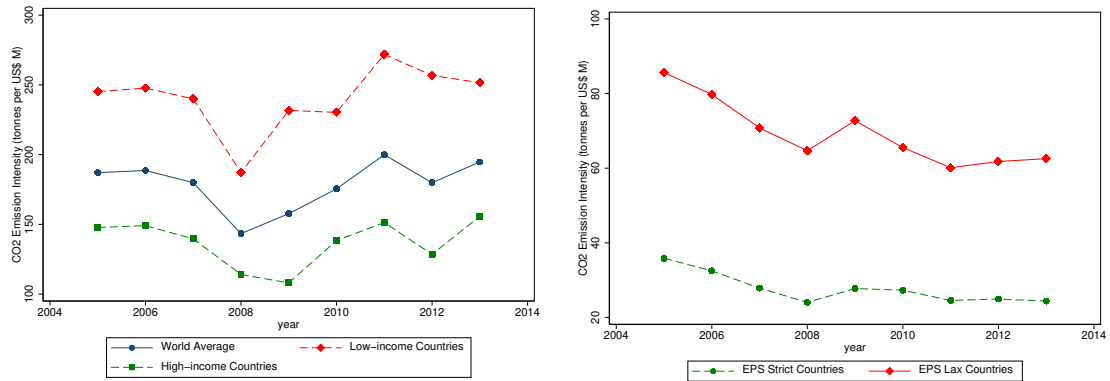
Table 1: Summary Statistics

	N	Mean	Std. dev	Min	10th perc.	Median	75th perc.	Max
CO <sub>2</sub> (tons)	26,092	1401.72	10489.98	0	10.96	73.47	252.48	467420.4
Energy(tons)	26,092	26.21	226.83	0	0.19	1.24	4.29	13284.57
Transport CO <sub>2</sub> (tons)	26,092	1.46	8.61	0	0	0	0.47	422.35
Transport Energy (tons)	26,092	0.26	1.54	0	0	0	0.08	77.53
CO <sub>2</sub> (tons) per sale(SEK)	26,092	0.003	0.024	0	0.0002	0.001	0.002	1.65
Energy(tons) 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. CO<sub>2</sub> intensity is calculated as total CO<sub>2</sub> emissions over sales. All nominal variables are in SEK and 2006 prices.

mental regulations (see Figure 1, Panel B), greater adoption of cleaner technologies, and more energy-efficient production processes in developed economies. In contrast, many low-income and developing countries rely heavily on carbon-intensive energy sources, such as coal, and operate under weaker environmental standards. For Swedish firms operating under stringent domestic environmental regulations and high carbon taxes, importing goods from these countries allows them to access cheaper inputs while adhering to domestic sustainability standards by outsourcing emissions to foreign producers.

Figure 1: Trend of emission intensity by income groups and level of environmental laxity



#### A. Low vs High Income Countries

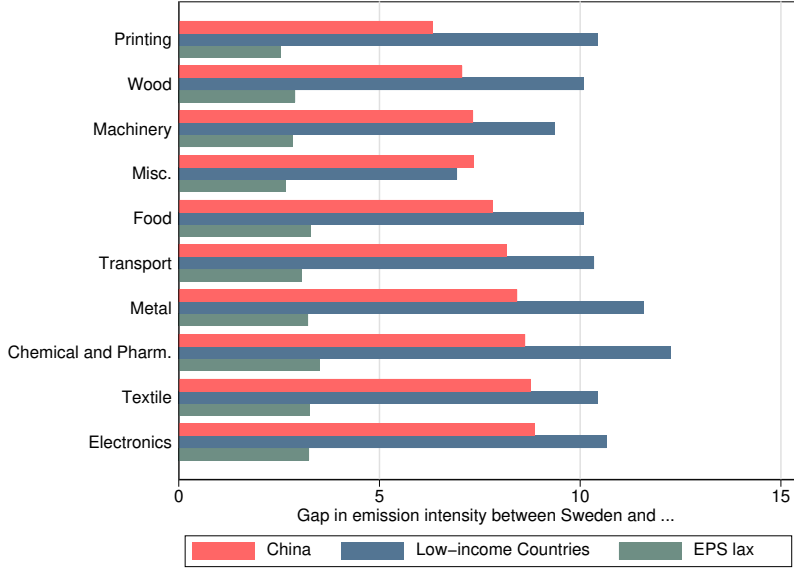
#### B. EPS Lax vs EPS Strict Countries

*Note:* This figure plots the yearly CO<sub>2</sub> emission intensity (in tons per millions of US\$). Low income countries includes lower middle income countries identified by the World Bank. EPS Lax and Strict countries are identified using the EPS index (see Appendix D).

Figure 2 also reinforces the substantial sectoral gaps in emission intensity between Sweden and key trading partners such as China, low-income countries, and EPS-lax countries. On average, Sweden is about eight times carbon efficient compared to China, 10 times more efficient

to an average low-income country, and 4 times efficient to countries with laxer environmental policies compared to Sweden. Energy-intensive industries, including metals, transport, and chemicals, show particularly large gaps, indicating that production in these sectors is significantly more carbon-efficient in Sweden. However, the higher relative cost of maintaining such efficiency domestically may incentivize Swedish firms to offshore production or import intermediate goods from countries where emission-intensive production remains more cost-effective. Sectors like textiles and electronics, which are less energy-intensive but involve complex supply chains, also show significant gaps, further supporting the case for global outsourcing. It therefore seems that, differences in environmental policies may not be the main drivers of emission intensity gaps. Trade openness may also offer an opportunity for very large polluters with little room for innovation to resort to carbon intensive imports to reduce their emissions to the home regulation level.

Figure 2: Sectorial Gap in emission intensities



**Decomposition of Swedish Emission.** To understand the role of trade on emissions, I decompose the manufacturing CO<sub>2</sub> 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 sectors towards less pollution-intensive industries – composition effect.<sup>22</sup> More formally, the CO<sub>2</sub> emissions from the manufacturing sector in year  $t$ ,  $E_t$  can be written as follows:

$$E_t = \sum_j E_{j,t} = \sum_j v_{j,t} z_{j,t} = V_t \sum_i \theta_{j,t} z_{j,t} \quad (2)$$

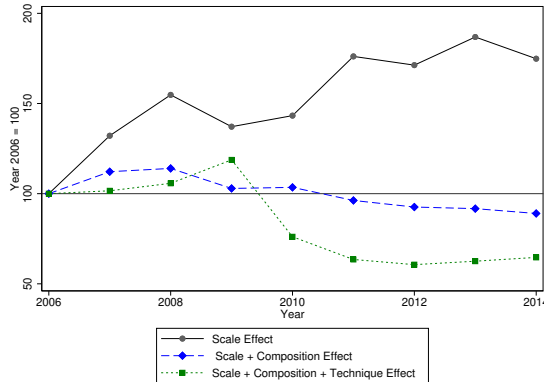
<sup>22</sup>My working assumption, as motivated by Copeland et al. (2022) and Choi et al. (2023) is that an increase in physical unit of output (and monetary value of output) does not scale 1-to-1 with emissions because, firm adjust their production processes which can affect emissions and value added. Subsequently, I follow the decomposition exercise of Choi et al. (2023); Copeland et al. (2022); Ustyuzhanina (2022).

where  $j = 1, \dots, n$  indexes manufacturing industries (defined at SIC 4-digits).  $V_t$  is the manufacturing monetary value of output,  $\theta_{j,t}$  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 CO<sub>2</sub> emissions in a particular year is the scale of the sector times weighted emission per monetary value of output ( $V_t \sum_i \theta_{j,t} z_{j,t}$ ) – where  $\theta$  and  $z$  are  $j \times 1$  vectors containing the output shares of each of the  $j$  sectors and their emissions intensities, respectively. Equation 2 can be rewritten in a vector notation form as  $E = V\theta'z$ . By applying a total differentiation on the vector notation, I obtain:

$$dE = \underbrace{\theta'z dV}_{\text{scale}} + \underbrace{Vz' d\theta}_{\text{composition}} + \underbrace{V\theta' dz}_{\text{technique}} \quad (3)$$

The three terms on the right-hand side in equation 3 can be interpreted as the 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 3 illustrates the results of decomposition, tracking changes in total manufacturing emissions of CO<sub>2</sub> relative to the year 2006. I observe that the aggregate decline in CO<sub>2</sub> emissions from manufacturing firms is driven by within-industry adjustments and technologies. The black line isolates the change attributed to the scale factor, whereas the 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<sub>2</sub> emissions. The gap between the black line (scale) and green line (composition) suggests a huge impact of composition effect on emissions over time. Without the composition, emissions would have trended upwards. Lastly, the green line, which represents the aggregate change in emissions, shows a declining trend in total manufacturing emissions of CO<sub>2</sub> emissions over time. Thus, the residual effect represents the contribution of the technique effect, which also accounts for the substantial effect of the decline in CO<sub>2</sub> emissions over time.

Figure 3: Decomposition of Aggregate Manufacturing Emissions



Note: The graph illustrates changes in the aggregate manufacturing CO<sub>2</sub> 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 the composition effect and the distance between all three lines, shows the magnitude of the composition and technique effects, respectively. All emission values are normalised to 1 in 2006.



Overall, I observe that despite a substantial increase in manufacturing output (in monetary value), air pollution emissions from Sweden manufacturing firms fell by 29% (see Figure B.3).<sup>23</sup> This crucial contribution of the 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<sub>2</sub>.<sup>24</sup> 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 to lower their emissions through the use of cleaner technologies, the reduction in emissions also reflects the composition of net trade flows across industries. The impact of the 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.<sup>25</sup> Take, for example, a multi-product firm  $i$  who produces final goods  $p = 1 \dots n$  (e.g., iWatch, iPhone etc.) and uses intermediate inputs  $j = 1 \dots n$ , where  $p \neq j$  (e.g., Tin, beryllium, mercury, phthalates etc.). 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 emission-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). To circumvent such environmental penalties, firms may choose to import these emission-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 emission-intensive production and a more lenient environmental regulatory framework can offer a cost-effective solution.

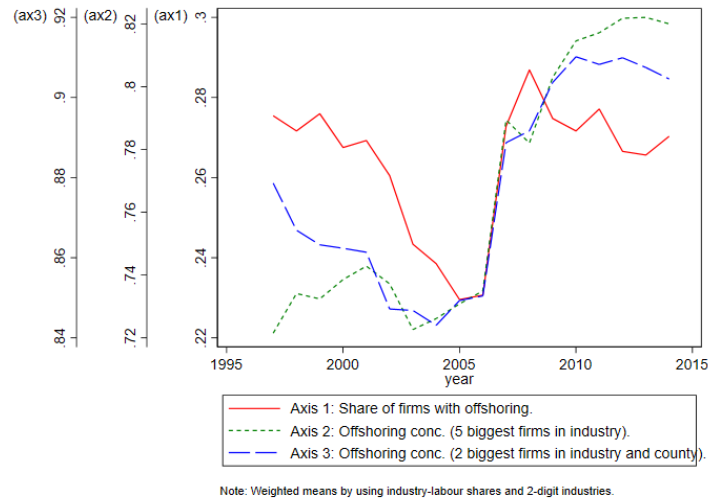
**Concentration of Carbon offshoring.** To give a rich background on the historical trends and changes in offshoring, I show the concentration of carbon offshoring within 2-digit industries between 1997 to 2015. I use these periods because the trade data go back to 1997, and I have

<sup>23</sup>Firm value added, on the other hand, is observed to fall (see Figure B.4). The difference is that outsourcing plays a significant role in manufacturing production processes, resulting in a decline in firm-level value added due to the cost associated with importing intermediate goods from abroad

<sup>24</sup>See <https://carbonpricingdashboard.worldbank.org/>

<sup>25</sup>The 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, because low-income countries have low-cost energy input, they may attract "dirty" firms, leading to the migration of dirty firms. Hence, firms are making strategic cost-benefit decisions about production and profit. It is also possible that offshoring leads to the technological transfer to low-income countries and hence improves their carbon-efficiency. This analysis is, however, outside the scope of this paper due to data limitation.

Figure 4: Within Sector Allocation

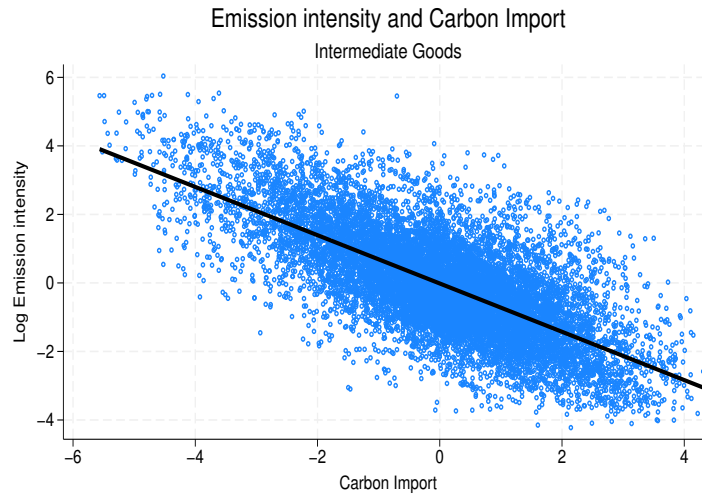


*Note:* This figure provides insights into the pollution offshoring patterns at the sector level by illustrating the concentration of offshoring within 2-digit industries. The concentration is measured in terms of the offshoring share represented by: (i) the offshoring activities of all firms engaged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

enough sample years to create pre-sample product shares for my empirical purpose. Figure 4 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 2006. However, this share gradually increased from 2006 (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. This also suggests that after 2005, the offshoring trends have been stable within sectors which is crucial for the construction of my instrument.

**Correlation between carbon offshoring and emission intensity.** As descriptive evidence, I show the correlation between carbon content of intermediate import and emission per sales (all in logs). I relate the initial trade carbon import to changes in CO<sub>2</sub> emissions. Figure 5 depicts a clear negative correlation between carbon import and CO<sub>2</sub> emission intensity with a firm. The subsequent session details how I isolate the carbon offshoring effect on the manufacturing firm clean-up.

Figure 5: 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 suggests that carbon offshoring is related to lower firm emission intensities.

## 4 Empirical Strategy

**Extensive Margin and Between Effect.** I begin with a preliminary empirical pattern of the difference in emission intensity between carbon offshoring firms and non-offshoring firms.<sup>26</sup> Such empirical investigation is challenging to test and infer causally.<sup>27</sup> This is because, 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. However, to reduce endogeneity concerns, 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; however, the firms in this group did not relocate their production activities abroad during the period 2006-2014.

First, I match all firms that engage in offshoring to those that do not using propensity score matching. The assumption is that if – conditional on observable covariates (e.g., firm revenue, fixed assets, number of employees, machine investment, productivity, and capital stock)<sup>28</sup> – two firms have the same probability of offshoring, then they have similar propensity scores, and all remaining variation in offshoring is due to chance.<sup>29</sup> Thus, insofar as the two firms A and B

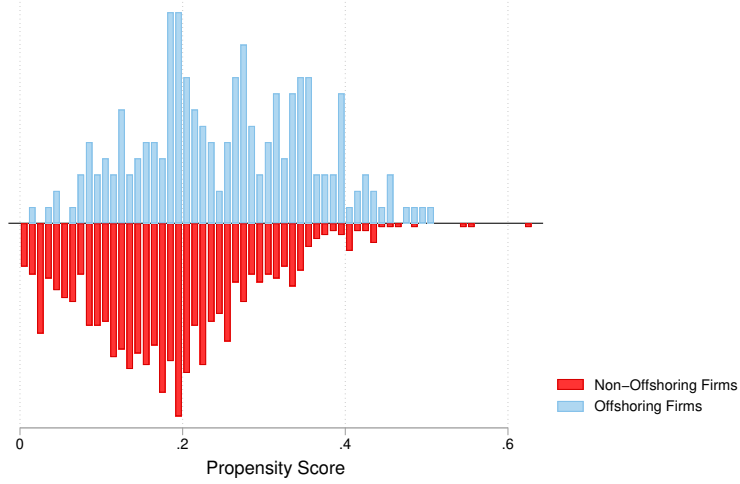
<sup>26</sup>Offshoring firms are firms that reduce their carbon-intensive products while increasing the import of carbon contents of inputs. In other words, if a firm's imports of carbon content of input increases in time  $t$ , while at the same time, the production of carbon content of products (at firm level) falls, I identify such firm as an offshoring firm. I include the production dimension to assess firms that are changing their production processes. By this definition, firms can appear at different year ( $t$ ) in my sample. However, I drop firms who change their offshoring status, once they are initially identified as an offshoring firm.

<sup>27</sup>I, therefore, offer a descriptive evidence of how offshoring firms may differ from non-offshoring firms in terms of emission intensity and do not make a causal claim at the extensive margin

<sup>28</sup>See Table C.1 for the before and after the matching descriptive statistics.

<sup>29</sup>For this empirical purpose, I do not use 1-to-1 matching due to power issues, and I do not claim to

Figure 6: Propensity Score Distribution



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

have the same propensity score, but one offshores and the other does not, and the conditional independence assumption credibly holds, then differences between their observed emissions are attributable to offshoring (see e.g. [Cunningham 2021](#)). The matching must satisfy the common support assumption, which requires the existence of both offshoring and non-offshoring firms across the estimated propensity score. In Figure 6, I show the common support test after matching offshoring and non-offshoring firms. The result is reassuring that the matched firms undergo comparable regulatory environments and are comparable in terms of economic conditions. Subsequently, I estimate the following regression:

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

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 which is equal to 1 if firms offshore, and 0, if otherwise. Therefore, the sample for this analysis includes both importing and non-importing firms. To ensure a higher level of similarity between offshoring and non-offshoring firms, I use a caliper of 0.85.<sup>30</sup> This means, I sacrificed a larger sample size for a more focused and relevant comparison. In other demanding specifications, I include both firm fixed effects ( $\theta_i$ ) and industry-year fixed effects ( $\theta_{kt}$ ) to control for broad changes in demand of different sectors.

**Intensive Margin and Within-Firm Adjustment.** Next, I turn my attention to how firms adjust their production processes with an increase in carbon imports. In particular, I estimate

have included all important variables determining offshoring status; rather, I include fixed effects to reduce the bias.

<sup>30</sup>However, some offshoring firms are excluded from the matched sample because no closely resembling firms can be found. Specifically, I used a pre-determined range of values defined within 0.85 radius of the estimated propensity. Any values that fall outside that range are removed.

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.

$$\ln(EI_{it}) = \alpha_1 \ln \text{CarbImp}_{it} + Z_{it}\beta + \theta_i + \theta_{kt} + \theta_{mt} + \epsilon_{it} \quad (5)$$

where  $\ln(EI) \in \{\text{global pollutant, local pollutant}\}$  is the logarithmic transformation of the emission intensity of firm  $i$  at time  $t$ . The primary variable of interest  $\ln \text{CarbImp}$  is the emission content of import of intermediate input, reflecting (dirty) input reallocation.<sup>31</sup> I estimate the model pollutant-by-pollutant in order to explore the relationship between carbon imports and emission intensity among firms emitting the same pollutant and within the same industry, as captured by the parameter of interest  $\alpha_1$ .

**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 firms' energy efficiency. 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 emission intensity through the adoption of energy-saving technologies. As Dussaux et al. (2023) argued, 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,  $\alpha_1$ , is negative, we expect the bias to be toward zero, which will be amplified by the standard attenuation bias due to a measurement error in imported emissions.<sup>32</sup> Overall, I expect the OLS estimate of  $\alpha_1$  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

<sup>31</sup>Import quantities are expressed in logs for easy interpretation (elasticities) and makes the results more robust to extreme values.

<sup>32</sup>Carbon offshoring activities may be measured with some degree of error because 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.

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 can construct the instrument using pre-sample<sup>33</sup> information about firms’ purchases of inputs. This eliminates any contemporaneous shocks due to technology that can affect both the types of 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).<sup>34</sup> That is,

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

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 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 the ROW. That is,

$$Shock_{it}^{Lax} = \sum_{p \in i} \bar{E}_{jc,t < t_0} \bar{M}_{ip,t < t_0} \times \underbrace{\frac{Exports_{pt}^{Lax}}{Exports_{pt}^{World}}}_{\text{Lax comparative advantage}} \quad (7)$$

The major question of validity is whether the instrument is relevant, the exclusion restriction holds and any errors in offshoring activities are independent.<sup>35</sup> The instrument assumes that changes in the export supply of intermediate inputs and produced-goods in other countries, is a

<sup>33</sup>The pre-sample year used for my empirical analysis is 2005.

<sup>34</sup>I exclude these countries to mitigate the possibility of picking up local or regional demand shocks instead of supply shocks. 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)

<sup>35</sup>If errors are independent, then I expect the IVs will eliminate attenuation bias due to measurement error. If not, then the IV estimates may be biased towards the OLS.



good predictor of firms' 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 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 expected, imports of inputs is positively correlated with the export shock and initial mix of imports (i.e., the instrument's share component). The instrument's strength is consistent with two well known facts of the Sweden trade 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*** (0.025)	0.378*** (0.018)	0.364*** (0.013)	0.387*** (0.032)				
PG export shock					0.455*** (0.004)	0.429*** (0.008)	0.421*** (0.001)	0.428*** (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: These data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. 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 the pre-sample share of products to make sure 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. \*, \*\*, and \*\*\* denotes significance at the 10% , 5% and 1% levels respectively.

The exclusion restriction requires that the components of export shocks are independent of shocks in the Swedish economy, as well as on firms' forward-looking behaviour . 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 [Borasyak et al. \(2022\)](#). My second approach is to condition offshoring on a number of factors including domestic energy prices (a proxy for domestic environmental policy).<sup>36</sup> I show that offshoring and energy price are quite

<sup>36</sup>I adopt a similar shift-share-style instrument for firms' energy prices. 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

independent in explaining variation in firm emission.<sup>37</sup> Lastly, in some specifications I account for the possibility of these 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 7 reveals a preliminary pattern suggesting that firms engaging in offshoring activities tend to have lower levels of CO<sub>2</sub> emissions and energy-use per unit of sales compared to firms that do not participate in offshoring. However, when I measure emission intensity by calculating emissions per unit of physical 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 results statistical power. In addition, note that in my matching approach, I sacrificed a larger sample size for a more focused comparison to draw a 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, the coefficients for both OLS and IV estimates are negative, suggesting that firms environmental performance improves with an increase in carbon offshoring activities. This aligns 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.<sup>38</sup>

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 discussions by Dussaux et al. (2020), Marin and Vona (2021) Sato et al. (2019), and Goldsmith-Pinkham et al. (2020)). Specifically:

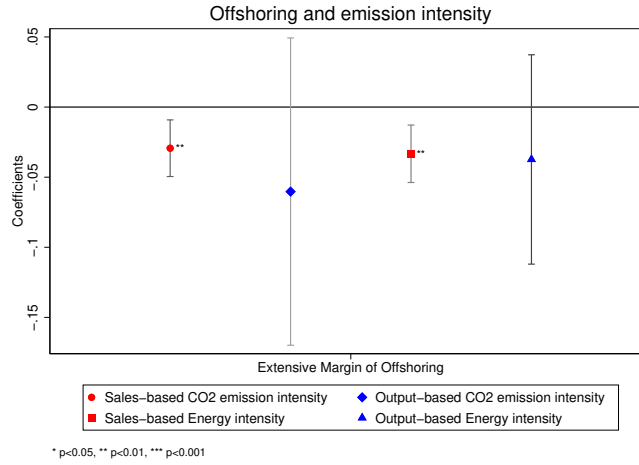
$$EP_{it}^{IV} = \sum_{j=1}^n \omega_{i,t=t_0}^j p_{st}^j.$$

For each firm, industry price variations are a 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, 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 mitigate concerns about reverse causality and simultaneity biases due to the adoption of technologies.

<sup>37</sup>In tandem with the literature, the energy price in the model reflects the role of the inducement effect of climate policies on emission intensity relative to the role of offshoring (Dussaux et al., 2020)

<sup>38</sup>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. To streamline and enhance clarity, 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

Figure 7: Offshoring Firms and Emissions



*Note:* The figure illustrates the estimated coefficients obtained from regressing the offshoring dummy variable against CO<sub>2</sub> emission intensity and energy intensity. Offshoring firms are firms that increase in the import of pollution-intensive inputs while simultaneously decreasing the production of such inputs. Thus, the sample for this analysis includes firms who import and those who do not import. The emission intensity is computed by dividing emissions by the value of sales (represented by red points) and by physical units of outputs (represented by blue points). All regressions incorporate firm fixed effects and industry-year fixed effects to account for potential confounding factors.

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 due to the low cost of offshoring<sup>39</sup>, 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<sub>2</sub> emission intensity is in line with the findings by Li and Zhou (2017) and Dussaux et al. (2023) who used data on the U.S. and French manufacturing industry, respectively.

In Columns 4 and 8 of Table 3, I include energy prices to capture the role of the inducement effect via domestic environmental policy (see Dussaux et al. (2023); Levinson (2010); Shapiro and Walker (2018)). The results show that for a given firm, in a year where the carbon content of input import is 1% higher than it typically is for that firm, then we would expect CO<sub>2</sub> emission and energy intensity to fall by 0.53% and 0.58% respectively. However, the inducement effect via energy prices will lead to about 0.43% and 0.44% reduction in CO<sub>2</sub> emission and energy intensity. These findings suggest two key implications. First, offshoring has a greater impact

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 columns 2 and 3, I find that without these controls, the estimates of the offshoring effect will be slightly larger, suggesting upward bias.

<sup>39</sup>The IV estimates capture what is termed the local average treatment effect (LATE) and do not capture a global effect (Angrist and Pischke, 2008).

Table 3: Carbon Offshoring and Firms Environmental Performance

	CO <sub>2</sub> emission intensity				Energy intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Carbon Import	-0.297*** (0.037)	-0.614** (0.259)	-0.518** (0.262)	-0.533*** (0.188)	-0.290*** (0.032)	-0.629*** (0.217)	-0.529** (0.225)	-0.576*** (0.191)
Energy Price				-0.429*** (0.027)				-0.442*** (0.027)
Control	✓	×	✓	×	✓	×	✓	×
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Municipal-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Estimation	<b>OLS</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>	<b>OLS</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>
Observation	20,960	20,960	20,960	20,960	20,967	20,967	20,967	20,967
KP		137.09	91.39	92.04		137.21	92.67	93.34

Note: The table presents a series of regression coefficients for different specifications 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. The data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. Standard errors are clustered at firm level in parentheses. First-stage regressions yield highly significant coefficients for the relevant instruments and the reported KP-Statistics. \*, \*\*, and \*\*\* denote significance at the 10%, 5% and 1% level respectively.

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.

## 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 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 shocks. To overcome this empirical issue, I follow Barrows and Ollivier (2021) by employing a dynamic 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 to and after the export shocks. In particular, I run the following regression:

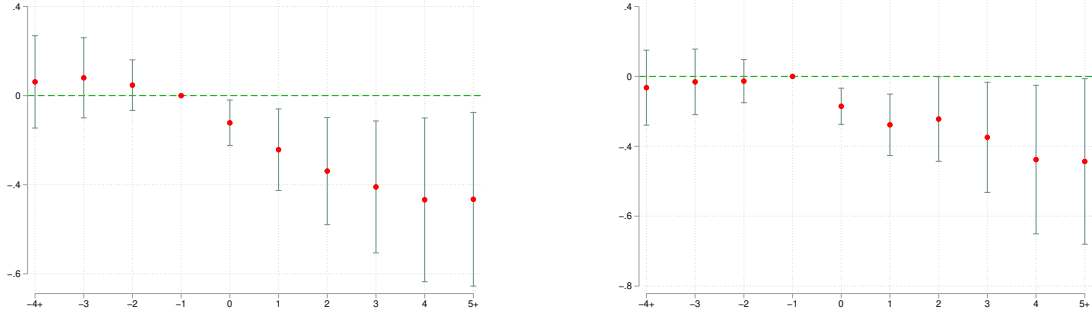
$$\Delta EI_{it,t-1} = \gamma_{st} + \sum_{m=-G}^M \beta_m \Delta CarbImp_{it-m,t-1-m} + Z'_{it} \psi + \varepsilon_{it} \quad (8)$$

where the outcome variable  $\Delta EI_{it,t-1}$  represents the firm-level emission intensity growth rate between  $t$  and  $t - 1$ . I instrument each  $\Delta CarbImp_{it-m,t-1-m}$  using  $Shock_{it-m,t-1-m}$ . I normalize  $\beta_{-1} = 0$  so  $\beta_m$  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  $\gamma_{st}$ . 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 the cumulative long-run impact of carbon offshoring on emissions.

I present the results in Figure 8. In both Panels 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 energy 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 ( $\beta_m = -1 \dots -4$ ) 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.

**In-house offshoring.** 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 the firm-level and industry-levels is rather imported by firms, I refer to this as *in-house offshoring*. Figure B.5 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. Typically, these imports are semi-finished goods and contain low carbon emissions. Consistently, I find that the point estimates for carbon offshoring through firm imports of own-produced goods are relatively smaller. Also, in contrast to the import of toxic inputs, the import of own-produced goods only exerts a short-term effect. The results indicate that

Figure 8: **Dynamic Effect: Carbon offshoring and Firms' Environmental Performance**



A. Carbon Import and CO<sub>2</sub> intensity

B. Carbon Import and Energy intensity

*Note:* Estimates of coefficients  $\beta_m$  for  $m = -4, \dots, 5$  from equation 8 are reported graphically. I normalize  $\beta_{-1} = 0$  so  $\beta_m$  is in normalized differences. Panel A. reports these coefficients for input import and CO<sub>2</sub> emissions intensity, and panel B. for input import and Energy intensity. The x-axis represents the value of  $m$ , the dots the point estimates of  $\beta_m$ , and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous carbon offshoring is instrumented by export supply shocks weighted by pre-sample shares of imports and energy mix. Here, I used a balanced sample spanning the period 2006-2014. Standard errors are clustered at the firm-level. Kleibergen-Paap rk LM statistics range from 50.25 to 74.34.

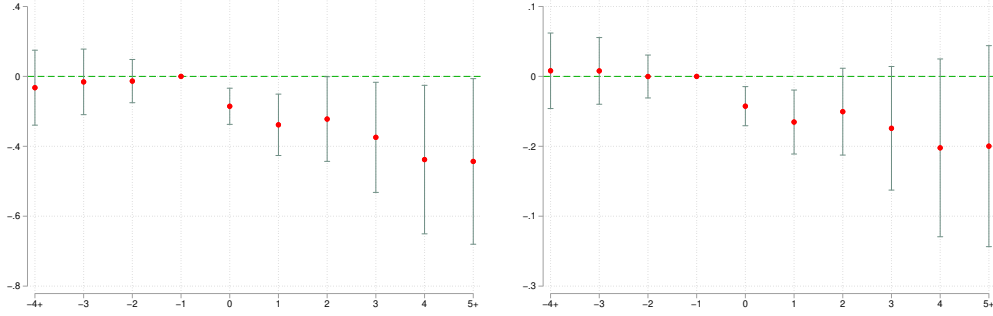
although there is a significant reduction in emissions in the short run as a results of in-house offshoring, the effect becomes noisier after the third year (Panel B of Figure 9). This result suggests that firms engaging in importing similar goods they produce do not offshore much local pollution abroad. 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 lower emission intensity through the reallocation of dirty inputs rather than importing their semi-finished goods.

**Import Competition and Value added.** 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 (Leisner 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 C.2, 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.2, Panels B and C, respectively.

Consistent with Akerman et al. (2021), the results indicate that imports of intermediate goods reduce emission intensity among Swedish manufacturing firms, although this effect appears modest relative to the broader impact of carbon offshoring. One explanation for these



Figure 9: **Dynamic Effect: In-house offshoring and Firms' Environmental Performance**



A. In-house offshoring and CO<sub>2</sub> intensity    B. In-house offshoring and Energy intensity

*Note:* Estimates of coefficients  $\beta_m$  for  $m = -4, \dots, 5$  from equation 8 are reported graphically. I normalize  $\beta_{-1} = 0$  so  $\beta_m$  is in normalized differences. Panel A. reports these coefficients for in-house offshoring and CO<sub>2</sub> emissions intensity, and B. in-house offshoring and Energy intensity. The x-axis represents the value of  $m$ , the dots the point estimates of  $\beta_m$ , and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous carbon offshoring is instrumented by export supply shocks weighted by pre-sample shares of imports and energy mix. Here, I used a balanced sample spanning the period 2006-2014. Standard errors are clustered at the firm-level. Kleibergen-Paap rk LM statistics range from 50.25 to 74.34.

differing estimates could be methodological, as my use of firm sales as the denominator for firm-level emission intensity contrasts with previous studies. To validate, I replicate the approach in [Akerman et al. \(2021\)](#), substituting emissions per value added in Table 4. If carbon offshoring is not driving manufacturing cleanup, then we should expect an increase or no significant results in emissions per value added. However, adjusting imports by their embedded carbon content reveals that carbon-intensive imports contribute a greater reduction than anticipated, suggesting that firm-level emissions reductions may indeed be influenced by offshoring, in contrast to findings that attribute changes in emissions intensity purely to competitive dynamics.

These findings suggest that import patterns could mask underlying carbon offshoring behavior, albeit with a less pronounced effect. To disentangle these forces more precisely, additional variation linked to pollution-intensive production advantages in source countries would be invaluable. I delve further into this point in Section 6, where I discuss avenues for isolating these effects more robustly.

**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 can 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.3 show

Table 4: Intermediate imports vs Carbon Offshoring effects

Dep. var: log (CO <sub>2</sub> per value added)	(1)	(2)	(3)	(4)
Input Import	-0.031*** (0.008)	-0.549** (0.264)		
Carbon Import			-0.184*** (0.028)	-1.771** (0.874)
Observations	8,821	8,818	8,821	8,818
KP		13.59		15.394
<b>Estimation Strategy</b>	<b>OLS</b>	<b>IV</b>	<b>OLS</b>	<b>IV</b>
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Municipal-Year FE	Yes	Yes	Yes	Yes

Note: Columns 1 and 2 replicate the results of [Akerman et al. \(2021\)](#) main results – that is estimating the effect of log of intermediate import on log of emissions per value added. Columns 3 and 4 adjust the intermediate import with emission intensity of the intermediate import (carbon import) and regress it on emissions per value added (all in logs). All specifications include firm, industry-year, and municipal-year fixed effects. The data is balanced for the period from 2005 to 2014. Standard errors are clustered at firm level in parentheses. First-stage regressions yield highly significant coefficients for the relevant instruments and the reported KP-Statistics. \*, \*\*, and \*\*\* denote significance at the 10% , 5% and 1% level respectively.

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.

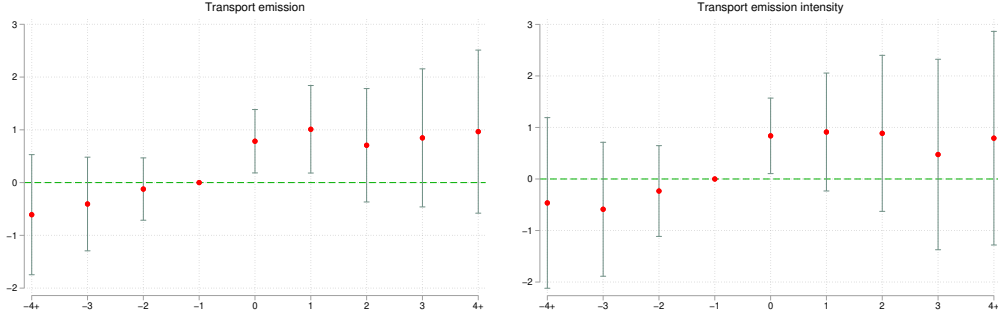
Overall, the results suggest that carbon offshoring has a significant effect on firms' environmental performance. Firms exposed to trade respond to foreign supply shocks by adjusting production decisions that subsequently lead to lower emissions intensity. This aligns with the notion that trade can yield 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 due to increased demand for emission-intensive inputs; however, the estimates are very small and mostly insignificantly different from zero in the long run (see Figure 10). 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

Figure 10: **Dynamic Effect: Carbon offshoring and Transport Emissions**



### C. Transport emissions

### B. Transport emission intensity

*Note:* Estimates of coefficients  $\beta_m$  for  $m = -4, \dots, 4$  from equation 8 are reported graphically. I normalize  $\beta_{-1} = 0$  so  $\beta_m$  is in normalized differences. Panel A. reports these coefficients for carbon import and transport CO<sub>2</sub> emissions, and B. carbon import and transport CO<sub>2</sub> emissions intensity. The x-axis represents the value of  $m$ , the dots the point estimates of  $\beta_m$ , and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous carbon offshoring is instrumented by export supply shocks weighted by pre-sample shares of imports and energy mix. Here, I used a balanced sample spanning the period 2006-2014. Standard errors are clustered at the firm-level.

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 relationship between production and transportation. For example, the 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. Because environmental policy arbitrage may 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 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.<sup>40</sup>

I approach the analysis and interpretation of the role of environmental policy arbitrage through three distinct methods. First, 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 (Bernard et al., 2020; Kander et al., 2020). For each input import and own-produced import, I construct a measure based on net imports by firms, encompassing those that are eventually re-exported (see e.g. Bernard et al. 2020). Let  $M_{ijt}$  represent the quantity of imports by firm  $i$  for product  $j$  at time  $t$ , and let  $M_{jt} = \sum_{i \in \text{Importers}} M_{ijt}$  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 follows:

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

Continuing to work in quantity units, I define net imports at the firm level as  $\text{Max}\{M_{ijt} - E_{ijt}, 0\}$  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 follows:

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

Table 5 and Table D.3 show the results for using  $IMP_{2jt}^{share}$  and  $IMP_{1jt}^{share}$  respectively. I estimate 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 low-income countries is a potent source of reduction in manufacturing CO<sub>2</sub> emissions.

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<sup>40</sup>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 5: Share of Export-corrected Carbon Offshoring by Country Groups

	1	2	3	4	5	6	7	8
Dependent Variable:	CO <sub>2</sub> emission intensity				Energy intensity			
EPS Lax/Income Group:	QL	VL	EL	LIC	QL	VL	EL	LIC
Share of Input import <sub>it</sub>	-0.105* (0.057)	-0.092** (0.038)	-0.477*** (0.007)	-0.156*** (0.020)	-0.190 (0.203)	-0.122* (0.069)	-0.102 (0.254)	-0.249*** (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
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 include inputs imports and PG imports. LIC denotes low-income countries; QL denotes quite lax; VL denotes very lax; and EL denotes, extremely lax. The data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. \*, \*\*, and \*\*\* denote significance at the 10%, 5% and 1% levels respectively.

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 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, distance, and friendly business environments, 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. Although 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 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 showed that the implicit pollution tax facing manufacturers accounts for most of the emission reductions compared to changes in trade.

## 7 Allowing for Firm and Industry 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 can modify their average emission intensity by adjusting their product mix. If each product within a firm generates a specific amount of CO<sub>2</sub> 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 equation 5 for each sub-sample.

The results in Table 6 suggest that multi-product firms behave differently from single-product firms. Although single-product response in emission intensity is negative, the coefficient is smaller whereas the multi-product firm response is negative and larger with a 5% level of significance. This suggests that the results are driven by multi-product firms as they have relatively more room to change their product mix to favor low-emission-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

Table 6: Heterogenous Effect: Single-Product vs Multi-Product Firms

	Single-Product		Multi-Product	
	CO <sub>2</sub> intensity	Energy intensity	CO <sub>2</sub> intensity	Energy intensity
Carbon Import	-0.158 (0.595)	-0.061 (0.494)	-0.618** (0.286)	-0.707** (0.276)
Observations	6,412	6,410	14,548	14,557
KP	13.81	13.62	35.78	35.45
Control	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓
Municipal-Year FE	✓	✓	✓	✓

Note: The table presents a series of regression coefficients for different specifications of equation 5. 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. The data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. Standard errors are clustered at the firm level in parentheses. First stage regressions yield highly significant coefficients for the relevant instruments and the reported KP-statistics. \*, \*\*, and \*\*\* denote significant at the 10% , 5% and 1% level respectively.

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 7: Heterogeneity: Dirty sectors vs Clean sectors

	Dirty Industries		Cleaner Industries	
	CO <sub>2</sub> intensity	Energy intensity	CO <sub>2</sub> intensity	Energy intensity
Carbon Import	-0.384 (0.277)	-0.492** (0.241)	-0.720* (0.374)	-0.599* (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. The data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. 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 7. 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. This suggests that a shift towards cleaner manufacturing is not entirely driven by dirty firms. However, Figure E.2 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 EU-ETS has had a profound effect on carbon leakage risk. Introduced in 2005, the EU-ETS initiative employs a two-step approach to address con-



cerns 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.

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 8. 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 8: Heterogeneity: EU-ETS Firms

	CO <sub>2</sub> emission intensity		Energy intensity	
	(1)	(2)	(3)	(4)
Carbon Import	-0.633** (0.273)	-0.550*** (0.198)	-0.649*** (0.230)	-0.594*** (0.202)
Carbon import $\times$ ETS <sub>it</sub>	0.342 (0.321)	0.307 (0.254)	0.352 (0.302)	0.323 (0.278)
Energy Price		-0.442*** (0.027)		-0.205*** (0.027)
Control	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓
Municipal-Year FE	✓	✓	✓	✓
Observations	16,544	16,498	16,548	16,502
KP	73.32	73.15	73.38	73.22

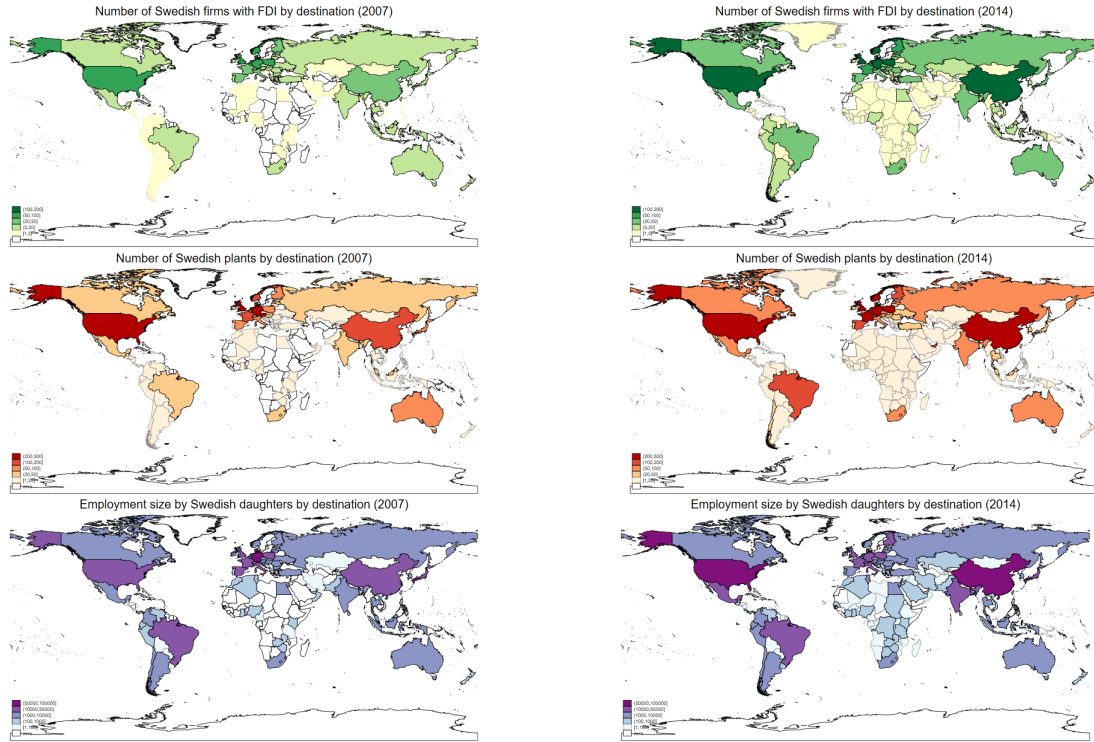
Note: Controls include lagged (up to three lags) information of firms’ productivity, machine investment and capital intensity. The data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. Standard errors clustered at firm level are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

## 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 firms' affiliate in such countries, reflecting the concentration of FDI in those regions.<sup>41</sup> My working hypothesis is that strict domestic environmental regulations may lead to an 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).

Figure 11: FDI Concentration by destination



*Note:* Figure 11 plots FDI concentration of Swedish manufacturing 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, the United States and EU countries close to Sweden.

I have access to information of many Swedish firms with FDI, number of plants by the affiliates, sales and employment (see Figure 11). 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 follows:

<sup>41</sup>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 of the migration of firms with high emissions has implications for emissions.

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

where  $X \in \text{lax, low-income country, and global employment}$  is the sum of employment in the parent firm and employment abroad. Before delving into the main analysis, I present a descriptive graph in Figure B.6, 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 MNCs in countries with lax environmental policies and improved emission performance domestically.

The results in columns 2 and 4 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<sub>2</sub> 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<sub>2</sub> emission intensity. Again, the study finds a negative and significant impact of input imports on CO<sub>2</sub> 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<sub>2</sub> emission intensity, whereas about 44.4% to 46.8% reduction in emissions is attributed to the intensification of imports of intermediate inputs from low-income countries.<sup>42</sup>

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

<sup>42</sup>I provide a robustness check of FDI concentration 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<sub>2</sub> 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.

Figure 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. (2023), 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. (2023), 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., a 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 occurs in countries with less stringent environmental policies. Firms engaging in international outsourcing in these countries can tap into the arbitrage created by the differences in policies 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 9, column 1, I find that offshoring increases firm productivity (TFP)<sup>43</sup> by about 3%. Therefore, productivity may provide a potential mechanism for the effect of offshoring on emissions.

Table 9: Carbon Offshoring and Firms’ Environmental Performance - Mechanisms

	Productivity		Firm Sales		Firm Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Import	0.266* (0.151)	0.264* (0.151)	0.874*** (0.149)	0.877*** (0.149)	0.842*** (0.143)	0.844*** (0.144)
Control	×	✓	×	✓	×	✓
Firm FE	✓	✓	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓	✓	✓
Municipal-Year FE	✓	✓	✓	✓	✓	✓
Observations	24,094	24,123	24,094	24,123	24,094	24,123
KP	135.07	134.61	134.73	134.27	134.73	134.27

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

Secondly, there is a possibility that as firms offshore, their costs decrease (because imported

<sup>43</sup>Total Factor Productivity (TFP) is calculated using the method outlined by Wooldridge (2009)

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 9, 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 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 have made in machinery and equipment aimed at reducing emissions.<sup>44</sup> These 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 10 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 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 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, hence the reduced allocation of available funds.

Table 11 presents a comprehensive breakdown of the components of abatement investment and expenditure. My primary emphasis is on dissecting the environmental investment and

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<sup>44</sup>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, R&D expenses, or fees paid for environmental permits or licenses.

Table 10: 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)
<b>Carbon Import</b>	0.052** (0.021)	-0.119 (0.080)	-0.579** (0.260)	-0.009 (0.020)	0.043 (0.086)	-0.344 (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 are in parentheses. \*\*, and \*\*\*, denote significance at the 10% , 5% and 1% levels respectively.

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. Although 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 11: Offshoring and Abatement Intensity

	Abatement Investment per sale				Abatement Expenditure per sale				R&D Cost
	Air	Water	Waste	Other	Air	Water	Waste	Other	
<b>Carbon Import</b>	-0.312* (0.187)	-0.571*** (0.208)	-0.433*** (0.162)	-0.243 (0.157)	-0.229 (0.147)	-0.467** (0.186)	-0.343*** (0.132)	-0.324** (0.150)	-0.467** (0.187)
Control	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Estimation	<b>IV</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>	<b>IV</b>
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 (R&D) geared towards environmental management. Standard errors clustered at firm level are in parentheses. \*, \*\*, and \*\*\* denote significance at the 10% , 5% and 1% levels 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 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 the composition effect of firms. The paper analyzes the effect of carbon offshoring on pollution in the context of Swedish manufacturing firms, utilizing 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 the 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. First, I estimate that firms can improve their production processes by approximately 5% with a 1% increase in carbon offshoring activities. However, this result conceals a significant amount of interesting heterogeneity in terms of offshoring strategies, the type of pollution, and the types of firms and industries involved in offshoring. Such heterogeneity provides a useful theoretical implication and is crucial for making policy recommendations. By conducting a rich heterogenous analysis, I find that the most significant form of carbon leakage occurs through the concentration of FDI, followed by the import of carbon inputs and semi-finished goods. When it comes to the type of pollution under consideration, the results show that transport emissions tend to increase disproportionately, suggesting that carbon offshoring can obscure a firm's overall environmental performance. Contrary to previous studies, I show that not all firms can enhance their production processes through carbon offshoring; instead, entities such as multi-product firms, non-EU-ETS, and multinationals are most at risk of carbon leakage.

Additionally, I provide 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 and 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 (which involves imposing taxes on imports based on their carbon content) 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. The effectiveness of border adjustments may vary depending on the stage at which carbon is taxed. [Farrokhi and Lashkaripour \(2021\)](#) highlight that border taxes can replicate, at most, 1% of the CO<sub>2</sub> reduction achievable through global climate cooperation. Therefore, careful consideration of when and how carbon taxes are applied is essential. Border adjustments shift the tax downstream, transitioning from a tax on domestic extraction to one on domestic production and, subsequently, to domestic consumption.

An alternative strategy involves the formation of climate-conscious governments into a climate club, as proposed by [Nordhaus \(2015\)](#) and further discussed by [Farrokhi and Lashkaripour \(2021\)](#). This collaborative approach aims to reduce global CO<sub>2</sub> emissions by up to 61%, emphasizing the importance of international cooperation in tackling climate challenges. As environmental policymakers consider these implications, attention must also be directed towards climate financing for low-income countries. Balancing these policy considerations is vital for the development of effective, globally coordinated strategies aimed at achieving meaningful and sustainable reductions in carbon emissions.

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# Appendix

## A Variable Definitions and Summary Statistics

Table A.1: Variable Definitions

Variable	Measurement/Definition
<i>Environmental Performance</i>	
CO2 Emission (tons)	Fuel-specific CO2 emission coefficients by fuel type
CO2 Emission Intensity (tons/SEK)	CO2/firm sales
Energy consumption	Heat (calorific) value by fuel type
Energy Intensity	Energy consumption /firm sales
<i>Offshoring Activities and Firm Relocation</i>	
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
<i>Other Variables</i>	
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 CEPIL as a low income country, otherwise, 0

Table A.2: Summary Statistics

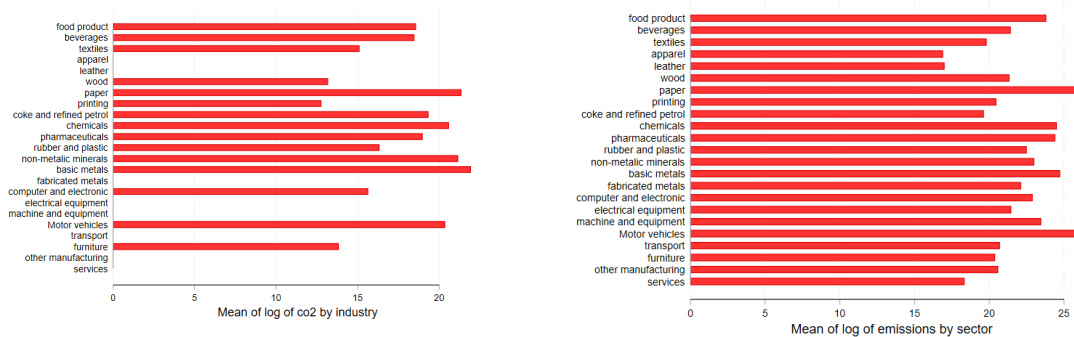
	N	Mean	SD	Min	Max
<i>Sourcing Patterns</i>					
Toxic content of input import	26,092	40.93	4.947	0	50.48
Toxic content of PG import	26,092	13.72	18.29	0	47.92
Share of toxic content of import <sup><i>lax</i></sup>	24,392	0.464	0.288	0	1
Share of toxic content of import <sup><i>LICs</i></sup>	26,092	0.114	0.556	0	1
Import share of OECD	26,092	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
<i>Stringency Index (OECD EPS)</i>					
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: LIC denotes low-income countries.



## B Figures

Figure B.1: Emissions by Sector

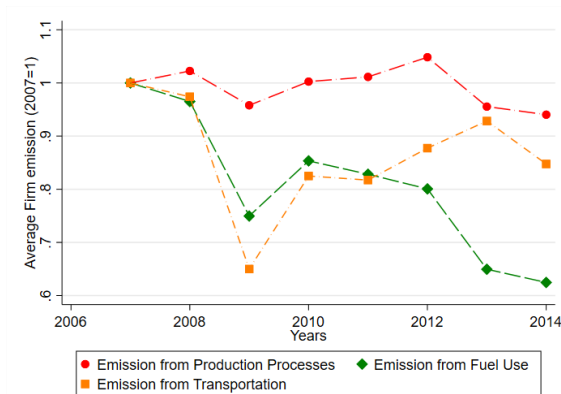


### B.1A. Self-reported emissions

### B.1B. fuel-based emissions

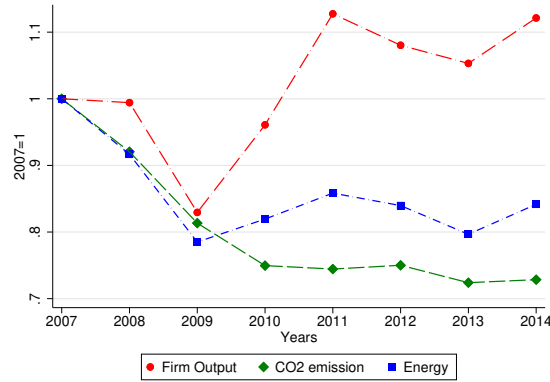
*Note:* Panel A plots sectorial emissions reported by firms. Although some firm-level emission data are available, the firms in the sample do not provide sufficient industry coverage to provide industry-level observations and comparison in results. Panel B plots the computed fuel-based emissions by each sector using emission factors conditional on the assumption that CO<sub>2</sub> emissions are directly proportional to the quantity of an energy source consumed.

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



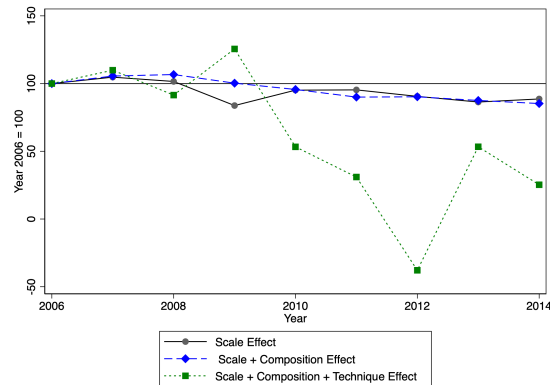
*Note:* Figure 3 plots the evolution of average emissions from Swedish firms. The dashed red line plots emission from production processes which appears to have declined marginally between 2012 and 2014. The dashed green line plots emissions from fuel use/combustion. The trend shows a substantial fall 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 is still lower than the 2007 average. All emission values are normalized to 1 in 2007.

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



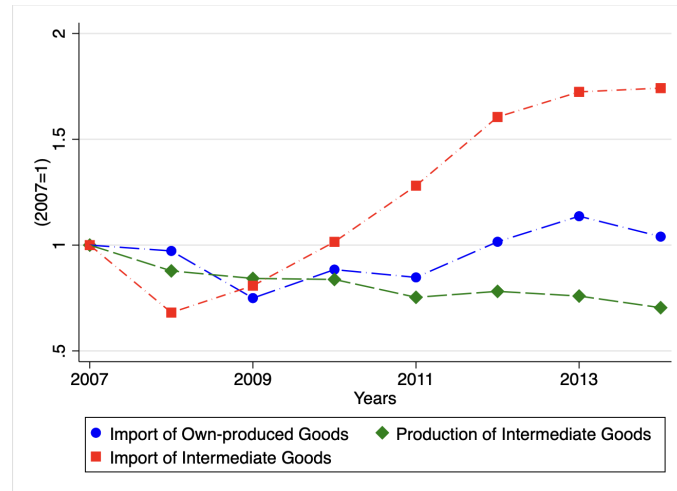
*Note:* Figure B.3 plots the evolution of average emissions from Swedish firms. The dashed red line plots firm output between 2007 and 2014. The dashed green line plots total CO<sub>2</sub> emissions from fuel use/combustion, transportation and production processes. The dashed blue line plots total local energy from fuel use/combustion, transportation and production processes. All emission values are normalised to 1 in 2007.

Figure B.4: Decomposition exercise using firm value added



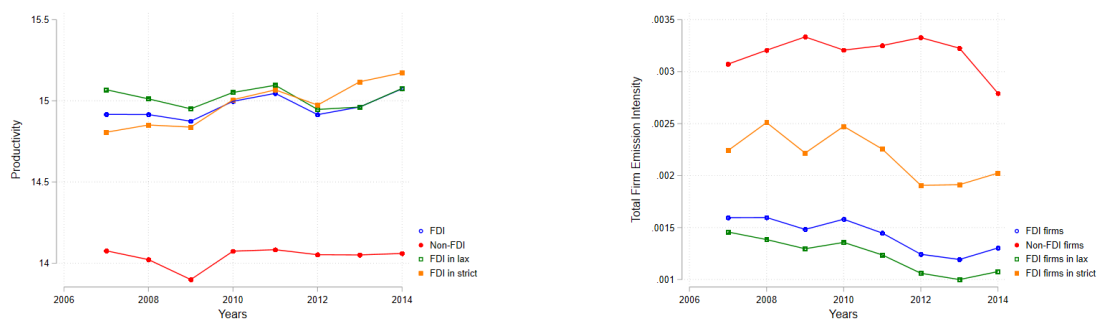
*Note:* Figure B.4 plots the decomposition of aggregate manufacturing emissions using value added. The black line shows the magnitude of the scale effect. The distances between the black line and blue line shows the magnitude of composition effect and the distance between all three lines, shows the magnitude of the composition and technique effect, respectively. All emission values are normalised to 1 in 2006

Figure B.5: 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. Although the import of intermediate goods increased after 2008, production of these products declined compared to 2007 values

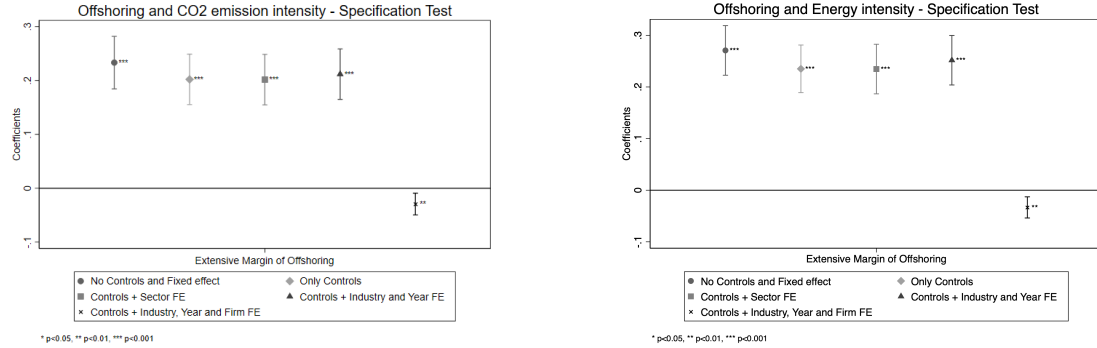
Figure B.6: Firm-level Emissions and Productivity by Firm-type and Destination



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<sub>2</sub> emission intensity and *Energy* emission intensity using several specifications. Recall that offshoring firms are those that increase the demand of dirty inputs but decrease the production of dirty inputs.

Table C.1: Descriptive Statistics before and after matching

Variables	Before Matching		After Matching		p-values
	Offshoring firms	Non-offshoring firms	Offshoring firms	Non-offshoring firms	
Firm sales (SEKmillion)	1370.68	365.26	1370.	1118	0.323
Firm employment	307	105	307	296.28	0.731
TFP('1000)	1397	991.95	1397	1688.5	0.281
Capital stock (SEKmillion)	383.34	98.61	383.34	318.85	0.148
Machine investment(SEKmillion)	49.59	10.49	49.59	34.31	0.121
Firm cost (SEKmillion)	1294.64	344.33	1294.64	1095.8	0.274

*Note:* All values are in means. Also, al nominal values are expressed in real terms.

Table C.2: Import and Firms Environmental Performance

	CO <sub>2</sub> emission intensity				Energy intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Panel A: Total import (excluding inputs)</b>								
Total import	-0.038*** (0.006)	-0.054*** (0.018)	-0.043 (0.028)	-0.027 (0.019)	-0.039*** (0.005)	-0.049*** (0.015)	-0.036 (0.023)	-0.029 (0.020)
Energy Price				-0.307*** (0.033)				-0.406*** (0.036)
KP		218.45	527.74	534.43		214.66	526.23	532.92
<b>Panel B: Inputs Import in Quantities</b>								
Input Import	-0.040*** (0.007)	-0.045** (0.020)	-0.060* (0.032)	-0.040* (0.022)	-0.044*** (0.007)	-0.046*** (0.017)	-0.061** (0.028)	-0.051** (0.024)
Energy Price				-0.329*** (0.045)				-0.432*** (0.048)
KP		52.02	374.87	380.047		50.27	374.90	379.95
<b>Panel C: Inputs Import in Values</b>								
Input Import	-0.039*** (0.008)	-0.047** (0.020)	-0.062* (0.033)	-0.042* (0.023)	-0.044*** (0.007)	-0.048*** (0.017)	-0.064** (0.029)	-0.053** (0.025)
Energy Price				-0.329*** (0.045)				-0.432*** (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 specifications 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 are in parentheses. First-stage regressions yield highly significant coefficients for the relevant instruments and the reported KP-statistics. \*, \*\*, and \*\*\* denotes significance at the 10% , 5% and 1% levels respectively.

Table C.3: Narrow definition of offshoring and firm emissions

	CO <sub>2</sub> emission intensity		Energy emission intensity	
	1	2	3	4
Narrow offshoring (Quantities)	-0.104** (0.049)		-0.106** (0.043)	
Narrow Offshoring (Values)		-0.168** (0.082)		-0.172** (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	✓	✓	✓	✓

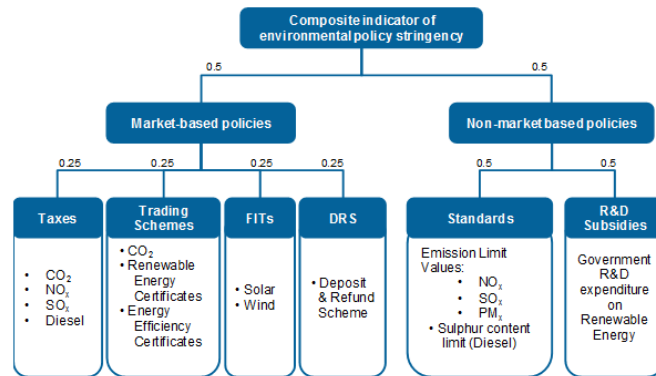
Note: Offshoring is measured as imports of products (excluding raw materials and finished machines) belonging to the 3-digit industry. \*, \*\*, and \*\*\* denotes significance at the 10% , 5% and 1% levels respectively.

## 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, whereas 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 for 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 <sup>45</sup>. 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 the EPS indicator where individual policies are aggregated with equal weight at each level and category. Source: Koziuk et al. (2019)

Unlike previous studies, Thus, offshoring firms' environmental costs in destination countries, if available, are 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, I normalize the EPS index to take the value of 0 to 1. I then

<sup>45</sup>In fact the data from the environmental policy stringency index show 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 compared to Sweden's environmental stringency.

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 strict in terms of environmental policies over time. This variable of laxity can be used to interact with offshoring to detect 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 must 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 follows:

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

Where  $EPS_{Sweden}$  is Sweden's average environmental policy stringency index between 2005 and 2014.  $EPS_{Trading\ Country}$  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  $\in \{0, 1, 2, 3\} = \{\text{Strict, Quite Lax, Very Lax, Extremely Lax}\}$  which indicates a country group classified according to the stringency index. Table D.1 shows the countries in each group of classification.

This classification supports the empirical patterns of pollution emission rates across country and over time. We expect that countries with more stricter environmental policies will be relatively cleaner. Figure D.2 maps CO<sub>2</sub> 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 the United States have slightly higher emissions compared to Europe, whereas Latin American 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 (for example Japan and Australia). These large differences in emissions across countries (and country groups) due to 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 con-



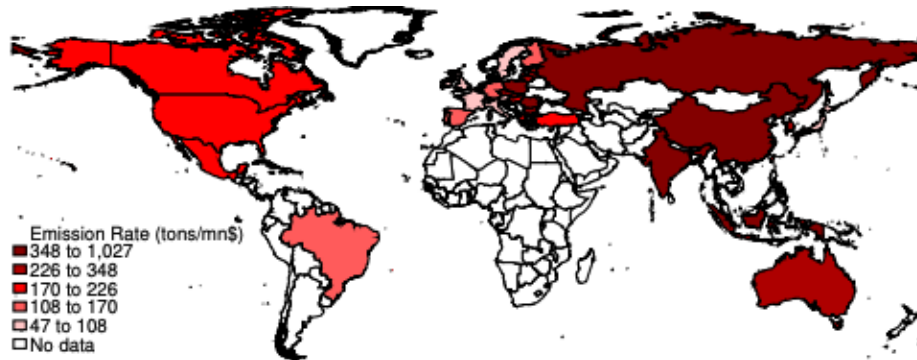
Table D.1: Classification of Countries based on EPS Index

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		

sequences 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. Simple descriptive statistics in Table A.2 in Appendix B show that although importing firms sources about 66.3% from EPS-lax countries, about 12.1% of toxic import comes from low-income countries.

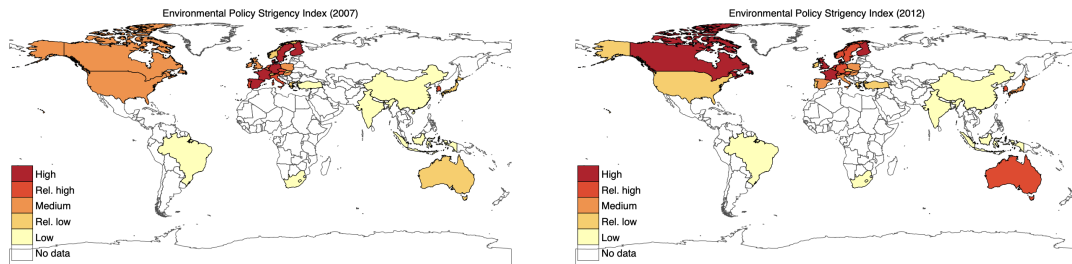
I observe that, at the national level, Sweden, compared to other countries, is the highest importer of CO<sub>2</sub> emissions (see Figure D.5). Also, over the sample period, I observed a substantial increase in carbon imports in countries (see Figure D.6). SCB data shows that significant parts of Swedish 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 emission imports and intermediate goods from these countries. Overall, an average manufacturing firm imported about 40.93 tons of carbon content of inputs. About 46.4% of total toxic import comes from EPS lax countries, whereas the share of emissions imported from low-income countries is about 12% (Table A.2).

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



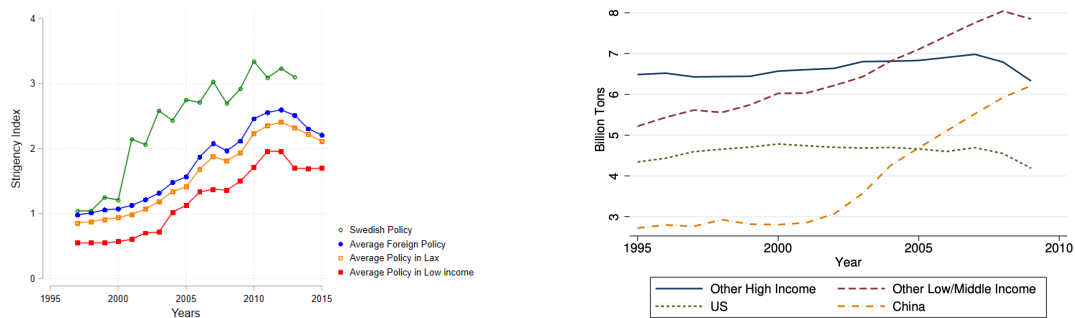
Note: The graph shows a direct CO<sub>2</sub> emission rate of all industries in a particular country in 2009, using data from the World Input Output Dataset. Source: [Copeland et al. \(2022\)](#)

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 are sourced from OECD Environmental Policy Stringency Index.

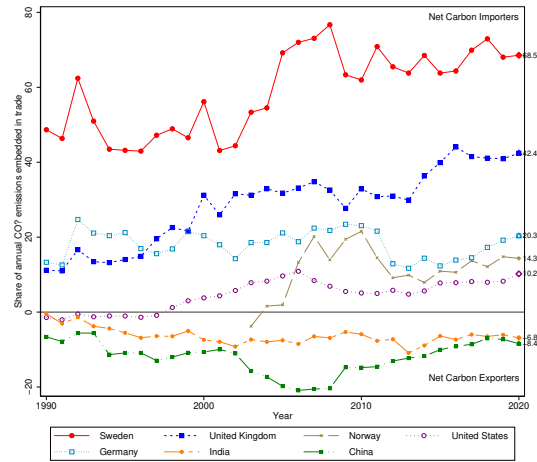
Figure D.4: Trends in Environmental Policy Stringency and CO<sub>2</sub> Emission Rate by Income Group



#### D.4A. Environmental Policy Stringency Index D.4B. CO<sub>2</sub> emission rate by group of country

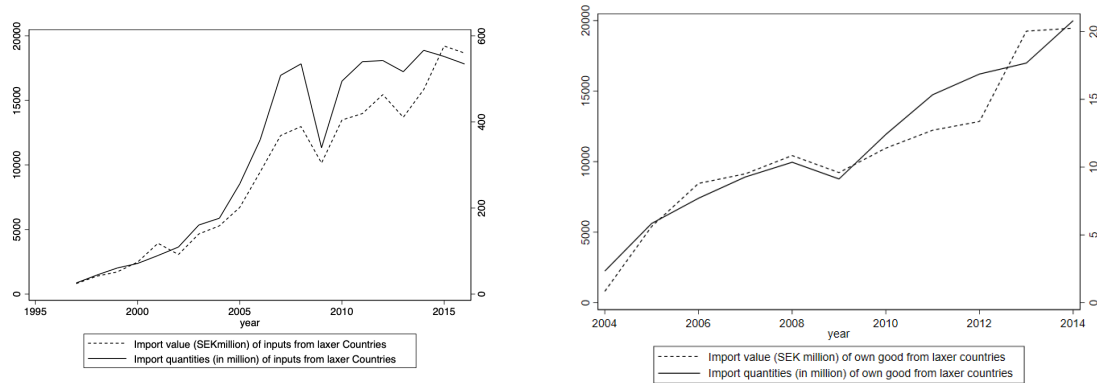
Note: Figure D.4A plots the average EPS index of Sweden (green line), the rest of the world (blue line), countries with laxer EPS compared to Sweden (orange line) and low-income countries (red line). Panel B shows CO<sub>2</sub> emission rate by group of country and year, as shown in [Copeland et al. \(2022\)](#) 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<sub>2</sub>. Negative values represent net exporters of CO<sub>2</sub>. Annual CO<sub>2</sub> 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 <sub>2</sub> emission intensity			CO <sub>2</sub> emission intensity			Energy intensity		
	1	2	3	4	5	6	7	8	9
Input import	-0.007** (0.003)	-0.012* (0.006)	-0.011** (0.006)	-0.097** (0.044)	-0.101** (0.046)	-0.104** (0.031)	-0.053* (0.031)	-0.062* (0.032)	-0.062* (0.032)
Input import × Lax	-0.001*** (0.000)			-0.041*** (0.007)			-0.013** (0.006)		
Input import × Rank		-0.003*** (0.000)			-0.092*** (0.050)			-0.018** (0.007)	
Input import × LIC			-0.009** (0.011)			-0.253*** (0.159)			-0.276*** (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
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 and 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 *Energy* 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

Dependent Variable:	1	2	3	4	5	6	7	8
	CO <sub>2</sub> emission intensity				Energy emission intensity			
	QL	VL	EL	LIC	QL	VL	EL	LIC
EPS Lax/Income Group:								
Share of Input import <sub>it</sub>	-0.043 (0.032)	-0.053** (0.019)	-0.058** (0.021)	-0.322*** (0.159)	-0.020 (0.023)	-0.026* (0.010)	-0.026** (0.002)	-0.245*** (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
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. \*, \*\*, and \*\*\* denote significance at the 10% , 5% and 1% levels respectively. Standard errors clustered at firm level are in parentheses.

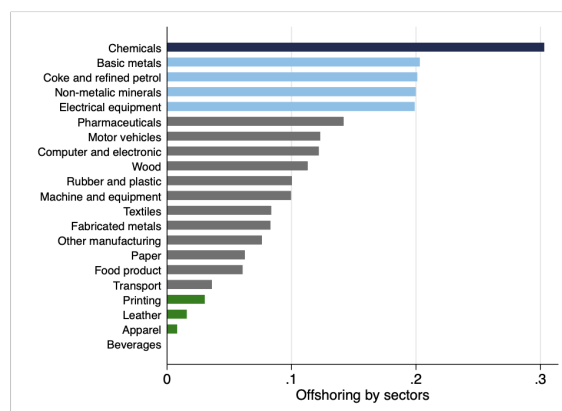
Table D.4: Emissions and Import Competition

	FE+ IV		FE+ IV	
	CO <sub>2</sub> emission intensity		Energy intensity	
	1	2	3	4
Import <sup>Pen</sup> (from EPS Lax)	-0.065** (0.028)		-0.032*** (0.009)	
Import <sup>Pen</sup> (from low-income)		-0.031 (0.022)		-0.047 (0.023)
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓
Municipal-Year FE	✓	✓	✓	✓
KP	100.1	54.2	112.0	35.3

Note: Import<sup>Pen</sup> denotes import penetration which is measured as all import from EPS lax and low-income countries. Standard errors are clustered at firm level. \*, \*\*, \*\*\* denote significance at the 10% , 5% and 1% levels respectively.

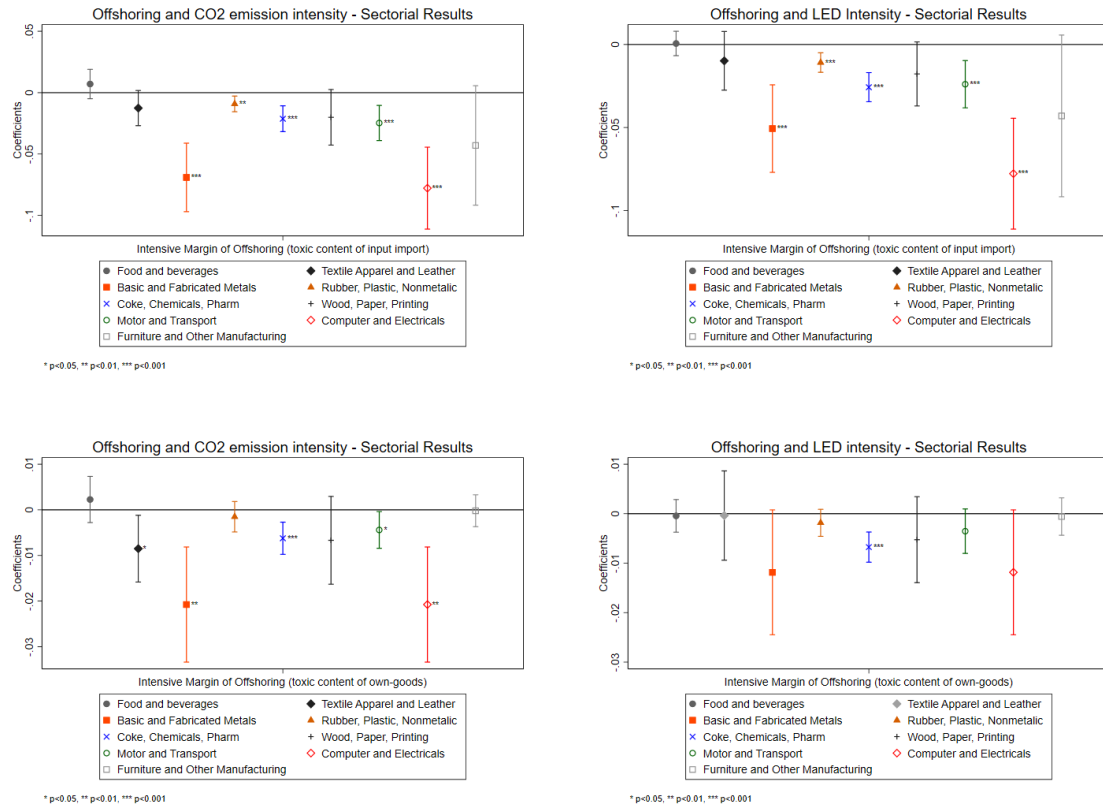
## E Heterogenous Effect

Figure E.1: Sectorial Distribution of Offshoring Firms



Note: The figure shows how offshoring firms are distributed across sectors. Most 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<sub>2</sub> emission intensity

Energy intensity.

*Note:* This figure plots the sector-specific coefficients of the extensive margin of offshoring on CO<sub>2</sub> emission intensity (left panel) and energy 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<sub>2</sub> Emissions

	CO <sub>2</sub> intensity			Energy intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
Multinationals	-0.206** (0.090)	-0.190*** (0.063)	-0.163** (0.073)	-0.248** (0.100)	-0.233*** (0.075)	-0.203** (0.083)
Productivity		-0.265*** (0.020)	-0.337*** (0.019)		-0.265*** (0.021)	-0.343*** (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<sub>2</sub> emission intensity varies with productivity and with being a multinational. Standard errors clustered at firm level are in parentheses. \*, \*\*, \*\*\* denote significance at the 10% , 5% and 1% levels respectively.

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

	Lax		LIC		Lax		LIC	
	CO <sub>2</sub> emission intensity				<i>Energy</i> emission intensity			
Input import	-0.096*** (0.000)	-0.146** (0.058)	-0.444* (0.156)	-0.468** (0.068)	-0.136 (0.153)	-0.146 (0.094)	-0.590 (0.392)	-0.468 (0.076)
FDI Concentration		-0.061*** (0.003)		-0.496*** (0.032)		-0.135* (0.094)		-0.452*** (0.087)
Energy Price	-0.249*** (0.036)	-0.245*** (0.043)	-0.259** (0.099)	-0.177*** (0.000)	-0.241*** (0.066)	-0.320** (0.109)	-0.165* (0.018)	-0.258*** (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
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Municipal-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: Lax and LIC denotes "environmentally laxer countries", and "Low income countries" respectively. Standard errors clustered at firm level are in parentheses. \*, \*\*, and \*\*\* denote significance at the 10% , 5% and 1% levels respectively.

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

	(1) CO <sub>2</sub> intensity	(2) CO <sub>2</sub> intensity	(3) CO <sub>2</sub> intensity
FDI concentration in EPS Lax	-0.141*** (0.009)		-0.103*** (0.009)
FDI concentration in Low-income		-0.265*** (0.022)	
Carbon Import			-0.003 (0.002)
Carbon Import $\times$ FDI dummy			-0.867*** (0.043)
Observations	1,274	1,274	1,274
Controls	✓	✓	✓
Firm FE	✓	✓	✓
Industry-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 CO<sub>2</sub> emissions reduced drastically among FDI firms as compared to domestic firms. Standard errors clustered at firm level are in parentheses \*\*, and \*\*\* denote significance at the 10% , 5% and 1% level respectively.



## F Carbon Offshoring and Abatement– Robustness

*Sampling issue.* The key econometric issue using the abatement data is that firms have the option to invest in technologies that reduce carbon emissions. This choice determines whether I can observe their abatement in my 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 a downward bias in the sample of observed abatement. Additionally, some firms may not report their environmental expenditure/investment because of the 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 the 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 a rich set of firm-level variables such as firm sales, cost, firm size, employment, capital, productivity, energy cost, and the amount of emission rights purchased. Next, I calculate the inverse Mills ratio (IMR), which serves as the correction term from the selection equation. By augmenting the main regression equation with the IMR, I can correct for the sampling bias and assess the extent to which offshoring affects firms' abatement.

The results in Table F.1 point to a strong positive selection bias in the OLS estimates but a robust effect of the instrumental variable (IV) estimate. Specifically, I find that total abatement intensity falls by about 5.4% compared to the baseline estimate of 5.8%, and there is 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)
<b>Carbon Import</b>	-0.538* (0.324)	-0.212 (0.263)	-0.518 (0.319)	-0.185 (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 5. Controls include inverse mills ratio (IMR) and lag information on firm capital, employment and machine investment. Standard errors clustered at firm level are in parentheses. \*, \*\*, and \*\*\* denote significance at the 10% , 5% and 1% levels 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 the 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	
<b>Carbon Import</b>	-0.590* (0.026)	-0.244 (0.216)	-0.520** (0.250)	-0.279* (0.170)	-0.054 (0.168)	-0.265 (0.251)	-0.088 (0.158)	-0.381* (0.215)	-0.136 (0.120)	-0.132 (0.146)	-0.376* (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 specifications of of equation 5. Controls include lag information on firm capital, employment and machine investment. Standard errors clustered at firm level are in parentheses. \*, \*\*, and \*\*\* denote significance at the 10% , 5% and 1% levels 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 to capture a larger number of firms that report their emissions in my sample. I adopt a theoretically consistent measure of abatement by [Rodrigue et al. \(2020\)](#) as follows:

$$Abatement_{it} \equiv -\ln(1 - \pi_{it}) = \ln\left(\frac{EFP_{it}}{EFU_{it}}\right) \quad (9)$$

where  $\pi_{it}$  theoretically, captures the fraction of labour redirected to reduce firm-level emission. For my empirical purpose, abatement is captured as the log of emission generated from fuel production processes (EFP) per emission emitted from fuel use (EFU). 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 my main results regarding abatement investment, albeit with slightly smaller magnitudes.

Table F.3: Carbon Offshoring and Theoretical Abatement

	Abatement per sale			
	(1)	(2)	(3)	(4)
<b>Carbon Import</b>	-0.143*** (0.018)	-0.142*** (0.018)	-0.137*** (0.018)	-0.423*** (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 specifications of equation 5. Controls lag information on firm capital, employment and machine investment. Standard errors clustered at firm level are in parentheses. \*, \*\*, and \*\*\* denote significance at the 10% , 5% and 1% level respectively.