2126

Discussion Papers

Deutsches Institut für Wirtschaftsforschung 2025

Clean Production, Dirty Sourcing: How Embodied Emissions Alter the Environmental Footprint of Exporters

Till Köveker, Philipp M. Richter, Alexander Schiersch and Robin Sogalla

IMPRESSUM

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
http://www.diw.de

ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
http://www.diw.de/discussionpapers

Discussion Papers of DIW Berlin are indexed in RePEc and Econstor:
http://ideas.repec.org/s/diw/diwwpp.html
https://www.econstor.eu/handle/10419/10

Clean Production, Dirty Sourcing: How Embodied Emissions Alter the Environmental Footprint of Exporters*

Till Köveker† Philipp M. Richter‡ Alexander Schiersch§ Robin Sogalla¶

July 2, 2025

Abstract

This paper revisits the exporter's environmental premium (EEP) by incorporating emissions embodied in domestically and internationally sourced intermediate inputs. Combining administrative firm-level data and customs records for German manufacturers with an environmentally extended input-output table and fuel specific emission factors, we document three stylized facts: (i) embodied emissions account for over half of firms' total emissions; (ii) exporters' production involves disproportionately more embodied emissions, particularly through international sourcing; and (iii) once embodied emissions are considered, the EEP reverses: exporters appear cleaner based on production-related emissions alone, but dirtier in total emissions. We rationalize these patterns in a sourcing model and test its predictions using a shift-share IV strategy based on foreign demand shocks. Export expansion lowers the production-related emission intensity without affecting total emissions, underscoring the role of sourcing in shaping firm-level environmental outcomes. These findings highlight the importance of accounting for embodied emissions when evaluating the welfare and environmental consequences of trade liberalization.

JEL-Classification: F18, F12, L23, Q54, Q56

Keywords: Exporter's environmental premium; CO_2 emission intensity; embodied emissions; international sourcing; heterogeneous firms

*We thank Pol Antràs, Tomaso Duso, Karsten Neuhoff, and Joschka Wanner for helpful comments and discussions. We also thank participants at the European Trade Study Group 2023, the Göttingen Workshop in International Economics 2025, and the 13^{th} Mannheim Conference on Energy and the Environment as well as seminar participants at the DIW Berlin, University of Leipzig, and JMU Würzburg for fruitful discussions. We gratefully acknowledge the Research Data Centre (FDZ) of the Federal Statistical Office and the Statistical Offices of the German Länder for granting us access to the AFiD data and for the use of their research facilities, in particular Tasso Brandt, Benjamin Gampfer, Katja de la Motte, Steffen Lauf, Anja Malchin, Ricarda Nauenburg for their advice and technical support.

The views expressed in this paper are those of the authors and do not necessarily reflect those of the institutions mentioned above. All errors remain the responsibility of the authors.

†DIW-Berlin & Technische Universität Berlin; E-mail: TKoeveker@diw.de.

‡Julius-Maximilians-Universität (JMU) Würzburg; E-mail: philipp.richter@uni-wuerzburg.de.

§DIW-Berlin; E-mail: ASchiersch@diw.de.

¶DIW-Berlin & Technische Universität Berlin; E-mail: RSogalla@diw.de.

1 Introduction

International trade reshapes the geography of CO_2 emissions, decoupling the location of production from final consumption and embedding a substantial share of emissions in traded goods. While this reallocation of emissions across borders is well documented at the aggregate level (Copeland et al. 2022), far less is known about how firm-level production and sourcing decisions relate to this pattern.

A well-established firm-level literature finds that exporters tend not only to be more productive but also less emission-intensive than non-exporters – a phenomenon commonly referred to as the exporter's environmental premium (EEP), see e.g., Holladay (2016), Richter and Schiersch (2017), Forslid et al. (2018), Rodrigue et al. (2022), and Kwon et al. (2023). These findings support the optimistic view that trade liberalization can help to reduce emissions by reallocating production toward cleaner firms. However, this perspective focuses primarily on direct emissions generated during production within firms (Scope 1) as well as from purchased electricity and heat (Scope 2), overlooking the indirect emissions embodied in firms' global supply chains (Scope 3 emissions).[1]

Recognizing the full environmental impact of trade thus requires accounting for all emissions associated with firms' activities, regardless of where they occur. Because greenhouse gas emissions are a global externality, what matters for climate change is the aggregate level of emissions, not their geographic location. International trade enables firms to outsource emissions through imported intermediates, and empirical evidence shows that high-income countries increasingly rely on carbon-intensive inputs from abroad (Copeland et al. 2022). Moreover, firms exhibit substantial heterogeneity in sourcing decisions (cf. Blaum et al. 2018; Antràs et al. 2017), suggesting that emissions embodied in their inputs will vary considerably as well. Yet, detailed firm-level evidence on how sourcing strategies shape the emissions intensity of firms remains scarce.

This paper adds to this literature by revisiting the exporter's environmental premium. Specifically, it examines whether the premium persists when emissions embodied in sourced inputs are accounted for. In addition, it investigates to what extent differences between production-related and total emission intensity premia reflect variation in sourcing behavior between exporters and non-exporters.[2]

To this end, we construct a novel firm-level dataset for German manufacturing firms that includes detailed measures of production-related emissions as well as those embodied in domestically and internationally sourced inputs. Specifically, we link administrative firm-level data with customs records, fuel-specific emission factors, and an environmentally extended input-output database (Exiobase). This dataset allows us to distinguish between physical energy use, domestically sourced and imported inputs, and to trace embodied emissions back to their country of

1. We follow the standard emissions classification defined by WRI and WBCS (2015). In this paper, we focus on a subset of Scope 3 emissions: those embodied in sourced intermediate inputs – i.e., emissions upstream in the supply chain associated with sourced materials. We thus exclude downstream emissions.

2. Throughout the paper, we refer to the sum of Scope 1 and Scope 2 emissions as *production-related* emissions, and the sum of all three scopes as *total* emissions.

origin.

Our analysis proceeds in four steps. First, we establish new stylized facts on the role of embodied emissions in firm-level carbon footprints and their contribution to the exporter's environmental premium. Second, we decompose the gap between production-related and total emission intensity premia to quantify the contribution of different margins, including firms' sourcing choices and differences in product-level emission factors. Third, we develop a theoretical sourcing model that rationalizes the observed patterns between exporters and non-exporters. Further focusing on exporters, it yields testable predictions on how foreign demand shocks affect their emission intensities. Finally, we test these predictions empirically using a shift-share identification strategy based on variation in foreign export demand.

The analysis reveals three stylized facts. First, a substantial share of firms' total carbon footprints stems from embodied emissions, underscoring the importance of accounting for them in any firm-level analysis of emissions. Second, embodied emissions – especially those from imports – make up a significantly larger share of total emissions for exporters than for non-exporters. Third, accounting for embodied emissions reverses the exporter's environmental premium: while exporters appear less emission-intensive based on production-related emissions alone, they exhibit a higher total emission intensity than non-exporting firms once embodied emissions are included. This provides the first firm-level evidence that ignoring embodied emissions may systematically underestimate the true carbon footprint of exporting firms.

To disentangle the relative importance of various contributing factors, we conduct a decomposition analysis, which reveals that exporters systematically rely on more material inputs and source inputs with higher embodied emissions – particularly from domestic suppliers. While exporters tend to use slightly cleaner imported inputs than non-exporting importers, their overall sourcing patterns lead to a higher total emission intensity, helping to explain the reversal of the exporter's environmental premium.

Building on these findings, we develop an analytical model that extends Antràs et al. (2017) to examine how sourcing decisions shape emission intensities. A key insight is that exporters, benefiting from access to cheaper intermediates, shift their input mix away from energy and toward materials. As a result, exporters exhibit a lower production-related emission intensity, but potentially a higher embodied emission intensity due to greater reliance on intermediate inputs. The model further predicts that an increase in foreign demand lowers exporters' production-related emission intensity through this shift. The sign and magnitude of the effect on an exporter's total emission intensity depend on the relative importance of embodied emissions for the firm and how a change in foreign demand affects the emission intensity of sourced inputs.

We test the model's predictions for exporters and find evidence that an increase in foreign market size reduces their production-related emission intensity, but has no significant effect on their total emission intensity. Consistent with the analytically derived mechanism, the results further suggest that a shift toward intermediate inputs is the main driver of this pattern.

The remainder of this paper is organized as follows. We begin in Section 2 to review the related literature. Section 3 introduces the data sources, describes our firm-level carbon accounting approach, and presents key descriptive statistics. In Section 4, we establish three stylized facts about embodied emissions and the exporter's environmental premium. The underlying mechanisms are then examined in Section 5, which decomposes emission intensity differences and highlights the role of firms' sourcing decisions and differences in emission factors. Section 6 develops a theoretical model linking firms' sourcing and exporting decisions to their emission intensity, providing both a conceptual framework and testable predictions regarding the impact of export demand shocks. These predictions are empirically tested in Section 7 using a shift-share identification strategy to assess the causal impact of export demand shocks on embodied emissions. Finally, Section 8 concludes with a discussion of policy implications and directions for future research.

2 Related literature

This paper contributes to research on the relationship of international trade and firm-level environmental outcomes, with a particular focus on how differences in production and sourcing decisions shape emissions.[3]

First and foremost, we contribute to the literature on the environmental performance of exporters.[4] While not their primary focus, Cole et al. (2013) find that a firm's export share is associated with lower emission intensity for Japanese firms. Batrakova and Davies (2012) document that exporters are less energy intensive in the case of energy-intensive Irish manufacturing firms. Roy and Yasar (2015) find that Indonesian exporting firms spend less on fuels relative to electricity, and Girma and Hanley (2015) show that UK exporters are more likely to report that their innovation activity reduces energy and material intensity.

One of the first studies that directly analyzes the EEP is Holladay (2016), who shows that US exporters have a lower Hazard score – based on more than 500 toxic pollutants – than non-exporting competitors, conditional on sales and a set of fixed effects. Using similar data and additionally controlling for productivity, Cui et al. (2016) find that exporters emit less of four different local pollutants per unit of sales. Cui and Qian (2017) confirm these findings using a matching approach, but document heterogeneity across industries. Forslid et al. (2018) report similar results for CO_2 emissions of Swedish firms. Acknowledging the fact that CO_2 emissions are linked to the use of fossil fuels, Richter and Schiersch (2017) argued that those should be modeled as an input in the production process, confirming that German exporters produce less carbon intensively using a structural production function approach. Rodrigue et al. (2022) combine an instrumental variable with a structural approach to estimate the emission intensity premium of Chinese exporters and abatement choices simultaneously. They find that exporters emit 36% less SO_2 and industrial dust, attributing this to various factors. On the other hand, Dardati and Saygili (2021) document for Chilean firms that exporters are less emission intensive in terms of sales, but not in terms value added, thereby indicating the potential role of differential sourcing behavior.

3. For overviews of the trade-environment literature, see Cherniwchan et al. (2017) and Copeland et al. (2022).
4. A long strand of literature has documented differences between exporting and non-exporting firms along several dimensions (see e.g., Bernard et al. (1995) and Bernard and Jensen (1999)).

Several recent studies focus on the intensive margin of exporting. Barrows and Ollivier (2021) use a shift-share instrument to show that larger foreign demand reduces the emission intensity of Indian manufacturing firms. Similarly, Wang et al. (2024) find that positive demand shocks decrease the sulfur dioxide emissions of Chinese firms. Blyde and Ramirez (2022) show that increased exports to high-income countries reduce the carbon emission intensity of Chilean firms, using changes in exchange rates.

Taken together, these studies consistently find a lower emission intensity among exporters, i.e., an exporter's environmental premium. However, the mechanisms behind this premium remain less well understood. Moreover, they focus solely on production-related emissions and overlook emissions embodied in intermediate inputs. Our study revisits the EEP using a broader measure of emissions and highlights a new channel: exporters' differential sourcing of intermediate inputs.

We thereby connect to the emerging literature on heterogeneous sourcing and environmental outcomes. Using administrative firm-level data for Germany, Stillger (2025) shows that larger firms source a greater share of inputs from abroad and have higher emission intensity of imports than smaller importing firms. Building on these patterns, she incorporates emissions in the heterogeneous sourcing model of Blaum et al. (2018) to examine the role of sourcing heterogeneity on the effectiveness of carbon pricing and carbon tariffs. More closely related to the model structure in this paper, Coster et al. (2024) introduce clean and dirty inputs into the heterogeneous sourcing model of Antràs et al. (2017) and simulate the effects of climate policies using French firm-level data. We complement this literature by studying the interdependence between sourcing and exporting activity and by accounting for the emissions embodied in both imported and domestically sourced inputs.

A related strand of literature studies the impact of offshoring opportunities on firm's emission intensities. Applying a shift-share design based on Hummels et al. (2014), Akerman et al. (2024) find that increased access to inputs reduces the emission intensity of Swedish manufacturing firms. In a mediation analysis they provide evidence that this effect is driven by productivity upgrading instead of outsourcing of emission intensive intermediate inputs. Leisner et al. (2023) estimate the joint effect of increased import competition and offshoring opportunities from China in a shift-share design on the emission intensity of Danish manufacturing firms. Similar to Akerman et al. (2024), they find that offshoring opportunities reduces the emission intensity, but attribute this mainly through outsourcing of emission intensive inputs. Dussaux et al. (2023) provide similar evidence that increased imports of emission intensive inputs reduce the domestic emission intensity for French manufacturing firms. Compared to Akerman et al. (2024) and Leisner et al. (2023) they estimate the effect of an increase in embodied emissions in imports instead of the impact of an increase in the value of imports. Choi et al. (2025) analyze the environmental effect of the USA granting Permanent Normal Trade Relations (PNTR) to China. They find that this reduction in trade policy uncertainty lead to a decline in the emission intensity of US establishments, providing suggestive evidence that this is driven by offshoring.

These papers do not include the selection of firms into exporting. A notable exception is Kwon et al. (2023), who explicitly address the interdependence between importing and exporting in relation to environmental outcomes. Using a shift-share design, they estimate that both importing and exporting reduce the emission intensity of four different local pollutants for a sample of Chinese firms. Different to our study, they do not account for embedded emissions in intermediate inputs.

We contribute to this literature in several ways. First, we provide evidence on the role of embodied emissions for manufacturing firms. While some studies account for the emissions embodied in imports at the firm-level, we are not aware of any other study that also includes the emissions embodied in domestically sourced materials. Moreover, we show both empirically and theoretically the role of the interdependency between exporting and importing decisions of heterogeneous firms for their direct and embodied emission intensity.

In doing so, we also speak to the literature on the interconnection between firm-level sourcing and exporting. Bernard et al. (2018) provide a theoretical framework that establishes the interdependence of firm-level decisions to participate along different dimensions in the international economy, providing evidence that the value of imports and the number of sourcing and destination countries and imported and exported products co-move along the distribution of firms. In a related model, Antràs et al. (2017) similarly show that better access to foreign intermediate inputs increases export market participation, with their model predicting that – under certain parameter restrictions – improved exporting opportunities can increase the number of a firm's sourcing countries. Blaum (2024) extends the heterogeneous sourcing models of Gopinath and Neiman (2014) and Blaum et al. (2018) for a decision to enter exporting. He shows that this interdependence between exporting and importing can rationalize the empirical finding that the share of imported inputs increases following a devaluation. Several empirical studies, such as Bas (2012), Bas and Strauss-Kahn (2014), Feng et al. (2016) and Máñez et al. (2020), support that better access to foreign inputs enhances exporting. Similarly, Handley et al. (2025) find that higher import tariffs reduce the exports of exposed firms. By contrast, evidence on whether exporting increases foreign sourcing is mixed: Aristei et al. (2013) find no significant relationship once controlling for firm size, while Kang and Whang (2023) find that firms that started exporting increase the share of inputs sourced from foreign suppliers. Similarly, Albornoz and Garcıa-Lembergman (2023) show for Argentinian firms that exporting to a new destination increases the likelihood that a firm will start importing from this country. We contribute to this literature by highlighting the interdependence between exporting and importing in an environmental context.

Finally, our paper relates to the extensive literature on emissions embodied in trade flows.[5] These studies typically rely on input-output databases to analyze patterns in embodied emission transfers across countries, sectors, and over time. A consistent finding is that a substantial of emissions is embodied in international trade. We advance this literature by computing embodied emissions at the firm level, rather than at the country-sector level. While a few recent studies compute emissions embodied in firm-level imports (Dussaux et al. 2023; Leisner et al. 2023; Stillger 2025), our analysis extends this approach by also incorporating emissions embodied in

5. Overviews on this literature are provided by e.g., Sato (2014), Grubb et al. (2022), Copeland et al. (2022), Felbermayr et al. (2024).

domestically sourced intermediate inputs.

3 Data

This study draws on a unique panel dataset covering German manufacturing firms between 2011 and 2019. The dataset combines several administrative firm-level data sources that provide granular information on production and export activity, physical energy use, and intermediate input use – both domestic and imported. The data are further enriched with emission factors for direct fuel use, purchased electricity and district heating, and intermediate inputs, enabling a comprehensive assessment of firm's emissions generated during production and indirectly along global supply chains.

In the following, we briefly describe the individual data sources, focusing on the components most relevant to our analysis, and refer to the existing literature for detailed documentation. We then outline how we calculate firms' production-related and embodied emissions.

3.1 Administrative firm-level data

Our dataset combines four administrative firm-level sources, merged using unique firm and plant-firm identifiers: the *AFiD-Panel Manufacturing Firms* , the *AFiD-Module Energy Usage* , the *Materials and Supply Survey* , and the *AFiD-Panel Foreign Trade Statistics*.[6] Each of these datasets is compiled and provided by the German Statistical Office, based on legal reporting obligations for firms. This ensures high data quality and low non-response rates.

The merged *AFiD-Module Energy Usage* and *AFiD Panel Manufacturing Firms*[7] form the basis of our dataset. This combined firm-level dataset has been extensively used to study energy use and environmental performance in German manufacturing.[8]

The *AFiD-Module Energy Usage* is a census of all manufacturing plants with more than 20 employees, reporting physical energy consumption (in kWh) across 14 sources, including fossil fuels and electricity. This allows for a precise calculation of direct and energy-related CO_2 emissions from purchased electricity and district heating (see next section).

The *AFiD Panel Manufacturing Firms* consists of three components, two of which are relevant here. The Investment Census (IC) covers all manufacturing firms with more than 20 employees and records investments in tangible and intangible assets, which are used to estimate capital stocks. The Cost Structure Survey (CSS) collects detailed data on inputs and outputs – including sales, employment, and material use – for a rotating sample of firms with 20–500

6. The data are not freely available but researchers can analyze them in regional research data centers of the German Statistical System. For detailed metadata of these datasets see RDC (2022, 2023b, 2017, 2023a).

7. The dataset has been widely used in studies of productivity and firm performance (Axenbeck and Niebel 2021; Duso and Schiersch 2022; Mouel and Schiersch 2024; Gornig and Schiersch 2024; Schiersch et al. 2024).

8. Applications include CO_2 emission intensity and exporting (Richter and Schiersch 2017), emission decomposition (Rottner and Graevenitz 2024), energy tax exemptions (Gerster and Lamp 2024), voluntary environmental programs (Kube et al. 2019), and electricity network charges (Graevenitz and Rottner 2024). It has also been employed to analyze the effects of the EU ETS on productivity, markups, cost pass-through, employment, value added, emissions, and overall firm performance (Hintermann et al. 2024; Lehr et al. 2024; Löschel et al. 2019; Lutz 2016). For an early presentation, see Petrick et al. (2011).

employees, which is representative at the two-digit industry and size-class level, and is complemented by full coverage of firms with more than 500 employees. These data are used to estimate Total Factor Productivity (TFP) and allow us to relate emissions to economic activity at the firm level.[9] In particular, sales are used to compute firms' CO_2 emission intensity.

In a next step, we complement this core dataset with information on firms' sourcing behavior, combining information on both domestically and internationally sourced intermediate inputs. This enables us to trace the carbon content of inputs across the full supply chain, as described in the following section.

The *Materials and Supply Survey* (MSS) is a representative firm-level survey conducted every four years by the German Federal Statistical Office.[10] Within our observation period, the survey was conducted in 2014 and 2018. We also use the 2010-wave of the MSS to infer firms' domestic sourcing in 2011-2013. It covers manufacturing firms and collects detailed information on the sourcing of materials and intermediate products. The sampling design ensures representativeness at the size class and four-digit industry. Each wave of the survey includes approximately 18,000 firms, corresponding to an average coverage rate of 45% of all manufacturing firms, with full inclusion of all firms employing 500 or more workers – similar to the CSS. Goods are classified according to the German List of Goods for Production Statistics (2009 edition), based on the PRODCOM classification. This high level of granularity enables the identification of input types and characteristics, allowing us to estimate the CO_2 emissions embodied in the domestic supply chain (see next section).

The *AFiD-Panel Foreign Trade Statistics* – recently made available to the scientific community (see Fauth et al. 2023) – is an annual census of cross-border transactions conducted by German firms. It provides firm-level data by year at the highly disaggregated 8-digit HS product level, including transaction value, direction (import/export), and partner country. The source for transactions with non-EU trading partners are customs declarations, while intra-EU trade flows are based on reports to the statistical office. The detailed product and geographic information enables a precise calculation of CO_2 emissions embedded in imported inputs and firms' international supply chains.

3.2 Firm-level carbon accounting

The leading standard of greenhouse gas (GHG) emission accounting classifies emissions into three scopes (WRI and WBCS 2015). Scope 1 covers direct emissions from fossil fuel combustion released during on-site production, while Scope 2 includes emissions from purchased electricity and district heating. Scope 3 encompasses all other indirect emissions occurring along the value chain.

In this paper, we limit our Scope 3 measure to emissions embodied in sourced intermediate inputs – i.e., upstream emissions associated with the production and transport of intermediates, whether sourced domestically or internationally. For ease of exposition, we refer to the sum

9. TFP is estimated using the method proposed by Ackerberg et al. (2015).

10. This is not a standard product and requires a separate application process for access. As a result, it is rarely used, with a notable exception by Gerster and Lamp (2024).

of Scope 1 and Scope 2 emissions as *production-related* emissions, and to the sum of Scope 1, Scope 2, and our measure of Scope 3 emissions as *total* emissions.

While most firm-level analyses focus exclusively on production-related emissions, our approach incorporates embodied emissions as well. This allows us to more comprehensively capture firms' carbon footprints and examine the role of sourcing decisions along the supply chain. In the following, we outline our approach to calculating production-related emissions and emissions embodied in materials at the firm level, based on the dataset described above.

We calculate production-related emissions using fuel-specific emission factors provided by Umweltbundesamt (2022) in combination with firm-level physical energy consumption (see above).[11]

$$e_{jst}^{prod} = \sum_{k \in K} \iota_t^k q_{jst}^k + \iota_t^{dh} q_{jst}^{dh} + \iota_t^{ele} q_{jst}^{ele}, \tag{1}$$

where K denotes the set of energy carriers combusted on-site, ι_t^k, ι_t^{ele}, and ι_t^{dh} are the emission factors (in tons of CO_2 per kwh) for fuel type k, electricity, and district heat, respectively, while q_{jst}^k, q_{jst}^{ele}, and q_{jst}^{dh} are the corresponding quantities of energy use in kilowatt-hours of firm j in sector s at time t.[12]

To extend our emissions measure beyond production-related emissions, we incorporate CO_2 emissions embodied in intermediate inputs at the firm level. This addition allows us to capture emissions that arise along the supply chain, beyond the firm's direct control, and which may constitute a significant share of a firm's overall carbon footprint.

To this end, we employ the environmentally extended multi-regional input-output (MRIO) database Exiobase to calculate detailed product- and country-specific emission factors (Stadler et al. 2018). Compared to other MRIO databases like WIOD or GTAP, Exiobase offers higher product granularity, distinguishing between 200 product categories. The input-output structure allows us to trace emissions along entire supply chains (Peters 2008).[13]

Consider, for example, a German car manufacturer that imports an engine from the Czech Republic for final assembly. The corresponding (calculated) emission factor for the engine captures direct emissions from assembly in the Czech Republic, emissions from Czech electricity generation, and upstream emissions from steel production in, say, China – including emissions from Chinese electricity use.[14]

11. This approach follows standard practice in carbon accounting, as recommended by the IPCC, and is widely used in the academic literature. Since no large-scale abatement technologies are currently in use, emissions are effectively proportional to the combustion of fossil fuels. We abstract from process emissions that arise during production, such as CO_2 emissions from the calcination process in clinker production.

12. Emissions from purchased electricity are included using the average emission intensity of the German electricity mix. This choice is due to the lack of detailed data on fuel inputs used for self-generated electricity. Including electricity-related emissions ensures a consistent and comparable measure of production-related emissions across firms, which may differ in their reliance on self-generated versus purchased electricity. This approach follows prior analyses on emissions from German manufacturing firms (Rottner and Graevenitz 2024; Richter and Schiersch 2017).

13. See Appendix A for details on Exiobase and the embodied emissions calculation. For a prominent application of Exiobase in trade-environment analysis, see Shapiro (2021)

14. While we employ very detailed information on embodied emissions in the value chain, a limitation of our approach is the reliance on average foreign emission factors. Existing evidence suggests that exporters tend to be cleaner than their national average in terms of production-related emissions. However, the relevant metric for our

For imported inputs, embodied emissions are calculated by multiplying product- and origin-specific emission factors from Exiobase with firm-level import data:

$$e_{jst}^{im} = \sum_{p \in P^{im}} \sum_{n \in N} \iota_{nt}^{p} m_{njst}^{im,p}, \tag{2}$$

where ι_{nt}^{p} is the emission rate (in tons of CO_2 per Euro) for product $p \in P^{im}$ from country $n \in N$, and $m_{njst}^{im,p}$ is the imported volume of that product-origin combination for firm j in sector s and year t.

To compute embodied emissions of domestically sourced inputs, we apply a similar approach as for calculating emissions embodied in imported inputs. We first multiply the product-specific emission factors for Germany from Exiobase with firms' domestic inputs using information from the MSS, which we observe for a subset of firms. Based on these firm-level embodied emissions for the MSS sample, we compute sector- and firm-trading-status specific emission factors for domestic inputs, $\iota_{st}^{do,x(j)}$.[15] As we observe aggregate expenditures for domestic inputs of all firms, we then use the firm-trading-status specific emission factors to calculate embodied emissions in domestic inputs for our full sample as described in Eq. (3). To avoid double counting, the material variable is adjusted for imports ($m_{njst}^{im,p}$) and electricity expenditures (m^{ele}):[16]

$$e_{jst}^{do} = \iota_{st}^{do,x(j)} \left(m_{jst} - \sum_{p \in P^{im}} \sum_{n \in N} m_{njst}^{im,p} - m_{jst}^{ele} \right), \tag{3}$$

Combining these components from Eqs. (1)-(3), which cover production-related emissions and emissions embodied in imported and domestic inputs, yields:

$$e_{jst}^{tot} = e_{jst}^{prod} + \underbrace{e_{jst}^{im} + e_{jst}^{do}}_{e_{jst}^{emb}}, \tag{4}$$

providing a comprehensive firm-level carbon footprint that reflects both direct emissions from production and indirect emissions embodied in input use.

For our analysis, we define emission intensity as emissions per unit of sales. The most comprehensive measure – based on a firm's full carbon footprint – is given by:

$$i_{jst}^{e,tot} \equiv \frac{e_{jst}^{tot}}{y_{jst}} = \frac{e_{jst}^{prod} + e_{jst}^{emb}}{y_{jst}} = i_{jst}^{e,prod} + i_{jst}^{e,emb}, \tag{5}$$

carbon accounting approach is a firm's total carbon footprint. The existing literature is silent on whether there is a difference in the total carbon footprint of exporters and non-exporting firms. Thus, we rely on average foreign emission factors in our carbon accounting to avoid taking an ex-ante stance on whether exporters have a higher or lower total carbon footprint – and we rather seek to explore this question in the analysis.

15. To retain as much heterogeneity as possible, the emission factors are calculated by 4-digit industries and trading statuses whenever feasible.

16. While the embodied emissions from purchased electricity are already included in the production-related emissions in Eq. 1, we do not subtract expenditures on other energy inputs to include emissions associated to their production in this step. For example, emissions from the combustion of natural gas are accounted for in Eq. (1), while emissions released during the natural gas extraction process are included here in Eq. (3).

which represents the sum of two emission intensity measures, based on production-related emissions and embodied emissions. This simplification holds because each term is divided by the same denominator, total sales y_{jst}. This measure enables comparisons of carbon efficiency between exporting and non-exporting firms, independent of their production scale.

3.3 Data cleaning and descriptive statistics

Our final dataset contains 119,342 firm-year observations for the period 2011–2019. To arrive at our final dataset, we drop outliers above the 99th and below the 1st percentile in the key variables of our main analysis. We restrict our sample to manufacturing firms and, following the literature, exclude firms from NACE codes 12 (Manufacture of tobacco products) and 19 (Manufacture of coke and refined petroleum products). Table 1 reports descriptive statistics for key firm-level variables for the full final sample as well as disaggregated by trading status.

Table 1: Descriptive statistics of key variables

Description (unit)	Mean	Std. dev.	p10	p90	N
	Full sample				
Production-related CO_2 emission intensity (t CO_2/1000 EUR)	0.11	0.24	0.01	0.21	119342
Total CO_2 emission intensity (t CO_2/1000 EUR)	0.32	0.34	0.12	0.54	119342
Exporting status (1=exporting, 0=not exporting)	0.81	0.39	0.00	1.00	119342
Exports (in % of sales)	0.23	0.25	0.00	0.62	119342
Imports (in % of sales)	0.08	0.11	0.00	0.24	119342
Employees (number)	293.09	2292.14	31.00	524.00	119342
Labor productivity (1000 EUR/employee)	63.44	39.18	29.08	102.79	119342
Capital labor ratio (1000 EUR/employee)	124.22	106.86	42.48	235.80	119342
Energy consumption per employee (1000 EUR/employee)	5.03	13.73	0.64	10.34	119342
	Exporting firms				
Production-related CO_2 emission intensity (t CO_2/1000 EUR)	0.11	0.24	0.01	0.22	96334
Total CO_2 emission intensity (t CO_2/1000 EUR)	0.33	0.35	0.13	0.56	96334
Exports (in % of sales)	0.28	0.25	0.01	0.66	96334
Imports (in % of sales)	0.10	0.12	0.00	0.26	96334
Employees (number)	334.69	2547.40	33.00	588.00	96334
Labor productivity (1000 EUR/employee)	67.47	40.18	33.67	106.85	96334
Capital labor ratio (1000 EUR/employee)	130.47	105.87	46.93	242.84	96334
Energy consumption per employee (1000 EUR/employee)	5.17	11.60	0.69	10.72	96334
	Non-exporting firms				
Production-related CO_2 emission intensity (t CO_2/1000 EUR)	0.11	0.23	0.01	0.19	23008
Total CO_2 emission intensity (t CO_2/1000 EUR)	0.27	0.28	0.09	0.45	23008
Imports (in % of sales)	0.02	0.06	0.00	0.07	23008
Employees (number)	118.91	210.13	26.00	252.00	23008
Labor productivity (1000 EUR/employee)	46.56	29.12	21.02	78.30	23008
Capital labor ratio (1000 EUR/employee)	98.04	106.99	33.16	190.37	23008
Energy consumption per employee (1000 EUR/employee)	4.47	20.35	0.46	8.64	23008

Exporting firms differ systematically from non-exporters along several dimensions. In particular, with respect to sourcing behavior, most exporting firms import much more inputs – on average 10% of sales – than non-exporting firms.Emission intensities appear similar when based on production-related emissions but are slightly higher for exporters when total emissions are considered. These patterns should be interpreted with caution and provide only a first snapshot; we turn to a more elaborated analysis below.

To better understand the emission content of sourced inputs, Figure 1 reports the average emission factors in our sample for the year 2018, distinguishing between domestically sourced materials and materials imported from major trading partners.

The first two bars indicate that, on average, imported materials have slightly higher emission factor than domestic materials. However, this average for imports masks substantial heterogeneity across countries of origin. Emission factors for EU imports are slightly lower than those for domestic materials, while imports from non-EU countries are, on average, 50% more emissions intensive. This heterogeneity becomes even more pronounced when looking at country-specific emission factors: for example, materials imported from France are only half as emission intensive as domestic inputs, whereas those imported from China have emission intensities approximately three times larger.

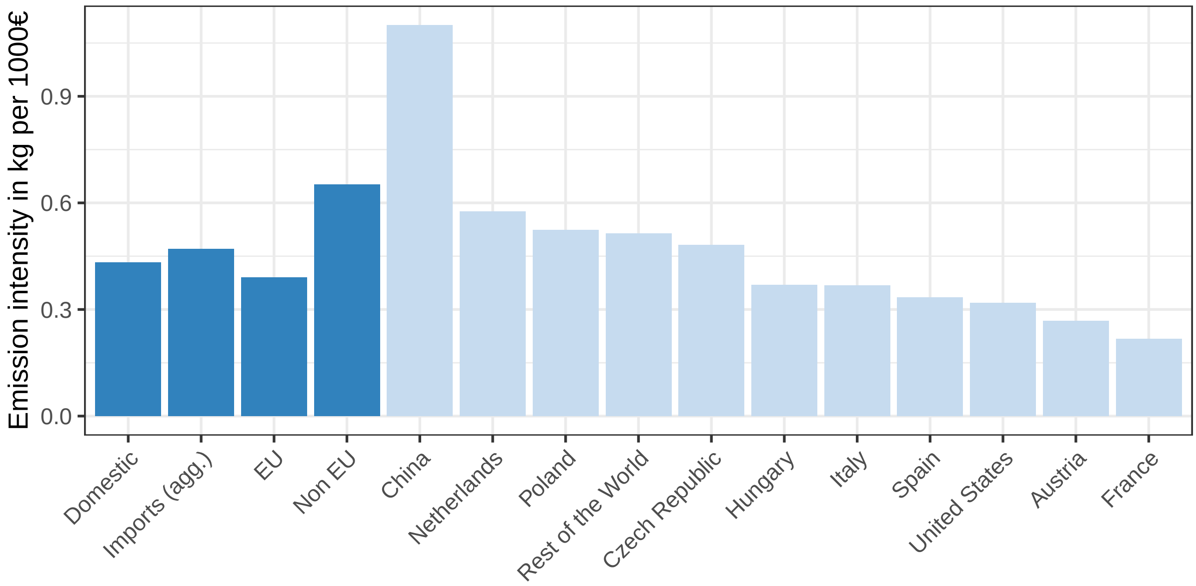


Figure 1: Average emission factors for Germany and key trading partners

Notes: The figure shows average emission factors of materials (emissions embodied in materials relative to total material expenditure) for the year 2018 by source country. The dark blue bars show weighted average emission factors of domestic materials, aggregate imports, and EU vs. Non-EU imports at the firm-level. The light blue bars show the emission factors by origin country for the top 10 trading partners based on the import value in 2018 and an aggregated "Rest of the World".

4 Stylized facts: The role of embodied emissions

In this section, we present three key stylized facts about the role of embodied emissions in firm-level carbon footprints and their implications for the exporter's environmental premium.

4.1 Embodied emissions constitute a large fraction of firm-level emissions

As a first stylized fact, we document that embodied emissions account for a substantial share of total firm-level CO_2 emissions. Figure 2 illustrates the distribution of the share of production-related and embodied emissions in firms' total emissions for the year 2018.[17] The first boxplot reveals that production-related emissions constitute around 30% of the average firm's total emissions and less than 45% for more than three quarters of firms. In contrast, emissions embodied in intermediate inputs represent the majority of firms' carbon footprints, contributing roughly 70% of total emissions on average (second boxplot). For 90% of the firms, embodied emissions contribute to more than one-third of total emissions. Further disaggregating by input origin, we find that most embodied emissions are associated with domestically sourced materials (third boxplot), which alone account for more than half of total emissions. Nevertheless, for about 25% of firms, imported materials contribute more than a quarter of total emissions (fourth boxplot).

These patterns are consistent across years in our sample and within the subsample of firms for which we directly observe the sectoral origin of domestic inputs via the *Materials and Supply Survey* (see Appendix B).

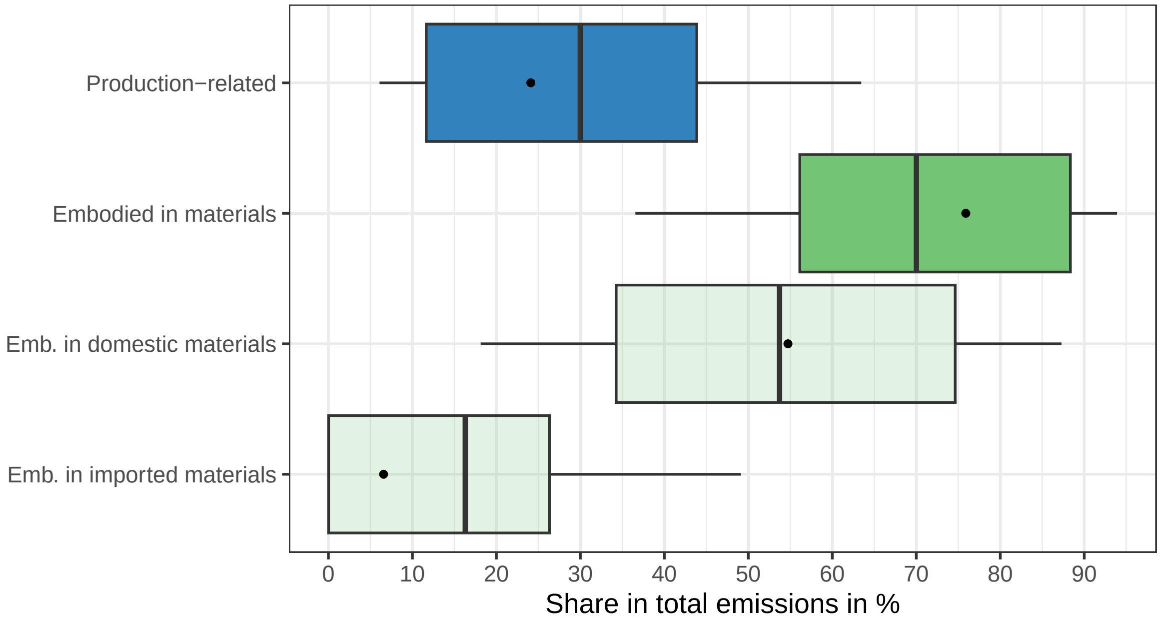


Figure 2: Share of production-related and embodied emissions in total emissions in 2018.

Notes: The figure shows box plots of the share of different emission measures in total emissions for the year 2018. For example, the first boxplot, *Production-related*, shows the distribution of $e^{prod}_{jst}/e^{tot}_{jst}$. The whiskers are the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile, the ends of the boxes indicate the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile, the middle line is the unweighted average and the point indicates the median.

17. The year 2018 is the most recent year of the *Materials and Supply Survey*.

4.2 Embodied emissions, especially those embodied in imports, are more relevant for exporting firms

As a second stylized fact, we document that embodied emissions – and particularly emissions embodied in imports – are more relevant for exporting firms. Figure 3 shows firms' total emissions, split into production-related and embodied emissions for the average exporting and non-exporting firm in 2018.

The bars are divided into three components: production-related emissions (blue), emissions embodied in domestically sourced materials (light green), and emissions embodied in imported materials (dark green), with the green parts jointly comprising embodied emissions in inputs. As pointed out in the first stylized fact, embodied emissions constitute the largest share of total emissions – for both exporting and non-exporting firms. However, they are more pronounced among exporting firms, accounting for about 72% of their total emissions on average, compared to around 61% for non-exporting firms. Disaggregating further by the origin of embodied emissions, exporters on average exhibit a substantially larger share of emissions embodied in imports (the dark green part of the bar), amounting to 19%, compared to only about 3% for non-exporters.

In Appendix B, we show that similar patterns hold across all years in our data and for the subsample of firms covered by the *Materials and Supply Survey*, for which we observe domestic intermediate inputs across origin sectors directly. We further provide evidence that these patterns are not driven by sectoral differences by reporting results from regressions of the share of embodied emissions in imported and total materials on an export dummy, controlling for 4-digit sector and year fixed-effects.

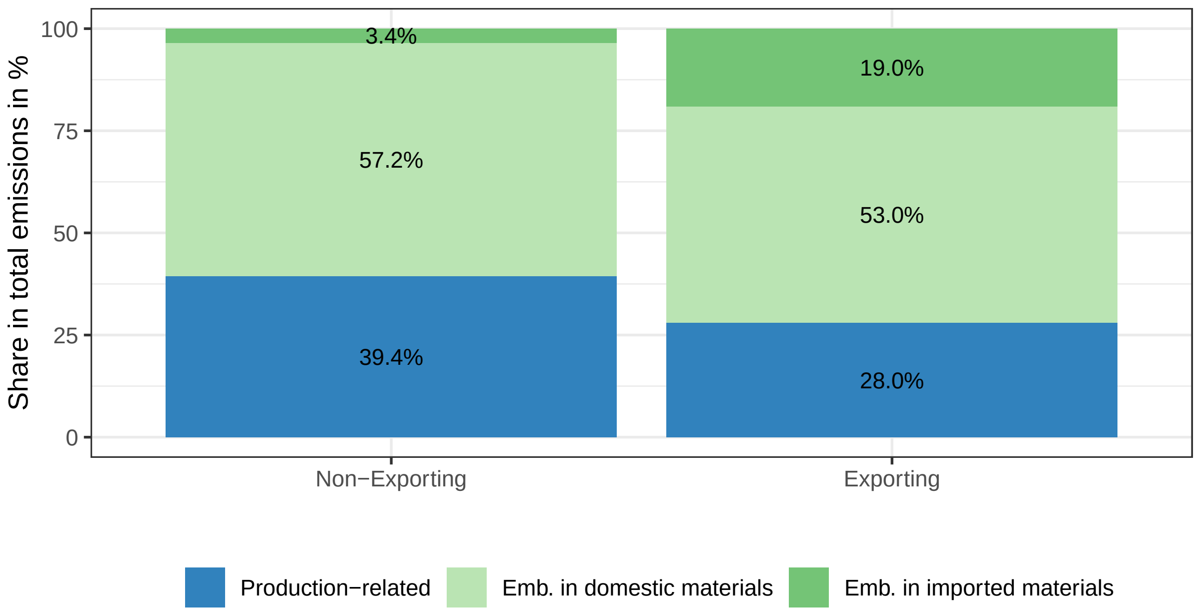


Figure 3: Composition of total emissions for the average exporter and non-exporter in 2018.

4.3 Exporters have a larger total emission intensity than non-exporters

As a third stylized fact, we find that exporters exhibit a higher total emission intensity than non-exporters – reversing the conventional exporter's environmental premium observed when only production-related emissions are considered.

It is well established that exporters differ systematically from non-exporters: they tend to be larger (in terms of employees and sales), more productive, and more capital-intensive (see e.g., Bernard et al. 2018). Moreover, prior research documents that exporters are cleaner than non-exporters in terms of production-related emission intensity – see Section 2. We confirm these empirical patterns in our data.[18] We then extend the analysis to the total emission intensity and assess whether the EEP persists once emissions embodied in inputs are accounted for.

To estimate the exporter's environmental premia, we run a set of two-way fixed effects regressions of firms' emission intensities on different measures of export activity. Specifically, we estimate the following equation:

$$ln\, i^{e}_{jst} = \delta exp_{jst} + \mathbf{x}'_{jst}\beta + \epsilon_{jst}, \tag{6}$$

where i^{e}_{jst} denotes the emission intensity (emissions per unit of output, in EUR) of firm j in sector s in year t, referring either to production-related emissions or total emissions. Our key explanatory variable exp_{jst} captures either export status (via a dummy), export intensity, or the log of export value. The vector of control variables $\mathbf{x}_{jst}$ includes a categorical firm size indicator and the log of TFP, the capital-labor ratio, and the energy-labor ratio. Industry and year fixed effects are included throughout. Our coefficient of interest, δ, captures the exporter's environmental premium in the specification using export status, or the effect of export intensity or export value on emission intensity in the other two sets of regressions.

Table 2 summarizes the regression results for all three exporting variables: export status in Panel A, export intensity in Panel B, and log export value in Panel C. Column (1) reports specifications with only industry and year fixed effects. In columns (2)-(4), we sequentially add controls for firm size, TFP, and capital and energy intensities. The full specification in column (4) corresponds to Eq. (6).

18. Appendix Table B.2 shows that exporting status, export intensity, and export value (in logs) are consistently associated with higher employment, sales, productivity and capital intensity.

Table 2: Exporter's environmental exporter premia

	Panel A: Exporter dummy			
	(1)	(2)	(3)	(4)
Log production-related emission intensity	-0.0518***	-0.0945***	-0.0525***	-0.133***
	(0.0148)	(0.0150)	(0.0149)	(0.0115)
Log total emission intensity	0.0918***	0.0652***	0.0775***	0.0411***
	(0.00832)	(0.00850)	(0.00853)	(0.00711)
Year & industry FEs	✓	✓	✓	✓
Size dummies		✓	✓	✓
Log TFP			✓	✓
Log K/L & Log E/L				✓
Observations	119,342	119,342	119,342	119,342
	Panel B: Export intensity			
	(1)	(2)	(3)	(4)
Log production-related emission intensity	-0.0871***	-0.179***	-0.0547**	-0.177***
	(0.0259)	(0.0271)	(0.0266)	(0.0178)
Log total emission intensity	0.184***	0.136***	0.174***	0.118***
	(0.0127)	(0.0134)	(0.0133)	(0.0110)
Year & industry FEs	✓	✓	✓	✓
Size dummies		✓	✓	✓
Log TFP			✓	✓
Log K/L & Log E/L				✓
Observations	119,342	119,342	119,342	119,342
	Panel C: Log export value			
	(1)	(2)	(3)	(4)
Log production-related emission intensity	-0.00234	-0.0374***	-0.0131***	-0.0602***
	(0.00242)	(0.00311)	(0.00309)	(0.00228)
Log total emission intensity	0.0286***	0.0280***	0.0374***	0.0205***
	(0.00118)	(0.00152)	(0.00155)	(0.00136)
Year & industry FEs	✓	✓	✓	✓
Size dummies		✓	✓	✓
Log TFP			✓	✓
Log K/L & Log E/L				✓
Observations	96,334	96,334	96,334	96,334

Notes: The table shows the estimated coefficients from regressing log production-related and log total emissions on exporting activity. Panel A uses an exporter dummy (1 if a firm exports and 0 otherwise), Panel B uses export intensity, and Panel C uses log export value. All specifications include year fixed effects and four-digit sector fixed effects. In columns 2-4, we subsequently add controls for firm size-class dummies, log TFP, log capital-labor ratio, and log energy consumption per employee. Standard errors in parentheses are clustered at the firm level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In line with previous studies, we find that exporting status, export intensity, and export value are consistently associated with lower production-related emission intensity. These negative coefficients are highly significant across all specifications, except for the first specification of log export value where the estimate remains negative but is statistically insignificant.

This pattern, however, reverses when considering total emission intensity. Across all specifications, the coefficients for the three types of exporting variables become positive and statistically significant at the 1 % level, indicating that exporters are more emission-intensive once embodied emissions are included.

To assess the robustness of these finding, we re-estimate the exporter's environmental premia using doubly robust estimators: Inverse Probability Weighted Regression Adjustment (IPWRA) and Augmented Inverse Probability Weighting (AIPW). The results, presented in Table B.3, confirm our main findings.

Taken together, these findings suggest that standard analyses based only on production-related emissions systematically overestimate the EEP. While exporters appear cleaner when only production-related emissions are considered, they exhibit higher overall emission intensity once emissions embodied in their sourced inputs are accounted for.

5 Decomposition

The observed reversal of the EEP – where exporters appear cleaner based on production-related emissions, but dirtier when total emissions are considered – warrants further investigation. To unpack the factors behind this pattern, we conduct a decomposition analysis that isolates the key contributing factors.

Specifically, we focus on three channels: First, the *sourcing intensity*: Do exporters use more material inputs per unit of sales? Second, the *sourcing composition*: Do exporters rely more on imported inputs than non-exporters? Finally, the *emission intensity of sourced inputs*: Do exporters source materials – within each category of domestic and foreign inputs – that are more carbon-intensive on average, for instance due to differences in the countries or industries of origin?

5.1 General framework

To investigate why exporters appear more emission-intensive overall despite having a lower production-related emission intensity, we decompose the difference in emission intensity premia – that is, the gap between exporter-to-non-exporter ratios for total versus production-related emissions. Based on the definition of emission intensity relative to sales in Eq. (5), this difference can be expressed as:

$$\tilde{i}^{e,tot} - \tilde{i}^{e,prod} = \omega \left(\tilde{i}^{m} \cdot \tilde{\iota}^{emb} - \tilde{i}^{e,prod} \right), \tag{7}$$

where the tilde denotes exporter-to-non-exporter ratios (e.g., $\tilde{i}^{e,tot} \equiv i_x^{e,tot}/i^{e,tot}$, with subscript x indicating exporters), and $\omega \equiv e^{emb}/e^{tot}$ is the average share of embodied emissions in total emissions for non-exporters.[19]

This expression builds on the identity $i^{e,emb} = i^m \cdot \iota^{emb}$, i.e., the embodied emission intensity equals the product of material intensity $i^m \equiv m/y$ and the average emission factor of material inputs $\iota^{emb} \equiv e^{emb}/m$. The latter reflects both the sourcing composition and the emission intensities of domestic and imported materials. We return to this component in more detail below.

We begin by focusing on the two main components in Eq. (7): (i) the sourcing intensity ($\tilde{\imath}^m$), and (ii) the average emission intensity of sourced inputs ($\tilde{\iota}^{emb}$). To assess their respective contributions to the overall gap in emission intensity premia, we simulate counterfactuals by separately setting each component equal to $\sqrt{\tilde{\imath}^{e,prod}}$, which corresponds to neutralizing its effect on the difference in premia.[20] This exercise allows us to isolate how much each margin contributes to the observed gap in total versus production-based emission intensity premia.

Using firm-level data from the year 2018, we find that the gap in emission intensity premia – i.e., the left-hand side of Eq. (7) – amounts to approximately 0.29. In other words, when accounting for embodied emissions, the exporter-to-non-exporter emission intensity ratio increases by 29 percentage points.[21]

Specifically, setting $\tilde{\imath}^m$ to the neutral value reduces the gap from 0.286 to 0.132, while neutralizing $\tilde{\imath}^{emb}$ yields a reduction to 0.103, as shown in Table 3. This suggests that both differences in sourcing intensity and the emissions content of inputs contribute positively to the higher emission intensity observed among exporters once embodied emissions are taken into account. Given the multiplicative structure of the decomposition, the two components also interact, and their individual contributions should not be interpreted as strictly additive. Nevertheless, the margin of differences in the emission intensity of sourced inputs appears to be somewhat more important in this setting, as neutralizing it alone produces a larger reduction in the observed gap – by approximately 64%, compared to a reduction of 54% in the alternative counterfactual with neutralized $\tilde{\imath}^m$.

Table 3: Contribution to gap in the exporter's environmental premia

	Observed	Counterfactuals	
	$\tilde{\imath}^{e,prod} - \tilde{\imath}^{e,tot}$	I) $\tilde{\imath}^m$ neutralized	II) $\tilde{\iota}^{emb}$ neutralized
Gap in premia	0.286	0.132	0.103

Notes: Based on firm-level data for 2018. "Neutralized" refers to setting the respective component to the value $\sqrt{\tilde{\imath}^{e,prod}}$; the remaining gap in the exporter's premia reflects the contribution of the other component, excluding interaction effects.

19. For readability, we drop firm-level indices and interpret variables as group averages for exporters and non-exporters.

20. The value $\sqrt{\tilde{\imath}^{e,prod}}$ serves as a neutral midpoint in the multiplicative relationship $\tilde{\imath}^{e,emb} = \tilde{\imath}^m \cdot \tilde{\iota}^{emb}$, ensuring that, when both components are set to this level, the overall gap in Eq. (7) becomes zero.

21. Unlike in Stylized Fact 3, we rely here on the raw dataset for a single year (2018). While specific values may differ from those reported in Table 2, the key pattern – an observed gap in total versus production-related emission intensity premia – remains consistent.

5.2 Shapley decomposition of $\tilde{\iota}^{emb}$

As a second step, we disentangle the underlying drivers of the difference in the average emission factor of material inputs, $\tilde{\iota}^{emb}$.

The average material emission factor – illustrated here for the average non-exporter – is a weighted average of the emission intensities of domestically and internationally sourced inputs:

$$\iota^{emb} = (1 - \eta^{im})\iota^{do} + \eta^{im}\iota^{im}, \tag{8}$$

where η^{im} denotes the import share of material inputs (sourcing composition), and ι^{do}, ι^{im} capture the average emission intensities of domestic and imported inputs, respectively.

Accordingly, the exporter-to-non-exporter ratio $\tilde{\iota}^{\text{emb}}$ reflects three underlying channels: (i) differences in sourcing composition (η^{im}), (ii) differences in the average emission intensity of domestic inputs (ι^{do}), and (iii) differences in average emission intensity of imported inputs (ι^{im}).

To quantify the individual contributions of these three channels, we use a Shapley decomposition (cf. Albrecht et al. 2002; Shorrocks 2013; Molnar 2019). Formally, the exporter to non-exporter ratio is decomposed as:

$$\tilde{\iota}^{emb} = \exp(\phi_{\eta^{im}}) \cdot exp(\phi_{\text{do}}) \cdot \exp(\phi_{\text{im}}). \tag{9}$$

Each Shapley value ϕ_z for component $z \in \{\eta^{im}, \iota^{do}, \iota^{im}\}$ is computed as the average of its marginal effect across all permutations ($3! = 6$) of the order in which exporter values replace non-exporter values:

$$\phi_z = \frac{1}{n!} \sum_{\pi \in \Pi} \left[f(z^x, \theta^{\pi}_{-z}) - f(z, \theta^{\pi}_{-z}) \right], \tag{10}$$

where Π is the set of all permutations of the three variables, $f(\eta^{im}, \iota^{do}, \iota^{im}) \equiv ln(\iota^{emb})$ as defined in Eq. (8), and θ^{π}_{-z} denotes the values of the remaining variables in permutation π.

In each permutation, we begin with all variables set to their non-exporter values and replace them one at a time with their exporter values, following the order given by the permutation. The marginal effect of a variable z is then defined as the change in the function value when switching z to its exporter value, holding previously switched variables at their exporter values and the remaining variables at non-exporter values. The Shapley value of each component, ϕ_z, thereby ensures a symmetric attribution, accounting for interaction effects that arise from the non-linear relationship between components.[22]

Table 4 presents the exporter-to-non-exporter ratios for the key components of embodied emission intensity, along with the results of the Shapley decomposition. The overall ratio, $\tilde{i}^{emb} = 1.17$, implies that exporters indirectly emit about 17% more CO_2 per euro of sales via sourced intermediates. This gap can be traced to two main drivers (see above): exporters' slightly higher material input use, $\tilde{i}^{m} = 1.04$, and the higher emission intensity of the materials

22. Unlike "hold-one-constant" counterfactuals, the Shapley approach accounts for interactions between components and avoids biases that can arise from the ordering of variable replacement.

they source, $\tilde{\iota}^{emb} = 1.12$.[23]

The three Shapley components – columns (4) to (6) – show the following: First, exporters rely more heavily on imported inputs: the sourcing composition effect contributes about 6 percentage points to the gap, with $exp(\tilde{\eta}^{im}) = 1.059$.[24] Second, the emission factor of domestically sourced materials is substantially higher for exporters, contributing about 10 percentage points, $exp(\tilde{\iota}^{do}) = 1.098$. This is the single largest contributor to exporters' higher embodied emission intensity. Third, imported materials used by exporters are slightly less carbon-intensive than those used by non-exporters: $exp(\tilde{\iota}^{im}) = 0.967$, corresponding to a 3 percentage point reduction.[25]

Table 4: Contribution of individual factors to embodied emission intensity ratio

	$\tilde{\iota}^{emb}$ (1)	$\tilde{i}^{m}$ (2)	$\tilde{\iota}^{emb}$ (3)	Shapley $exp(\phi_z)$: $\tilde{\eta}^{im}$ (4)	$\tilde{\iota}^{do}$ (5)	$\tilde{\iota}^{im}$ (6)
Exp.-to-non-exp. ratio	1.172	1.043	1.124	1.059	1.098	0.967

Notes: Based on firm-level data for 2018. Columns (1) to (3) show average exporter-to-non-exporter ratios with (1)=(2)×(3), while columns (4) to (6) are estimated contributions of (3), calculated by means of a Shapley decomposition, with (3)=(4)×(5)×(6). Hence, (1) = (2)×(4)×(5)×(6).

Taken together, all four drivers – higher material input intensity, a greater reliance on imports, dirtier domestic sourcing, and slightly cleaner imports – work in the same direction: they reduce the exporter's environmental premium when shifting from production-based to total emissions. Among these, the higher emission intensity of domestically sourced materials stands out as the largest single contributor to exporters' higher total emission intensity once embodied emissions are accounted for.

6 Model

This section develops a model of heterogeneous firms that make joint decisions about exporting and sourcing intermediate inputs, highlighting how these interdependencies shape firm-level emissions. Building on Antràs et al. (2017), we extend the framework to explicitly incorporate energy as an additional factor of production, whose use generates emissions.

The model serves two purposes: first, to provide a theoretical rationale for the empirical patterns documented in Sections 4 and 5; and second, to derive testable predictions regarding

23. That both underlying ratios exceed one indicates that exporters have a higher embodied emission intensity originating from both margins. While this does not necessarily imply a reversal of the exporter premium, it shows that a reversal is possible – depending on the relative magnitude of the differences in production-based and embodied emission intensities, as shown in Eq (7).

24. Note that this Shapley value reflects the contribution of sourcing composition to the emission intensity gap, not the ratio of import shares themselves.

25. While imported inputs used by exporters are slightly less carbon-intensive on average than those of non-exporters, the resulting ratio still exceeds that for production-related emission intensity, which is at 0.566. As a result, this channel also contributes to the weakening of the exporter's environmental premium when moving to a total emissions measure.

the impact of foreign demand shocks on firms' emission intensity.

The economy consists of $N = n(\mathcal{N})$ countries, indexed by i and j, each endowed with L_i primary factors. Along the value chain of manufacturing products, emissions are generated and taxed. All income from factor remuneration and tax revenues accrues to a country's households and is spent on private consumption.

6.1 Preferences and final demand

Consumers allocate their income in fixed proportions between consuming manufacturing and other products, following Cobb-Douglas preferences.[26] Manufacturing products are considered imperfect substitutes with an elasticity of substitution $\sigma > 1$ in a standard CES utility function across different varieties of manufactured goods, which is identical across countries.

Accordingly, consumers in country j have the following demand for variety ν produced in country i that is priced at $p_{ij}(\nu)$:

$$q_{ij}(\nu) = p_{ij}^{\sigma}(\nu) P_j^{\sigma-1} E_j \tag{11}$$

where $P_j^{\sigma-1} E_j$ denotes a measure of country j's market size with E_j being the total expenditure on manufacturing goods and P_j the standard CES price index.

6.2 Manufacturing firms

Firms with heterogeneous productivity φ each produce a unique variety of the manufacturing good, using primary factors, emissions-intensive energy, and a bundle of intermediate products sourced either domestically or from abroad. We index varieties by the productivity level of the firms that produce them. Assuming a two-tier Cobb-Douglas-CES production function, the output of an individual firm with φ is given by

$$q_i(\varphi) = \varphi l_i(\varphi)^{\alpha_i} \left[\mu_i d_i(\varphi)^{(\delta-1)/\delta} + (1-\mu_i) m_i(\varphi)^{(\delta-1)/\delta} \right]^{(1-\alpha_i)\delta/(\delta-1)},$$

where output is generated from primary factors l_i and materials, defined as a CES aggregation of energy d_i and intermediate inputs m_i. Parameter μ_i denotes the country-specific CES shift parameter, $\alpha_i \in (0, 1)$ represents the country-specific production costs share of primary factors, and δ is the elasticity of substitution between energy and intermediate inputs, assumed to be country-independent.

Throughout the remainder of the model section, we focus on the case of $\delta > 1$, i.e., where energy and intermediate inputs are gross substitutes. This assumption not only simplifies the exposition but also aligns with the stylized facts documented in Section 4, as we will show below.

The use of energy results in CO_2 emissions. By exploiting the physical proportionality inherent in complete combustion, we scale the relationship to arrive at a 1:1 mapping:
$e_i(\varphi) = d_i(\varphi)$, where emissions are directly proportional to energy consumption. Thus, emissions

26. The non-manufacturing good is freely tradable, generates no emissions in its production, and serves to pin down wages as an outside sector.

can be viewed as a production input factor.[27] Its price, t_i, consists of both a carbon tax and the energy price.

Intermediate inputs are composed of a continuum of differentiated products, which can be sourced either domestically or internationally. Each variety $v \in [0,1]$ is manufactured using energy, d, and labor, l according to the following CES aggregation:

$$m_i(\varphi) = \left(\left[\int_0^1 x_i(v;\varphi)^{(\rho-1)/\rho} dv \right]^{\rho/(\rho-1)} \right),$$

where $x_j(v) = a_j(v) d_j(v)^{\zeta_j} l_j(v)^{1-\zeta_j}$ is the unit input bundle from country j for variety v, and ζ_j denotes the energy share. The unit factor input requirement $a_j(v)$ is drawn from a Fréchet distribution that is homogeneous across producers within country j: $Pr\{a_j(v) \geq a\} = e^{(-T_j a^\theta)}$, with shape parameter θ and location parameter T_j.

Cost minimization yields unit cost of production for variety v in country j of:

$$z_j(v) = a_j(v) \left[\left(\frac{t_j}{\zeta_j} \right)^{\zeta_j} \left(\frac{w_j}{1-\zeta_j} \right)^{1-\zeta_j} \right] = a_j(v) \bar{z}_j,$$

where w_j is the wage rate. When sourcing variety v firms need to pay iceberg trade costs and tariffs, jointly incorporated in τ_{ji}. The unit price for a firm with productivity φ in country i to procure intermediate input v are given by:

$$z_i(v,\varphi,J_i^s(\varphi)) = \min_{j \in J_i^s(\varphi)} \{\tau_{ji} a_j(v) \bar{z}_j\},$$

where $J_i^s(\varphi)$ denotes the set of countries firm φ in i sources from. The resulting unit costs for the material input bundle are:

$$c_i^M(\varphi, J_i^s(\varphi)) = \left(\left[\int_0^1 z_i^{1-\rho}\left(v,\varphi,J_i^s(\varphi)\right) dv \right]^{1/(1-\rho)} \right).$$

Firm behavior conditional on sourcing strategy Solving the minimization problem yields that conditional on sourcing from j firm φ in i spends the following share on varieties from j:

$$\lambda_{jiJ_i^s(\varphi)} = \frac{T_j \left(\tau_{ji}\bar{z}_j\right)^{-\theta}}{\Xi_{iJ_i^s(\varphi)}} \quad \text{if} \quad j \in J_i^s(\varphi), \quad \text{with} \quad \Xi_{iJ_i^s(\varphi)} = \sum_{k \in J_i^s(\varphi)} T_k \left(\tau_{ki}\bar{z}_k\right)^{-\theta}.$$

27. This approach follows a long-standing tradition established by Copeland and Taylor (1994). Alternatively, this production structure of treating emissions as an input can be micro-founded by assuming that firms decide how much labor is devoted to productive purposes and to abate emissions (see Copeland and Taylor (2003) for details).

Similarly, the share in embodied emissions in trade flows from country j in overall embodied emissions is given by:

$$\lambda^e_{jiJ^s_i(\varphi)} = \frac{\frac{\zeta_j}{t_j} T_j \left(\tau_{ji}\bar{z}_j\right)^{-\theta}}{\Xi^e_{iJ^s_i(\varphi)}} \quad \text{if} \quad j \in J^s_i(\varphi), \quad \text{with} \quad \Xi^e_{iJ^s_i(\varphi)} = \sum_{k \in J^s_i(\varphi)} \psi_k T_k \left(\tau_{ki}\bar{z}_k\right)^{-\theta}.$$

$\Xi_{iJ^s_i(\varphi)}$ and $\Xi^e_{iJ^s_i(\varphi)}$ are the value and emission sourcing capabilities of firm φ and $\psi_k = \zeta_k/t_k$ is the emission intensity of country k.

Hence, the unit costs of the intermediate input bundle can be expressed in terms of the sourcing capability, i.e.:

$$c^M_{iJ^s_i(\varphi)} = \left(\gamma \Xi_{iJ^s_i(\varphi)}\right)^{-1/\theta}, \quad \text{where} \quad \gamma = \left[\Gamma\left(\frac{\theta+1-\rho}{\rho}\right)\right]^{\theta/(1-\rho)}.$$

The unit costs of production are thus given by:

$$c_{i\varphi} = \tilde{\alpha}_i \varphi^{-1} w_i^{\alpha_i} \left(\mu_i^\delta t_i^{1-\delta} + (1-\mu_i)^\delta (c^M_{iJ^s_i(\varphi)})^{1-\delta}\right)^{(1-\alpha_i)/(1-\delta)} = \varphi^{-1} c_{iJ^s_i(\varphi)}, \tag{12}$$

where $\tilde{\alpha}_i \equiv \alpha_i^{-\alpha_i}(1-\alpha_i)^{\alpha_i - 1}$.

Profit maximization and exporting/sourcing decision Firms engage in monopolistic competition and thus charge a constant mark-up over marginal costs, i.e. $p_{ij\varphi} = \frac{\sigma}{\sigma-1}\tau^F_{ij} c_{i\varphi}$. Firms need to pay three different types of fixed costs in terms of primary factors. First, f^e_i to enter the market and draw a productivity, second, f^s_{ji} to source inputs from j and, third, f^x_{ij} to enter exporting, which leads to profits of

$$\pi_{i\varphi} = \sum_{j \in J^x_i(\varphi)} \left[p_{ij\varphi} - \tau^F_{ij} c_i(\varphi)\right] q_{ij\varphi} - w_i \sum_{j \in J^s_i(\varphi)} f^s_{ji} - w_i \sum_{j \in J^x_i(\varphi)} f^x_{ij} - w_i f^e_i,$$

where $J^x_i(\varphi)$ is the set of countries a firm in country i with productivity φ sells to. Plugging in Eqs. (11) and (12) yields sales from i to j of

$$r_{ij\varphi} = \varphi^{\sigma-1}\left(\tilde{\alpha}_i w_i^{\alpha_i}\left(\mu_i^\delta t_i^{1-\delta} + (1-\mu_i)^\delta (c^M_{i\varphi})^{1-\delta}\right)^{(1-\alpha_i)/(1-\delta)}\right)^{1-\sigma} B_{ij},$$

where $B_{ij} = \left(\frac{\sigma}{\sigma-1}\tau^F_{ij}\right)^{1-\sigma} E_j P_j^{\sigma-1}$. Hence, profits can be written in terms of revenues:

$$\pi_i(\varphi) = \frac{r_{i\varphi}}{\sigma} - w_i \sum_{j \in J^s_{i\varphi}} f^s_{ji} - w_i \sum_{j \in J^x_{i(\varphi)}} f^x_{ij}, \quad \text{with} \quad r_{i\varphi} = \sum_{j \in J^x_i(\varphi)} r_{ij\varphi}.$$

Given the pricing decision on each market, firms decide which markets they want to serve and which countries they serve their inputs from. Define $V^x(i, j, \varphi, J^s_i(\varphi))$ as 1 if firm with productivity φ in country i with sourcing strategy $J^s_i(\varphi)$ serves country j and zero otherwise.

Hence, $V^x(i,j,\varphi) = 1$ as long as:

$$\varphi^{\sigma-1}\left(\tilde{\alpha}_i w_i^{\alpha_i}\left(\mu_i^{\delta} t_i^{1-\delta} + (1-\mu_i)^{\delta}(\gamma \Xi_{iJ_i^s(\varphi)}^{(\delta-1)/\theta}\right)^{(1-\alpha_i)/(1-\delta)}\right)^{\sigma-1} B_{ij} \geq w_i f_{ij}^x. \tag{13}$$

Clearly, $V^x(i,j,\varphi,J_i^s(\varphi)$ increases in the sourcing capability of a firm. Similarly, define $V^s(i,j,\varphi,J_i^s(\varphi),J_i^x(\varphi))$ as 1 if the firm with productivity φ in country i with sourcing and exporting strategy J^s and J^x respectively, sources inputs from country j and zero otherwise. Hence, $V^s(i,j,\varphi,J_i^s(\varphi),J_i^x(\varphi)) = 1$ as long as:

$$\left[\left(\mu_i^{\delta} t_i^{1-\delta} + (1-\mu_i)^{\delta}(c_{iJ_i^s(\varphi)}^M)^{1-\delta}\right)^{\frac{(1-\alpha_i)(\sigma-1)}{(1-\delta)}} - \left(\mu_i^{\delta} t_i^{1-\delta} + (1-\mu_i)^{\delta}(c_{iJ_i^s(\varphi)\cup j}^M)^{1-\delta}\right)^{\frac{(1-\alpha_i)(\sigma-1)}{(1-\delta)}}\right]$$
$$(\varphi \tilde{\alpha}_i w_i^{\alpha_i})^{\sigma-1} \sum_{j' \in J_i^x(\varphi)} B_{ij'} \geq w_i f_{ij}^s$$

These two expression show that a firm's sourcing and exporting decision are interdependent. The following proposition highlights how these two decisions interact.

Proposition 6.1. *(i) A firm's sourcing capability and the number of export destinations are non-decreasing in productivity φ.*

(ii) Exporting firms have a weakly higher sourcing capability and a weakly higher cost share of non-energy materials (i.e., intermediate inputs) in total materials.

Proof. See Appendix C. □

Firm-level emissions Firm-level emissions follow directly from cost minimization. The production-related emissions of firm φ in country i are given by:

$$e_{i\varphi}^{prod} = \frac{\sigma-1}{\sigma}\frac{(1-\alpha_i)}{t_i}\mu_i^{\delta}\frac{t_i^{1-\delta}}{\left(\mu_i^{\delta} t_i^{1-\delta} + (1-\mu_i)^{\delta}(c_{iJ_i^s(\varphi)}^M)^{1-\delta}\right)} x_{i\varphi} = \frac{(1-\alpha_i)}{t_i}\frac{\sigma-1}{\sigma}(1-\chi_{iJ_i^s(\varphi)}^M) r_{i\varphi},$$

where $\chi_{iJ_i^s(\varphi)}^M = \frac{(1-\mu_i)^{\delta}(c_{iJ_i^s(\varphi)}^M)^{1-\delta}}{\left(\mu_i^{\delta} t_i^{1-\delta} + (1-\mu_i)^{\delta}(c_{J_i^s(\varphi)}^M)^{1-\delta}\right)}$ is the expenditure share of non-energy materials (i.e., intermediate inputs) in total materials. Similarly, embodied emissions are given by:

$$e_{i\varphi}^{emb} = \frac{\sigma-1}{\sigma}(1-\alpha_i)\chi_{iJ_i^s(\varphi)}^M \tilde{\Xi}_{iJ_i^s(\varphi)} r_{i\varphi} \quad \text{with} \quad \tilde{\Xi}_{iJ_i^s(\varphi)} = \frac{\Xi_{iJ_i^s(\varphi)}^e}{\Xi_{iJ_i^s(\varphi)}}. \tag{14}$$

The corresponding emission intensities are given by $i_{i\varphi}^{prod} = \frac{e_{i\varphi}^{prod}}{r_{i\varphi}}$ and $i_{i\varphi}^{emb} = \frac{e_{i\varphi}^{emb}}{r_{i\varphi}}$. Hence, the production-related emission intensity is heterogeneous across firms, as long as firms have a differential set of countries they source from and therefore face heterogeneous unit costs $c_{iJ_i^s(\varphi)}^M$ of the material cost bundle.[28] Differences in the sourcing strategy across firms are also the only

28. Note that in models with a selection into exporting but without heterogeneous sourcing, more productive and exporting firms have a lower production-related emission intensity than non-exporting firms due to productivity differences (e.g., Shapiro and Walker (2018)). However, these papers consider the emission intensity in terms of

reason why the embodied emission intensity varies across firms. Compared to the production-related emission intensity these differences are not fully captured by the non-energy material share, but further depend on a firm's relative emission sourcing capability. Comparing the production-related emission intensity of an exporting firm, φ_x, and a non-exporting firm, φ_x, yields

$$i^{prod}_{i\varphi_x} - i^{prod}_{i\varphi_{nx}} = \frac{\sigma-1}{\sigma}\frac{(1-\alpha_i)}{t_i}\left(\chi^M_{i\varphi_{nx}} - \chi^M_{i\varphi_x}\right). \tag{15}$$

Hence, the direct emission intensity premium of exporters is fully driven by differences in the non-energy material cost share reflecting the different sourcing behavior. Similarly, the difference in the embodied emission intensity of an exporting firm, φ_x, and a non-exporting firm, φ_{nx}, can be expressed as:

$$i^{emb}_{i\varphi_x} - i^{emb}_{i\varphi_{nx}} = \frac{\sigma-1}{\sigma}(1-\alpha_i)\left[\left(\chi^M_{i\varphi_x} - \chi^M_{i\varphi_{nx}}\right)\tilde{\Xi}_{iJ^s_i(\varphi_{nx})} + \chi^M_{i\varphi_x}\left(\tilde{\Xi}_{iJ^s_i(\varphi_x)} - \tilde{\Xi}_{iJ^s_i(\varphi_{nx})}\right)\right]. \tag{16}$$

The first term captures differences in the material cost share, the second term differences in the emission intensity across sourcing origins.

The following proposition summarizes how emission intensities differ between exporting and non-exporting firms under the assumption that energy and materials are substitutes ($\delta > 1$).

Proposition 6.2. *Compared to non-exporting firms, exporters have*

(i) a weakly lower production-related emission intensity;

(ii) a weakly higher embodied emission intensity as long as

$$\frac{\chi^M_{i\varphi_x}}{\chi^M_{i\varphi_{nx}}} \geq \frac{\tilde{\Xi}_{iJ^s_i(\varphi_{nx})}}{\tilde{\Xi}_{iJ^s_i(\varphi_x)}}. \tag{17}$$

Proof. Consider an exporting firm with productivity φ_x and a non-exporting firm with productivity φ_{nx}.

(i) Eq. (15) shows that exporters have weakly lower (higher) production-related emission intensity if and only if they have a weakly higher (lower) non-energy material cost share. By Proposition 6.1, exporters have a weakly higher material cost share $\chi^M_{\varphi_x} \geq \chi^M_{\varphi_{nx}}$, implying a lower production-related emission intensity.

(ii) Eq. (16) implies that exporters have a weakly higher embodied emission intensity if:

$$\frac{\chi^M_{i\varphi_x} - \chi^M_{i\varphi_{nx}}}{\chi^M_{i\varphi_x}} \geq \frac{\tilde{\Xi}_{iJ^s_i(\varphi_{nx})} - \tilde{\Xi}_{iJ^s_i(\varphi_x)}}{\tilde{\Xi}_{iJ^s_i(\varphi_{nx})}},$$

which can be rearranged to Eq. (17).

physical output. Here, instead, we consider the emission intensity in terms of sales, which is directly related to the empirical evidence. This emission intensity in terms of sales is unrelated to productivity in the standard Melitz-type export selection model (see Sogalla et al. (2024) for details). Thus, our finding that the production-related emission intensity differs solely due to differences in sourcing behavior is consistent with these findings.

□

Since energy and materials are substitutes ($\delta > 1$), exporting firms facing lower costs of non-energy material inputs use them relatively more compared to energy. This implies a lower production-related emission intensity, consistent with the empirical patterns documented in Section 4. Given $\delta > 1$, the left-hand side of condition (17) is weakly greater than one. Hence, exporters have a weakly higher embodied emission intensity as long as their relative emission sourcing capability is not too low compared to non-exporters.

The difference in the total emission intensity between exporting and non-exporting firms is the sum of the difference in the production-related and embodied emission intensity, i.e.:

$$i^{tot}_{i\varphi_x} - i^{tot}_{i\varphi_{nx}} = \frac{\sigma-1}{\sigma}(1-\alpha_i)\left[\left(\chi^M_{i\varphi_x} - \chi^M_{i\varphi_{nx}}\right)\left(\tilde{\Xi}_{iJ^s_i(\varphi_{nx})} - \frac{1}{t_i}\right) + \chi^M_{i\varphi_x}\left(\tilde{\Xi}_{iJ^s_i(\varphi_x)} - \tilde{\Xi}_{iJ^s_i(\varphi_{nx})}\right)\right].$$

The total emission intensity premium of exporters is lower than the production-related emission intensity premium provided that exporting firms have higher embodied emission intensities and it reverses only if exporters' embodied emission intensity is substantially higher.

An informative special case arises when intermediate inputs from all source countries have identical emission intensity. In this case, the relative emission sourcing capability does not vary between exporting and non-exporting firms. Thus, even in the absence of cross-country differences in emission intensity, exporters would still exhibit a weakly larger embodied emission intensity due to their weakly higher use of intermediate inputs.

To isolate the role of differences in emission intensities across sourcing origins, suppose that the emission intensity of all imported intermediate inputs is identical, but differs from that of domestically sourced inputs. Formally, assume:

$$\psi_f = \frac{\zeta_k}{t_k}\ \forall\, k \neq i \quad \text{and} \quad \psi_f \neq \psi_i.$$

Under this assumption, Eq. (16) simplifies to

$$i^{emb}_{i\varphi_x} - i^{emb}_{i\varphi_{nx}} = \frac{\sigma-1}{\sigma}(1-\alpha_i)\left[\left(\chi^M_{i\varphi_x} - \chi^M_{i\varphi_{nx}}\right)\tilde{\Xi}_{iJ^s_i(\varphi_{nx})} + \chi^M_{i\varphi_x}\left(\lambda_{ii,\varphi_{nx}} - \lambda_{ii,\varphi_x}\right)(\psi_f - \psi_i)\right].$$

Assuming that all active firms source at least domestically, Proposition 6.1 implies that the domestic material share of exporting firms is lower than for non-exporting firms, i.e., $\lambda_{ii\varphi_x} \leq \lambda_{ii\varphi_{nx}}$. Thus, in this case a sufficient condition for exporters to exhibit a higher embodied emission intensity is that imported intermediate inputs are more emission-intensive than domestic ones ($\psi_f > \psi_i$), and that non-energy materials and energy are gross substitutes ($\delta > 1$).

6.3 Export demand shocks and within-firm emissions intensity

So far, we have compared exporters and non-exporters in terms of their emission intensity. A related question is how a firm's emission intensity responds to an increase in its export activity.

Proposition 6.1 shows that more productive firms tend to source more extensively and export to more destinations. Proposition 6.2 then implies that such firms exhibit lower production-related but potentially higher embodied emissions.

Proposition 6.3 extends these findings to a within-firm setting, showing that a rise in foreign demand generates similar predictions as the cross-sectional comparison between exporters and non-exporting firms:

Proposition 6.3. *Holding wages w_i and emission taxes t_i fixed, an increase in demand B_{ij}*

(i) weakly increases a firm's value sourcing capability;

(ii) weakly increases a firm's non-energy material cost share and lowers its production-related emission intensity;

(iii) increases a firm's embodied emission intensity, provided that the relative emission sourcing capability does not decline by more than the increase in the non-energy material cost-share.

Proof. The proof proceeds along similar lines to those of Propositions 6.1 and 6.2. □

The change in the total emission intensity due to a foreign demand shock is given by:

$$\left.\frac{\partial \ln i^{tot}_{i\varphi}}{\partial B_{ij}}\right|_{w,t} = \frac{\omega^{emb}_{i\varphi} - \chi^M_{i\varphi}}{1-\chi^M_{i\varphi}} \left.\frac{\partial \ln \chi^M_{i\varphi}}{\partial B_{ij}}\right|_{w,t} + \omega^{emb}_{i,\varphi} \left.\frac{\partial \ln \tilde{\Xi}_{iJ^s_i(\varphi)}}{\partial B_{ij}}\right|_{w,t}. \tag{18}$$

Hence, a foreign demand shock affects a firm's total emission intensity via two channels. Through a change in the non-energy material intensity and by affecting the relative emission sourcing capability. When the embodied emission share, $\omega^{emb} = \frac{e^{emb}}{e^{total}}$, is larger than the non-energy material share, the total emission intensity of a firm is increasing in a change of the non-energy material intensity. In this case, the increasing effect of the material intensity on the embedded intensity outweighs the decreasing effect on the direct emission intensity. From (ii) of Proposition 6.3, a foreign demand shock increases the non-energy material share, while the effect on the emission sourcing capability is unclear.

The model is closed by solving for the industry-equilibrium, which is provided in Appendix C.

7 Increase in foreign demand and firm-level emission intensity

We have documented in Section 4 that exporting firms have lower production-related emission intensity and a higher total emission intensity that non-exporters. The theoretical model in Section 6 highlights the role of the larger market of exporters in this process: it enables them to source their inputs from the least expensive origin.

This market size channel affects the emission intensity of exporting firms not only at the extensive but also at the intensive margin: An increase in foreign demand leads exporting firms to shift their input mix from energy towards intermediate inputs. Thus, the model predicts the production-related emission intensity of exporters to decline following an increase in the market size solely due to an increase in the use of intermediate inputs. On the other hand, the effect on the total emission intensity can be positive or negative.

This section empirically tests the model's prediction for the intensive margin, by assessing the effect of a market size driven change in a firm's export activity on its production-related and total emission intensity. To isolate the effect of a demand-driven export shock we construct a shift-share instrument. The argument for identification is that changes in the demand for products in destination countries affect a firm's export activity, but are unrelated to supply-side effects on the emission intensity and sourcing behavior. To attribute destination-product specific demand changes across different firms, we weight them by the corresponding firm-level export shares. Thus, the shift-share instrument for firm f at time t is given by:

$$Z_{f,t} = \sum_{p,c} s_{fcp,t_0} \Delta X_{cp,t}, \tag{19}$$

where exposure share s_{fcp,t_0} is the value of exports of product p firm f ships to destination c in year t_0, r_{fcp,t_0}, relative to its overall exports in year t_0, i.e.:

$$s_{fcp,t_0} \equiv \frac{r_{fcp,t_0}}{\sum_{c',p'} r_{fc'p',t_0}}.$$

Following Mayer et al. (2021) and Aghion et al. (2024) we construct the Davis-Haltiwanger growth rate to measure the shock in foreign demand:

$$\Delta X_{cp,t} = \frac{X_{cp,t} - X_{cp,t-1}}{0.5(X_{cp,t} + X_{cp,t-1})},$$

where $X_{cp,t}$ are the imports of country c of product p from the world (excluding Germany) at time t.[29] This growth rate can assume values between -2 and 2. Compared to a logarithmic transformation of $X_{cp,t}$, this growth rate includes country-product pairs for which the demand goes to zero in a specific year. Because many regulations are common across EU member states, demand changes of EU-countries may be correlated with changes in domestic German demand. In constructing the shift-share instrument, we therefore only include changes in foreign demand in non-EU countries to isolate the foreign demand driven effect.[30]

The shift-share instrument captures variation in the exposure shares and the shocks. Identification can either be obtained by assuming exogeneity of exposure shares (Goldsmith-Pinkham et al. 2020) or through many uncorrelated exogenous shocks (Adão et al. (2019), Borusyak et al. (2022)). As the export shares to a specific destination may be correlated with other supply-side driven changes, we argue that identification stems from exogeneity of the shocks. Thus, the identifying assumption is that that the foreign demand shocks are as-good-as random. This implies that firms experiencing large supply-side-driven changes in emission intensity should not

29. We construct the changes in foreign demand using data from CEPII-BACI, which is based on UN-Comtrade – see Gaulier and Zignago (2010) for details.

30. Another reason to focus only on exports to non-EU countries is reporting of intra-EU trade flows. Only firms with an annual intra-EU trading volume of 500, 000 Euro for exports and 800,000 Euros for imports are obliged to report trade flows to the Federal Statistical Office. For firms below these thresholds imports and exports are estimated by the Federal Statistical Office using advance VAT returns and the VAT Information Exchange System. These estimation strategies allow for a differentiation by partner country but not by product such that we can only observe aggregate country-specific intra-EU trade flows for firms with small trade volumes.

be systematically exposed to foreign demand shocks that differ from those faced by firms with smaller supply-side changes.

By using a first-differences specification, we remove any bias that could arise from correlation between time-invariant firm characteristics influencing its emission intensity and the level of the foreign demand shock, $D_{f,t}$. We further include 2-digit sector fixed effects and their interaction with year dummies, to control for industry specific trends in the growth rate of emission intensities. Moreover, we control for the baseline values of TFP, size class as well as the capital and energy to labor ratio. In our first-differences specification this controls for potential correlations between firm-characteristic-specific trends in emission-intensity with changes in the foreign demand shock.

Finally, to address a potential correlation between foreign demand shock and input-supply shock, we control for changes in the input supply. Our measure of input supply changes is constructed similarly to the shift-share instrument for exports. Here, the exposure shares are based on a firm's baseline imports by product and origin relative to the firms total imports. The shock is the change in the foreign supply of this product from this origin. This foreign supply change is measured as the Davis-Haltiwanger growth rate in the exports of a non-EU country in a specific product to the world (excluding Germany).

The exogenous shocks identification approach relies on having a large number of quasi-random shocks, and shock exposure to be not too concentrated. As detailed in Appendix D, we conduct several diagnostic checks suggested by Borusyak et al. (2022). We additionally generate a dataset containing weighted shock-level aggregates of the variables used in the estimation.[31] Using this transformed dataset, an equivalent shock-level regression is estimated which yields the same SSIV-coefficients as the traditional firm-level SSIV-regression. However, in contrast to the traditional SSIV-regression, the equivalent shock-level yields standard errors are robust to the correlation of unobserved shocks for similar exposure shares and allows to account for a correlation in the shocks (Borusyak et al. 2022).

Table 5 shows the results for the Davis-Haltiwanger growth rate in production-related emission and total emission intensity as dependent variables. The OLS estimates in Panel A indicate that an increase in the growth rate of the export value is associated with a decline in both the growth rate of the production-related and the total emission intensity. However, the coefficient for the total emission intensity is smaller in absolute value suggesting that part of the decline in the production-related emission intensity is offset by a higher embodied emission intensity. The result that higher export activity leads to a lower production-related emission intensity is confirmed once isolating the part, which is driven by the foreign demand shock. Both the reduced form (Panel B) and the IV estimate (Panel C) are negative and statistically significant at the 5% or 1% level (columns 1-3). The IV coefficient is even larger in absolute value than the OLS estimator, indicating that a 10 percent increase in exports leads to a 2 percent decline in the production-related emission intensity. However, the coefficient of the total emission intensity is

31. We generate the shock-level dataset using the Stata *ssaggregate* command by Borusyak et al. (2020). For more details on the transformation of the firm-level dataset to the shock-level dataset see Appendix D and Borusyak et al. (2022).

positive and insignificant (columns 4-6).

The result that a foreign demand shock reduces the production-related emission intensity are in line with part (ii) of Proposition 6.3. The insignificant effect on the total emission intensity suggests that this effect is driven by changes in sourcing pattern as highlighted by the model.

Table 5: OLS and Shift-share estimation

	Panel A: OLS					
	HW production-related emission intensity			HW total emission intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
HW Export Value	-0.0313***	-0.0313***	-0.0313***	-0.0111***	-0.0111***	-0.0111***
	(0.00269)	(0.00269)	(0.00269)	(0.00257))	(0.00257)	(0.00256)
	Panel B: REDUCED FORM					
HW Foreign Demand Shock	-0.0238**	-0.0239**	-0.0237**	0.00816	0.00832	0.00834
	(0.00925)	(0.00926)	(0.00926)	(0.00865)	(0.00866)	(0.00866)
	Panel C: IV					
HW Export Value	-0.245**	-0.248**	-0.246**	0.0839	0.0862	0.0867
	(0.113)	(0.114)	(0.115)	(0.0932)	(0.0942)	(0.0947)
	Panel D: FIRST STAGE					
	HW Export Value					
HW Foreign Demand Shock	0.0973***	0.0966***	0.0961***	0.0973***	0.0966***	0.0966***
	(0.0289)	(0.0289)	(0.0289)	(0.0289)	(0.0289)	(0.0289)
Year & industry FEs	✓	✓	✓	✓	✓	✓
Baseline controls		✓	✓		✓	✓
Input Supply shock			✓			✓
First stage F-Statistic	11.30	11.15	11.06	11.30	11.15	11.06
Observations (Shock-level)	1,044,364	1,044,364	1,044,364	1,044,364	1,044,364	1,044,364
Observations (Firm-year level)	51,584	51,584	51,584	51,584	51,584	51,584

Notes: Panel A shows the OLS regression of the Davis-Haltiwanger difference in the production-related emission intensity (columns 1-3) and the total emission intensity (columns 4-6) on the Davis-Haltiwanger difference in Export Value. Panel B shows the reduced form estimation of the Davis-Haltiwanger difference in the two emission intensities on the shift-share instrument of the foreign demand shock. Panel C shows the IV-estimate and Panel D the first stage regression. All specifications include year and 2-digit industry fixed effects. In columns 2 and 5 we additionally control for the baseline values of TFP, size class and the capital and energy to labor ratio. The specifications in columns 3 and 6 further control for the shift-share instrument of the input-supply shock. Panels B-D are estimated on the shock level (product*destination*year) as proposed by Borusyak et al. (2022). Standard errors are clustered at the 6 digit HS product classification. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Next, we analyze the drivers for the difference between the effect on the production-related and the total emission intensity. From model Eq. (18), the effect on the total emission intensity can be decomposed in the effect on the material intensity and the relative emission sourcing capability, which is directly linked to the emission intensity. The results in Table 6 confirm the model's prediction that a foreign demand shock increases the material intensity of a firm, although the effect is only significant at the 10% level. In contrast, the effect on the emission intensity of materials is insignificant.

Table 6: SHIFT-SHARE ESTIMATION - MECHANISMS

	HW material intensity			HW emission intensity of materials		
	(1)	(2)	(3)	(4)	(5)	(6)
HW Export Value	0.148*	0.146*	0.146*	0.914	0.968	0.963
	(0.0818)	(0.0823)	(0.0826)	(1.068)	(1.082)	(1.086)
Year & industry FEs	✓	✓	✓	✓	✓	✓
Baseline controls		✓	✓		✓	✓
Input Supply shock			✓			✓
Observations (Shock-level)	1,044,364	1,044,364	1,044,364	1,044,364	1,044,364	1,044,364
Observations (Firm-year level)	51,584	51,584	51,584	51,584	51,584	51,584

Notes: The table shows the SSIV estimation of the Davis-Haltiwanger difference in the material intensity (columns 1-3) and the total emission intensity of materials(columns 4-6). All specifications include year and 2-digit industry fixed effects. In columns 2 and 5, we additionally control for the baseline values of TFP, size class and the capital and energy to labor ratio. The specifications in columns 3 and 6 further control for the shift-share instrument of the input-supply shock. All specifications are estimated at the shock level dataset (product*destination*year) as proposed by Borusyak et al. (2022). Standard errors are clustered at the 6 digit HS product classification. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

8 Conclusion

This paper revisits the exporter's environmental premium (EEP) by incorporating firm-level embodied emissions. Using a novel dataset that links administrative firm-level data, customs records, and environmentally extended input-output tables, we trace CO_2 emissions across global supply chains for German manufacturing firms.

We present three stylized facts. First, embodied emissions account for a substantial share of firms' total carbon footprints. Second, exporters systematically generate higher indirect emissions through their international sourcing strategies. Third, accounting for embodied emissions reverses the conventional EEP: while exporters appear cleaner based on production-related emissions alone, they exhibit a higher total emission intensity once sourcing-related emissions are accounted for.

We rationalize these findings with a theoretical model in which exporters, by accessing the larger international market, can source materials from lower cost-suppliers and thus rely more heavily on intermediate inputs relative to energy. The model further predicts that an increase in the international market size induces exporting firms to switch from using energy toward intermediate inputs, thereby lowering their production-related emission intensity. We test this channel empirically using a shift-share identification strategy. Consistent with the model, we find that an increase in foreign demand reduces exporters' production-related emission intensity. Moreover, we provide suggestive evidence that this decline is driven by a switch toward intermediate inputs, as we find an insignificant effect on the total emission intensity and an increase in the material intensity.

These results challenge the prevailing view that trade liberalization reallocates production toward cleaner firms. They also underscore the importance of accounting for firm-level sourcing behavior and embodied emissions into analyses of trade and the environment.

Future work could further quantify the role of sourcing adjustments in response to carbon pricing and assess the implications for designing effective environmental and trade policies. This issue is particularly relevant in the context of the newly implemented European Union's Carbon Border Adjustment Mechanism (CBAM), which directly targets CO_2 emissions embodied in imports of upstream products. The CBAM may thereby limit firms' ability to substitute energy consumption with intermediate inputs and alter the relative environmental performance of internationally active firms compared to firms who source domestically.

References

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica* 83 (6): 2411–2451. doi:10.3982/ECTA13408.

Adão, Rodrigo, Michal Kolesár, and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *The Quarterly Journal of Economics* 134, no. 4 (November): 1949–2010. doi:10.1093/qje/qjz025.

Aghion, Philippe, Antonin Bergeaud, Matthieu Lequien, and Marc J. Melitz. 2024. "The Heterogeneous Impact of Market Size on Innovation: Evidence from French Firm-Level Exports." *The Review of Economics and Statistics* 106 (3): 608–626. doi:10.1162/rest_a_01199.

Akerman, Anders, Rikard Forslid, and Ossian Prane. 2024. "Imports and the CO_2 emissions of firms." *Journal of International Economics* (September): 104004. doi:10.1016/j.jinteco.2024.104004.

Albornoz, Facundo, and Ezequiel Garcıa-Lembergman. 2023. "Importing after Exporting."

Albrecht, Johan, Delphine François, and Koen Schoors. 2002. "A Shapley decomposition of carbon emissions without residuals." *Energy Policy* 30, no. 9 (July): 727–736. doi:10.1016/S0301-4215(01)00131-8.

Antràs, Pol, Teresa C. Fort, and Felix Tintelnot. 2017. "The Margins of Global Sourcing: Theory and Evidence from US Firms." *American Economic Review* 107 (9): 2514–2564. doi:10.1257/aer.20141685.

Aristei, David, Davide Castellani, and Chiara Franco. 2013. "Firms' exporting and importing activities: Is there a two-way relationship?" *Review of World Economics* 149 (1): 55–84. doi:10.1007/s10290-012-0137-y.

Axenbeck, Janna, and Thomas Niebel. 2021. *Climate protection potentials of digitalized production processes: Microeconometric evidence?* Working paper. Publication Title: ZEW Discussion Papers Volume: 21-105. Mannheim.

Barrows, Geoffrey, and Hélène Ollivier. 2021. "Foreign demand, developing country exports, and CO2 emissions: Firm-level evidence from India." *Journal of Development Economics* 149:102587. doi:10.1016/j.jdeveco.2020.102587.

Bas, Maria. 2012. "Input-trade liberalization and firm export decisions: Evidence from Argentina." *Journal of Development Economics* 97 (2): 481–493. doi:10.1016/j.jdeveco.2011.05.010.

Bas, Maria, and Vanessa Strauss-Kahn. 2014. "Does importing more inputs raise exports? Firm-level evidence from France." *Review of World Economics* 150 (2): 241–275. doi:10.1007/s10290-013-0175-0.

Batrakova, Svetlana, and Ronald B. Davies. 2012. "Is there an environmental benefit to being an exporter? Evidence from firm-level data." *Review of World Economics* 148, no. 3 (September): 449–474. doi:10.1007/s10290-012-0125-2.

Bernard, Andrew B., and J. Bradford Jensen. 1999. "Exceptional exporter performance: cause, effect, or both?" *Journal of International Economics* 47 (1): 1–25. doi:10.1016/S0022-1996(98)00027-0.

Bernard, Andrew B., J. Bradford Jensen, and Robert Z. Lawrence. 1995. "Exporters, jobs, and wages in U.S. manufacturing: 1976-1987." *Brookings Papers on Economic Activity. Microeconomics* 1995:67–119. doi:10.2307/2534772.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott. 2018. "Global Firms." *Journal of Economic Literature* 56 (2): 565–619. doi:10.1257/jel.20160792.

Blaum, Joaquin. 2024. "Global Firms in Large Devaluations." *The Quarterly Journal of Economics,* qjae017. doi:10.1093/qje/qjae017.

Blaum, Joaquin, Claire Lelarge, and Michael Peters. 2018. "The Gains from Input Trade with Heterogeneous Importers." *American Economic Journal: Macroeconomics* 10 (4): 77–127. doi:10.1257/mac.20160426.

Blyde, Juan S., and Mayra A. Ramirez. 2022. "Exporting and environmental performance: Where you export matters." *The Journal of International Trade & Economic Development* 31, no. 5 (July): 672–691. doi:10.1080/09638199.2021.2003424.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2020. "SSAGGREGATE: Stata module to create shock-level aggregates for shift-share IV." Publisher: Boston College Department of Economics, *Statistical Software Components* (August).

———. 2022. "Quasi-Experimental Shift-Share Research Designs." *The Review of Economic Studies* 89, no. 1 (January): 181–213. doi:10.1093/restud/rdab030.

———. 2025. "A practical guide to shift-share instruments." Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2418, *Journal of Economic Perspectives* 39 (1): 181–204.

Cherniwchan, Jevan, Brian R. Copeland, and M. Scott Taylor. 2017. "Trade and the Environment: New Methods, Measurements, and Results." *Annual Review of Economics* 9 (1): 59–85. doi:10.1146/annurev-economics-063016-103756.

Choi, Jaerim, Jay Hyun, Gueyon Kim, and Ziho Park. 2025. "The cleanup of US manufacturing through pollution offshoring." *Journal of International Economics* 154:104046. doi:10.1016/j.jinteco.2025.104046.

Cole, Matthew A., Robert J. R. Elliott, Toshihiro Okubo, and Ying Zhou. 2013. "The carbon dioxide emissions of firms: A spatial analysis." *Journal of Environmental Economics and Management* 65, no. 2 (March): 290–309. doi:10.1016/j.jeem.2012.07.002.

Copeland, Brian R., Joseph S. Shapiro, and M. Scott Taylor. 2022. "Chapter 2 - Globalization and the environment." In *Handbook of International Economics,* edited by Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, 5:61–146. Handbook of International Economics: International Trade, Volume 5. Elsevier. doi:10.1016/bs.hesint.2022.02.002.

Copeland, Brian R., and M. Scott Taylor. 1994. "North-South Trade and the Environment." Publisher: Oxford University Press, *The Quarterly Journal of Economics* 109 (3): 755–787. doi:10.2307/2118421.

———. 2003. *Trade and the Environment: Theory and Evidence.* STU - Student edition. Princeton University Press.

Coster, Pierre, Julian di Giovanni, and Isabelle Mejean. 2024. "Firms' Supply Chain Adaptation to Carbon Taxes." *Federal Reserve Bank of New York Staff Reports* 1136.

Cui, Jingbo, Harvey Lapan, and GianCarlo Moschini. 2016. "Productivity, Export, and Environmental Performance: Air Pollutants in the United States." *American Journal of Agricultural Economics* 98 (2): 447–467. doi:10.1093/ajae/aav066.

Cui, Jingbo, and Hang Qian. 2017. "The effects of exports on facility environmental performance: Evidence from a matching approach." *The Journal of International Trade & Economic Development* 26, no. 7 (October): 759–776. doi:10.1080/09638199.2017.1303079.

Dardati, Evangelina, and Meryem Saygili. 2021. "Are exporters cleaner? Another look at the trade-environment nexus." *Energy Economics* 95:105097. doi:10.1016/j.eneco.2021.105097.

Duso, Tomaso, and Alexander Schiersch. 2022. *Let's Switch to the Cloud: Cloud Adoption and Its Effect on IT Investment and Productivity.* SSRN Scholarly Paper. Rochester, NY. doi:10.2139/ssrn.4226411.

Dussaux, Damien, Francesco Vona, and Antoine Dechezleprêtre. 2023. "Imported carbon emissions: Evidence from French manufacturing companies." *Canadian Journal of Economics/Revue canadienne d'économique* 56 (2): 593–621. doi:10.1111/caje.12653.

Fauth, Matthias, Benjamin Jung, and Wilhelm Kohler. 2023. "German Firms in International Trade: Evidence from Recent Microdata." *Jahrbücher für Nationalökonomie und Statistik* 243 (3-4): 199–284. doi:10.1515/jbnst-2022-0040.

Felbermayr, Gabriel, Sonja Peterson, and Joschka Wanner. 2024. "Trade and the environment, trade policies and environmental policies—How do they interact?" *Journal of Economic Surveys* n/a (n/a). doi:10.1111/joes.12628.

Feng, Ling, Zhiyuan Li, and Deborah L. Swenson. 2016. "The connection between imported intermediate inputs and exports: Evidence from Chinese firms." *Journal of International Economics* 101:86–101. doi:10.1016/j.jinteco.2016.03.004.

Forslid, Rikard, Toshihiro Okubo, and Karen Helene Ulltveit-Moe. 2018. “Why are firms that export cleaner? International trade, abatement and environmental emissions.” *Journal of Environmental Economics and Management* 91:166–183. doi:10.1016/j.jeem.2018.07.006.

Gaulier, Guillaume, and Soledad Zignago. 2010. *BACI: International Trade Database at the Product-Level. The 1994-2007 Version.* Working Papers 2010-23. CEPII.

Gerster, Andreas, and Stefan Lamp. 2024. “Energy Tax Exemptions and Industrial Production.” *The Economic Journal* (June): ueae048. doi:10.1093/ej/ueae048.

Girma, Sourafel, and Aoife Hanley. 2015. “How Green are Exporters?” *Scottish Journal of Political Economy* 62 (3): 291–309. doi:10.1111/sjpe.12075.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. “Bartik Instruments: What, When, Why, and How.” *American Economic Review* 110, no. 8 (August): 2586–2624. doi:10.1257/aer.20181047.

Gopinath, Gita, and Brent Neiman. 2014. “Trade Adjustment and Productivity in Large Crises.” *American Economic Review* 104 (3): 793–831. doi:10.1257/aer.104.3.793.

Gornig, Martin, and Alexander Schiersch. 2024. “Agglomeration economies: different effects on TFP in high-tech and low-tech industries.” *Regional Studies,* 1–12. doi:10.1080/00343404.2024.2318454.

Graevenitz, Kathrine von, and Elisa Rottner. 2024. “Climate Policies and Electricity Prices: To Abate or to Generate?” Number: crctr224_2024_504 Publisher: University of Bonn and University of Mannheim, Germany, *CRC TR 224 Discussion Paper Series* (February).

Grubb, Michael, Nino David Jordan, Edgar Hertwich, Karsten Neuhoff, Kasturi Das, Kaushik Ranjan Bandyopadhyay, Harro van Asselt, et al. 2022. “Carbon Leakage, Consumption, and Trade.” *Annual Review of Environment and Resources* 47 (1): 753–795. doi:10.1146/annurev-environ-120820-053625.

Handley, Kyle, Fariha Kamal, and Ryan Monarch. 2025. “Rising Import Tariffs, Falling Exports: When Modern Supply Chains Meet Old-Style Protectionism.” *American Economic Journal: Applied Economics* 17, no. 1 (January): 208–238. doi:10.1257/app.20210051.

Hintermann, Beat, Maja Žarković, Léo Picard, Corrado Di Maria, and Wagner, Ulrich J. 2024. *The effect of climate policy on productivity and cost pass-through in the German manufacturing sector.*

Holladay, J. Scott. 2016. “Exporters and the environment.” *Canadian Journal of Economics/ Revue canadienne d’économique* 49 (1): 147–172. doi:10.1111/caje.12193.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang. 2014. “The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data.” *American Economic Review* 104 (6): 1597–1629. doi:10.1257/aer.104.6.1597.

Kang, Youngho, and Unjung Whang. 2023. “Exporting and sourcing strategies.” *Review of International Economics* 31 (4): 1414–1441. doi:10.1111/roie.12671.

Kube, Roland, Kathrine von Graevenitz, Andreas Löschel, and Philipp Massier. 2019. “Do voluntary environmental programs reduce emissions? EMAS in the German manufacturing sector.” *Energy Economics,* Eighth Atlantic Workshop on Energy and Environmental Economics, 84:104558. doi:10.1016/j.eneco.2019.104558.

Kwon, Ohyun, Hao Zhao, and Min Qiang Zhao. 2023. "Global firms and emissions: Investigating the dual channels of emissions abatement." *Journal of Environmental Economics and Management* 118:102772. doi:10.1016/j.jeem.2022.102772.

Lehr, Jakob, Andreas Gerster, Sebastian Pieper, and Ulrich J. Wagner. 2024. *The Impact of Carbon Trading on Industry: Evidence from German Manufacturing Firms.*

Leisner, Jonathan, Jakob R. Munch, August Twile Nielsen, and Georg Schaur. 2023. "The Impact of Offshoring and Import Competition on Firm-Level Carbon Emissions." Number: 16556 Publisher: Institute of Labor Economics (IZA), *IZA Discussion Papers* (October).

Löschel, Andreas, Benjamin Johannes Lutz, and Shunsuke Managi. 2019. "The impacts of the EU ETS on efficiency and economic performance – An empirical analyses for German manufacturing firms." *Resource and Energy Economics,* Recent Advances in the Economic Analysis of Energy Demand - Insights for Industries and Households, 56 (May): 71–95. doi:10.1016/j.reseneeco.2018.03.001.

Lutz, Benjamin Johannes. 2016. "Emissions trading and productivity: Firm-level evidence from German manufacturing." Number: 16-067 Publisher: ZEW - Leibniz Centre for European Economic Research, *ZEW Discussion Papers.*

Máñez, Juan A., María E. Rochina-Barrachina, and Juan A. Sanchis. 2020. "Foreign sourcing and exporting." *The World Economy* 43 (5): 1151–1187. doi:10.1111/twec.12929.

Mayer, Thierry, Marc J. Melitz, and Gianmarco I. P. Ottaviano. 2021. "Product Mix and Firm Productivity Responses to Trade Competition." *The Review of Economics and Statistics* 103, no. 5 (November): 874–891. doi:10.1162/rest_a_00952.

Molnar, Christoph. 2019. *Interpretable Machine Learning: A Guide For Making Black Box Models Explainable.* Leanpub.

Mouel, Marie Le, and Alexander Schiersch. 2024. "Intangible capital and productivity divergence." *Review of Income and Wealth* 70 (3). doi:10.1111/roiw.12653.

Peters, Glen P. 2008. "From production-based to consumption-based national emission inventories." *Ecological Economics* 65 (1): 13–23. doi:10.1016/j.ecolecon.2007.10.014.

Peters, Glen P., and Edgar G. Hertwich. 2008. "CO2 Embodied in International Trade with Implications for Global Climate Policy." Publisher: American Chemical Society, *Environmental Science & Technology* 42, no. 5 (March): 1401–1407. doi:10.1021/es072023k.

Petrick, Sebastian, Katrin Rehdanz, and Ulrich J. Wagner. 2011. "Energy Use Patterns in German Industry: Evidence from Plant-level Data." Publisher: De Gruyter Oldenbourg, *Jahrbücher für Nationalökonomie und Statistik* 231, no. 3 (June): 379–414. doi:10.1515/jbnst-2011-0306.

RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany. 2017. *Material- und Wareneingangserhebung 2010,2014,2018.*

———. 2022. *AFiD-Modul Energieverwendung 1995-2019".* doi:10.21242/43531.2019.00.03.1.1.0.

———. 2023a. *AFiD-Panel Außenhandelsstatistik 2011-2020.* doi:10.21242/51911.2019.00.05.1.1.0.

RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany. 2023b. *AFiD-Panel Industrieunternehmen 1995-2021.* doi:https://doi.org/10.21242/42221.2021.00.01.1.1.0.

Richter, Philipp M., and Alexander Schiersch. 2017. "CO2 emission intensity and exporting: Evidence from firm-level data." *European Economic Review* 98:373–391. doi:10.1016/j.euroecorev.2017.07.011.

Rodrigue, Joel, Dan Sheng, and Yong Tan. 2022. "Exporting, Abatement, and Firm-Level Emissions: Evidence from China's Accession to the WTO." *The Review of Economics and Statistics,* 1–45. doi:10.1162/rest_a_01194.

Rottner, Elisa, and Kathrine von Graevenitz. 2024. "What Drives Carbon Emissions in German Manufacturing: Scale, Technique or Composition?" *Environmental and Resource Economics* 87 (9): 2521–2542. doi:10.1007/s10640-024-00894-7.

Roy, Jayjit, and Mahmut Yasar. 2015. "Energy efficiency and exporting: Evidence from firm-level data." *Energy Economics* 52 (December): 127–135. doi:10.1016/j.eneco.2015.09.013.

Sato, Misato. 2014. "Embodied Carbon in Trade: A Survey of the Empirical Literature." *Journal of Economic Surveys* 28 (5): 831–861. doi:10.1111/joes.12027.

Schiersch, Alexander, Irene Bertschek, and Thomas Niebel. 2024. "To diversify or not? The link between global sourcing of ICT goods and firm performance." *Economics of Innovation and New Technology* 0 (0): 1–23. doi:10.1080/10438599.2024.2309675.

Shapiro, Joseph S. 2021. "The Environmental Bias of Trade Policy." *The Quarterly Journal of Economics* 136, no. 2 (May): 831–886. doi:10.1093/qje/qjaa042.

Shapiro, Joseph S., and Reed Walker. 2018. "Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade." *American Economic Review* 108, no. 12 (December): 3814–3854. doi:10.1257/aer.20151272.

Shorrocks, Anthony F. 2013. "Decomposition procedures for distributional analysis: a unified framework based on the Shapley value." *The Journal of Economic Inequality* 11 (1): 99–126. doi:10.1007/s10888-011-9214-z.

Sogalla, Robin, Joschka Wanner, and Yuta Watabe. 2024. "New Trade Models, Same Old Emissions?" *SSRN Electronic Journal,* doi:10.2139/ssrn.4792312.

Stadler, Konstantin, Richard Wood, Tatyana Bulavskaya, Carl-Johan Södersten, Moana Simas, Sarah Schmidt, Arkaitz Usubiaga, et al. 2018. "EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables." *Journal of Industrial Ecology* 22 (3): 502–515. doi:10.1111/jiec.12715.

Stillger, Sabine. 2025. "The Role of Firm Heterogeneity and Intermediate Inputs for Carbon Leakage." *Discussion Paper Series – CRC TR 224* 670.

Umweltbundesamt. 2022. *CO2 Emission Factors for Fossil Fuels.* Climate change 29/2022. Umweltbundesamt.

Wang, Shufei, Xinyu Ma, Xiang Zhang, and Meiling Kang. 2024. "Can foreign demand shocks reduce the pollution emission intensity? Evidence from exporters in China." *Energy Economics* 133:107515. doi:10.1016/j.eneco.2024.107515.

WRI and WBCS. 2015. *The Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard. Revised Edition.*

Appendix

A Details on emissions calculations

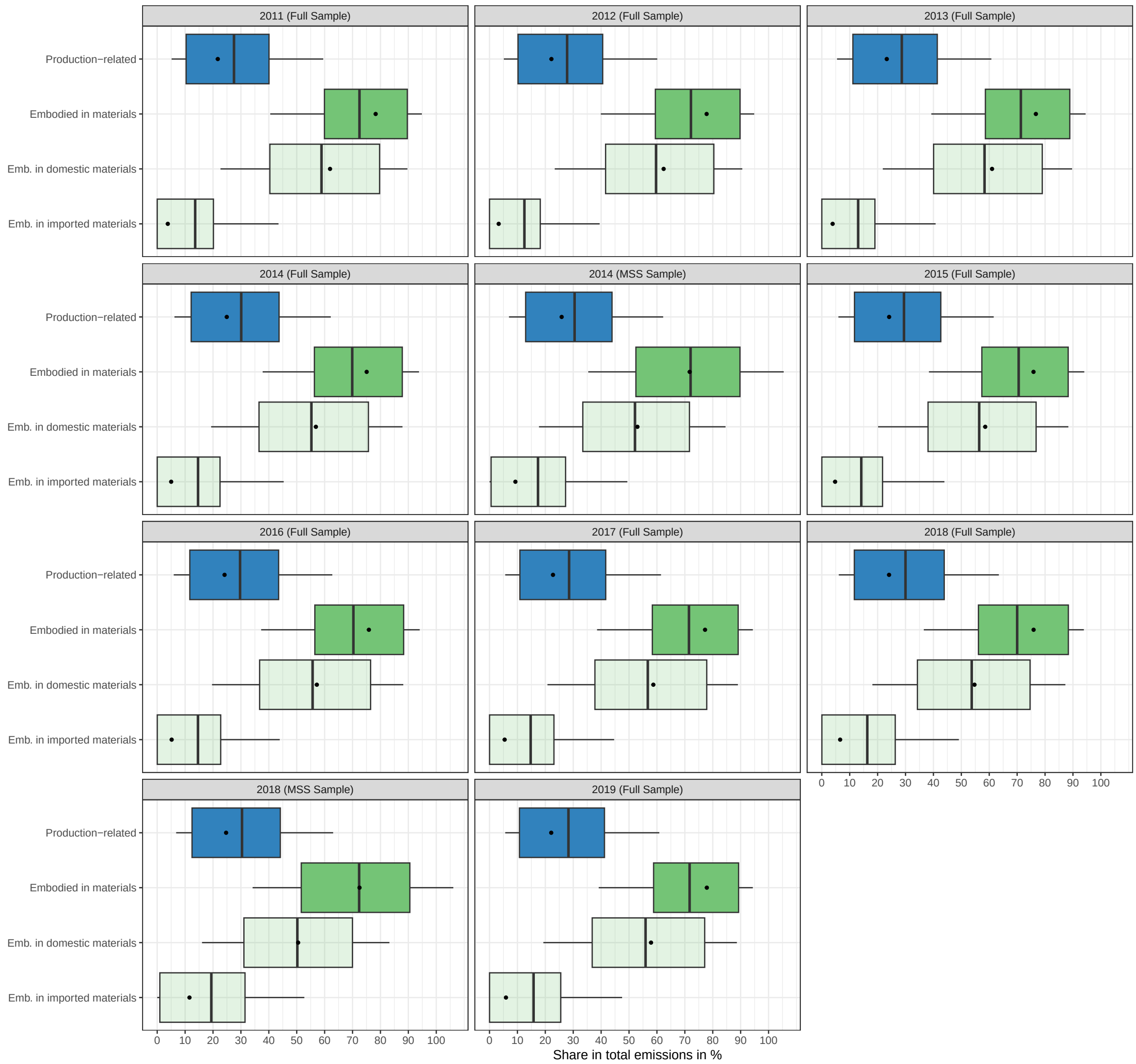
Exiobase distinguishes between 44 countries and 5 aggregated regions, Asia and Pacific, America, Europe, Africa and the Middle East, which cover the remaining countries. The 44 countries are the 27 EU member states, the United Kingdom, United States, Japan, China, Canada, South Korea, Brazil, India, Mexico, Russia, Australia, Switzerland, Turkey, Taiwan, Norway and Indonesia.

The covered products are based on standard sector classifications, but are more detailed for emission intensive sectors. We map the 200 Exiobase product categories into the HS-code classification of imports and the sector level classification of domestically sourced materials. We follow the standard approach to calculate the emissions embodied in a particular good (see e.g., Peters (2008), Peters and Hertwich (2008), Grubb et al. (2022) or Shapiro (2021) for examples). Specifically, let A be the matrix of input-output coefficients with dimension (N*SxN*S), where N indicates countries and S indicates products. Each element $a_{ns,mk}$ of A is the value of inputs of product s country n, which are required to produce one unit of gross output of product k in country m. The $N * S$ vector of gross output of a product, x, has to be equal to the output used for intermediate inputs and final demand, y, i.e. $x = Ax + y$. This accounting identity can be rearranged to $x = (I - A)^{-1}y$. The element $l_{ns,mk}$ of the so-called Leontief-inverse $L = (I - A)^{-1}$ measures the value of inputs from country n, product s required to produce one unit of final good in sector k, country n, including all the intermediate inputs used in the production process. Finally, let e be the $N * S$ vector of direct emission intensities of producing good s in country n, i.e. the emissions released during the production process. The emission intensity including the emissions arising along the entire supply chain of final product s from country m are thus given by $e^T * L$.

B Stylized facts

B.1 Details on stylized fact 1

Figure B.1: Distribution of the share of production-related and embodied emissions in total emissions across years



Notes: The figure shows boxplots of the share of production-related and embodied emissions in total emissions for all years. For example, the first boxplot, *Production-related*, shows the distribution of $e^{prod}_{jst}/e^{tot}_{jst}$. The whiskers are the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile, the ends of the boxes indicate the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile, the middle line is unweighted average and the dot indicates the median. The Figure is shown for the full sample and the subset of firms that are represented in the *Materials and Supply Survey* for the available years 2014 and 2018

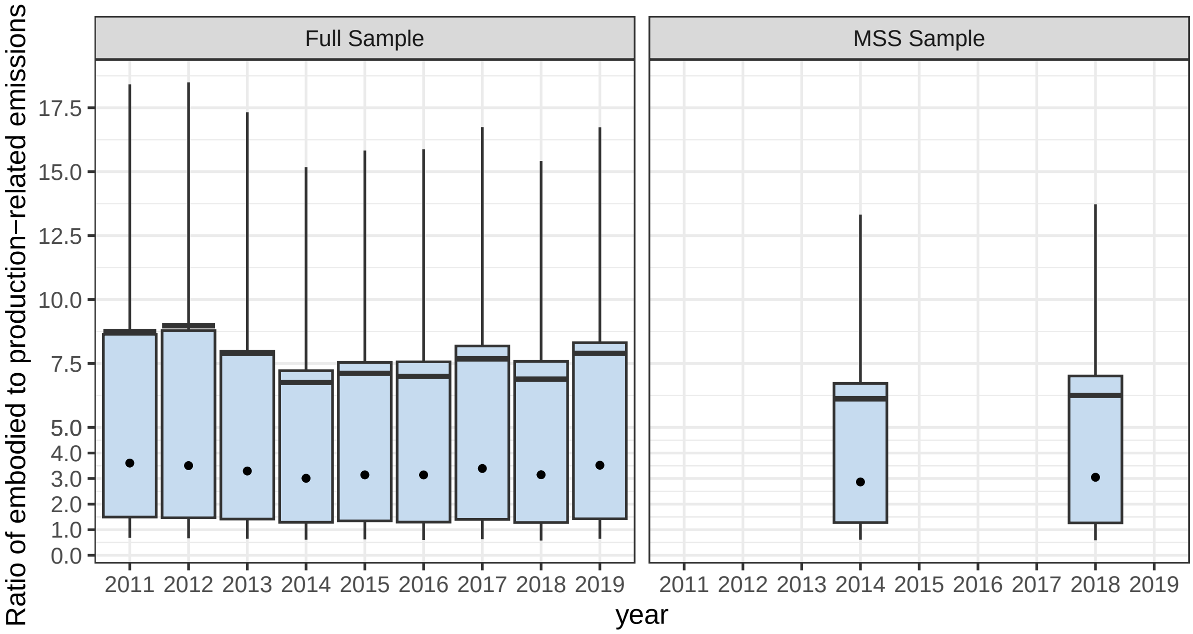


Figure B.2: Distribution of the ratio of emissions embodied in materials to production-related emissions

Notes: The figure shows box plots for the ratio of embodied emissions in materials to production-related emissions for the full sample and the subset of firms the firms represented in the *Materials and Supply Survey.* The whiskers are the 10^{th} and 90^{th} percentile, the ends of the boxes indicate the 25^{th} and 75^{th} percentile, the middle line is the unweighted average and the dot indicates the median.

B.2 Details on stylized fact 2

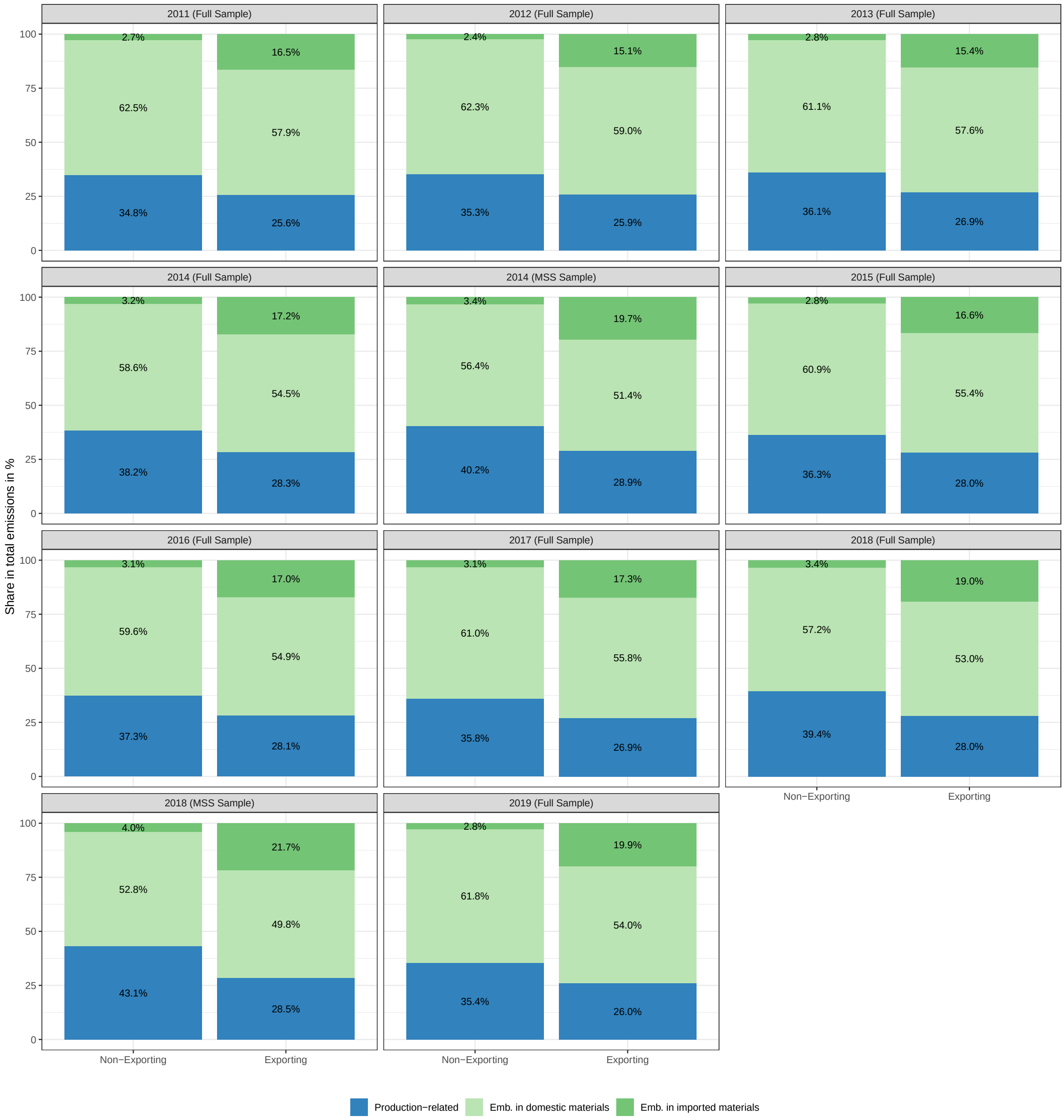


Figure B.3: Distribution of the share of production-related and embodied emissions in total emissions

Notes: The graph shows the share of production-related and embodied emissions in total emissions for the average non-exporting and exporting firm for the full sample and and the subset of firms that are represented in the *Materials and Supply Survey* for the available years 2014 and 2018.

Table B.1: EMBODIED EMISSIONS AND EXPORTING STATUS

	Exporter Dummy	
	Full sample	*MSS* sample
Share of embodied emissions in materials	0.0539***	0.0445***
	(0.00146)	(0.00707)
Share of embodied emissions in imports	0.103***	0.103***
	(0.00151)	(0.00490)
Ratio of embodied emissions in materials to production-related emissions	0.474***	1.146***
	(0.209)	(0.289)
Observations	119,342	18,186

Notes: Regression results of the variable in rows on a dummy variable, which is 1 if a firm exports and 0 otherwise. Standard errors in parentheses. All regressions include 4-digit sector and year fixed effects. The first column shows the results for the full sample for the years 2011-2019. The second column only includes firms that are present in the Materials and Supply Survey for the years 2014 and 2018. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.3 Details on stylized fact 3

Table B.2 shows the results of regressing various firm characteristics on an exporting dummy or log export value and 4-digit sector fixed effects and year fixed effects.

Table B.2: Exporter premia

	Employment	Sales	Labor prod.	TFP	Capital/labor
Exporter dummy	0.650***	1.058***	0.224***	0.0741***	0.158***
	(0.0150)	(0.0203)	(0.00655)	(0.00547)	(0.00888)
Year & industry FEs	✓	✓	✓	✓	✓
Observations	119,342	119,342	119,342	119,342	119,342
	Employment	Sales	Labor prod.	TFP	Capital/labor
Export intensity	1.425***	2.157***	0.508***	0.213***	0.308***
	(0.0333)	(0.0407)	(0.0114)	(0.00982)	(0.0148)
Year & industry FEs	✓	✓	✓	✓	✓
Observations	119,342	119,342	119,342	119,342	119,342
	Employment	Sales	Labor prod.	TFP	Capital/labor
Log export value	0.306	0.4287***	0.0743***	0.0230***	0.0496***
	(0.00309)	(0.00340)	(0.00102)	(0.000952)	(0.00138)
Year & industry FEs	✓	✓	✓	✓	✓
Observations	96,334	96,334	96,334	96,334	96,334

Notes: The table shows the estimated coefficients from regressing the variables in the column heads (log employment, log sales, log labor productivity, log TFP and log capital labor ratio) on an exporter dummy taking the value of 1 if a firm exports and 0 otherwise (upper panel), on the export intensity (middle panel), and on the log export value (lower panel). All specifications include year fixed effects and four-digit sector fixed effects. Standard errors in parentheses are clustered at the firm-level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.3: Exporter's Environmental Premia

	Panel A: IPWRA			
	(1)	(2)	(3)	(4)
Log production-related	-0.0399**	-0.1341***	-0.0939***	-0.1578***
emission intensity	(0.0192)	(0.0241)	(0.0238)	(0.0154)
Log total	0.1037***	0.0770***	0.0805***	0.054***
emission intensity	(0.0104)	(0.0125)	(0.0124)	(0.0099)
	Panel B: AIPW			
	(1)	(2)	(3)	(4)
Log production-related	-0.0389**	-0.1186***	-0.0814***	-0.2438***
emission intensity	(0.0192)	(0.0237)	(0.0237)	(0.0204)
Log total	0.1043***	0.0861***	0.0884***	0.0294**
emission intensity	(0.0104)	(0.0123)	(0.0122)	(0.0121)
Year & industry FEs	✓	✓	✓	✓
Size dummies		✓	✓	✓
Log TFP			✓	✓
Log K/L & Log E/L				✓
Observations	119,342	119,342	119,342	119,342

Notes: Exporter's environmental premia for log production-related and log total emissions. Premia are estimated using two doubly robust treatment effect estimation methods: inverse probability weighted regression adjustment (IPWRA) in Panel A and augmented inverse probability weighting (AIPW) in Panel B. The treatment variable is a binary exporter dummy taking the value of 1 if a firm exports and 0 otherwise. All specifications include year fixed effects and two-digit sector fixed effects. In columns 2-4 we subsequently include additional controls for size-class dummies, log TFP, log capital-labor ratio and log energy consumption per employee. Standard errors in parentheses are obtained using 100 bootstrap replications. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

C Model

Proof of Proposition (6.1)

Proof. **Part (i):**
Consider two firms, φ_L and φ_H such that $\varphi_L < \varphi_H$. Let $J_i^s(\varphi_L) = \{j : I_{ij}^S(\varphi_L = 1\}$ and $J_i^s(\varphi_H) = \{j : I_{ij}^S(\varphi_H = 1\}$ be the optimal sourcing strategies of the firms and $J_i^x(\varphi_L) = \{j : I_{ij}^X(\varphi_L = 1\}$ and $J_i^x(\varphi_H) = \{j : I_{ij}^X(\varphi_H = 1\}$ be the set of exporting destinations of the two firms. Suppose $J_i^s(\varphi_H) \neq J_i^s(\varphi_L)$ and $J_i^x(\varphi_H) \neq J_i^x(\varphi_L)$. Then firm φ_H prefers $\{J_i^x(\varphi_H), J_i^x(\varphi_H)\}$ if and only if :

$$\varphi_H^{\sigma-1} c_{iJ^s(\varphi_H)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_H)} B_{ij} - \sum_{j\in J_i^s(\varphi_H)} w_i f_{ji}^S - \sum_{j\in J_i^x(\varphi_H)} w_i f_{ij}^X >$$
$$\varphi_H^{\sigma-1} c_{iJ^s(\varphi_L)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_L)} B_{ij} - \sum_{j\in J_i^s(\varphi_L)} w_i f_{ji}^S - \sum_{j\in J_i^x(\varphi_L)} w_i f_{ij}^X .$$

Similarly, φ_L prefers $\{J_i^s(\varphi_L), J_i^x(\varphi_L)\}$ if and only if :

$$\varphi_L^{\sigma-1} c_{iJ^s(\varphi_L)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_L)} B_{ij} - \sum_{j\in J_i^s(\varphi_L)} w_i f_{ji}^S - \sum_{j\in J_i^x(\varphi_L)} w_i f_{ij}^X >$$
$$\varphi_L^{\sigma-1} c_{iJ^s(\varphi_H)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_H)} B_{ij} - \sum_{j\in J_i^s(\varphi_H)} w_i f_{ji}^S - \sum_{j\in J_i^x(\varphi_H)} w_i f_{ij}^X .$$

Combining the two constraints yields

$$\left[\varphi_H^{\sigma-1} - \varphi_L^{\sigma-1}\right] \left[c_{iJ^s(\varphi_H)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_H)} B_{ij} - c_{iJ^s(\varphi_L)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_L)} B_{ij}\right] > 0. \tag{C.1}$$

Moreover, firm φ_H will prefer $J_i^S(\varphi_H)$ over $J_i^S(\varphi_L)$ if and only if:

$$\varphi_H^{\sigma-1} c_{iJ^s(\varphi_H)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_H)} B_{ij} - \sum_{j\in J_i^s(\varphi_H)} w_i f_{ji}^S > \varphi_H^{\sigma-1} c_{iJ^s(\varphi_L)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_H)} B_{ij} - \sum_{j\in J_i^s(\varphi_L)} w_i f_{ji}^S$$

Similarly, φ_L prefers $J_i^s(\varphi_L)$ if and only if :

$$\varphi_L^{\sigma-1} c_{iJ^s(\varphi_L)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_L)} B_{ij} - \sum_{j\in J_i^s(\varphi_H)} w_i f_{ji}^S > \varphi_L^{\sigma-1} c_{iJ^s(\varphi_H)}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_L)} B_{ij} - \sum_{j\in J_i^s(\varphi_H)} w_i f_{ji}^S$$

Adding the two inequalities yields

$$\varphi_H^{\sigma-1}(\sum_{j\in J_i^x(\varphi_H)} B_{ij}) \left(c_{iJ^s(\varphi_H)}^{1-\sigma_s} - c_{iJ^s(\varphi_L)}^{1-\sigma_s}\right) + \varphi_L^{\sigma-1}(\sum_{j\in J_i^x(\varphi_L)} B_{ij}) \left(c_{iJ^s(\varphi_L)}^{1-\sigma_s} - c_{iJ^s(\varphi_H)}^{1-\sigma_s}\right) > 0$$
$$\left[\varphi_H^{\sigma-1} \sum_{j\in J_i^x(\varphi_H)} B_{ij} - \varphi_L^{\sigma-1} \sum_{j\in J_i^x(\varphi_L)} B_{ij}\right] \left[c_{iJ^s(\varphi_H)}^{1-\sigma_s} - c_{iJ^s(\varphi_L)}^{1-\sigma_s}\right] > 0$$

If $J_i^x(\varphi_L) \subseteq J_i^x(\varphi_H)$, the first term is positive. Hence, $c_{iJ^s(\varphi_H)}^{1-\sigma_s} > c_{iJ^s(\varphi_L)}^{1-\sigma_s}$. Because $\sigma > 1$, this implies that $c_{iJ^s(\varphi_H)} < c_{iJ^s(\varphi_L)}$, which in turn implies that $\Xi_{iJ(\varphi_H)} \geq \Xi_{iJ(\varphi_L)}$. It remains to proof that $J_i^x(\varphi_L) \subseteq J_i^x(\varphi_H)$. Suppose per contra that $J_i^x(\varphi_H) \subset J_i^x(\varphi_L)$. Then, there exists a destination k such that

$$\varphi_H^{\sigma-1} c_{iJ^s(\varphi_H)}^{1-\sigma_s} B_{ik} - w_i f_{ik}^X < 0 \quad \text{and} \quad \varphi_L^{\sigma-1} c_{iJ^s(\varphi_L)}^{1-\sigma_s} B_{ik} - w_i f_{ik}^X > 0.$$

Combining the two constraints implies that

$$\left(\varphi_L^{\sigma-1} c_{iJ^s(\varphi_L)}^{1-\sigma_s} - \varphi_H^{\sigma-1} c_{iJ^s(\varphi_H)}^{1-\sigma_s}\right) > 0. \tag{C.2}$$

From (C.1), $c_{iJ^s(\varphi_H)}^{1-\sigma_s} > c_{iJ^s(\varphi_H)}^{1-\sigma_s}$, when $J_i^X(\varphi_H) \subset J_i^X(\varphi_L)$, which contradicts (C.2). Hence, $J_i^X(\varphi_L) \subseteq J_i^X(\varphi_H)$, which concludes the proof of part (i).

Part (ii):
Consider an exporting firm with productivity φ_x and a non-exporting firm with productivity φ_{nx}. Let $J_i^s(\varphi_x) = \{j : I_{ij}^S(\varphi_x = 1\}$ and $J_i^s(\varphi_{nx}) = \{j : I_{ij}^S(\varphi_{nx} = 1\}$ be the optimal sourcing strategies of the firms. Suppose $J_i^s(\varphi_x) \neq J_i^s(\varphi_{nx})$. Then firm φ_{nx} prefers $J_i^s(\varphi_{nx})$ if and only if

$$\varphi_{nx}^{\sigma-1} c_{iJ^s(\varphi_{nx})}^{1-\sigma_s} B_{ii} - \sum_{j\in J_i^s(\varphi_{nx})} w_i f_{ji}^S > \varphi_{nx}^{\sigma-1} c_{iJ^s(\varphi_x)}^{1-\sigma_s} B_{ii} - \sum_{j\in J_i^s(\varphi_x)} w_i f_{ji}^S$$

Similarly, φ_x prefers $J_i^s(\varphi_x)$ if and only if

$$\varphi_x^{\sigma-1} c_{iJ^s(\varphi_x)}^{1-\sigma_s} \sum_{j\in J_i^X(\varphi_x)} B_{ij} - \sum_{j\in J_i^s(\varphi_x)} w_i f_{ji}^s > \varphi_x^{\sigma-1} c_{J^s(\varphi_{nx})}^{1-\sigma_s} \sum_{j\in J_i^x(\varphi_x)} B_{ij} - \sum_{j\in J_i^s(\varphi_{nx})} w_i f_{ji}^S$$

Adding these two condition yields:

$$\left[c_{iJ^s(\varphi_x)}^{1-\sigma_s} - c_{iJ^s(\varphi_{nx})}^{1-\sigma_s}\right] \left[\varphi_x^{\sigma-1} \sum_{j\in J_i^X(\varphi_x)} B_{ij} - \varphi_{nx}^{\sigma-1} B_{ii}\right] > 0 \tag{C.3}$$

From Proposition $\varphi_x \geq \varphi_{nx}$, and hence the second part is larger than zero. Hence, $c_{iJ^s(\varphi_x)}^{1-\sigma_s} > c_{iJ^s(\varphi_{nx})}^{1-\sigma_s}$. Because $\sigma > 1$, $c_{iJ^s(\varphi_x)} < c_{iJ^s(\varphi_{nx})}$, which implies $\Xi_{J_i^S(\varphi_x)} \geq \Xi_{J_i^S(\varphi_{nx})}$. Finally, differentiating the material share with respect to the sourcing capability yields:

$$\frac{\partial \chi_{i\varphi}^M}{\partial \Xi_{J_i^S(\varphi)}} = \frac{(\delta-1)}{\theta} \frac{1}{\Xi_{J_i^s(\varphi)}} \chi_{i\varphi}^M (1 - \chi_{i\varphi}^M), \tag{C.4}$$

which is larger than zero as long as $\delta > 1$. Because $\Xi_{J_i^s(\varphi_x)} > \Xi_{J_i^s(\varphi_{nx})}$, $\chi_{i\varphi_x}^M \geq \chi_{i\varphi_{nx}}^M$, which concludes the proof. $\square$

Industry Equilibrium Let φ_{iD}^* be the productivity of the least productive, active firm and N_i the number of firms that enter the manufacturing firms. Firms enter the manufacturing sector as long as they earn positive profits. The free entry condition is thus given by:

$$\int_{\varphi_{iD}^*} \left[\sum_{j\in J_i^x(\varphi)} \left(r_{\varphi ij} - w_i f_{ij}^x\right) - \sum_{j\in J^s(\varphi)} w_i f_{ji}^s\right] dG(\varphi) = w_i f_i^e. \tag{C.5}$$

Final goods trade flows are given by:

$$R_{ij} = N_i \int_{\varphi^*_{ijX}} r_{\varphi,ij} dG(\varphi) \tag{C.6}$$

Intermediate good flows from i to j are given by:

$$M_{ji} = \frac{\sigma-1}{\sigma}(1-\alpha_i)\int_{\varphi^*_{jiS}} \left(\chi^M_{iJ^s_i(\varphi)} \lambda_{jiJ^s_i(\varphi)} \sum_{k\in J^x_i(\varphi)} r_{ik\varphi} \right) dG(\varphi) \tag{C.7}$$

Emissions are given by:

$$E^{dir}_i = \frac{\sigma-1}{\sigma}\frac{(1-\alpha_i)}{t_i}\int_{\varphi^*_{iD}} \left((1-\chi^M_{iJ^s_i(\varphi)}) \sum_{k\in J^x_{i\varphi}} r_{ik\varphi} \right) dG(\varphi); \quad E^{emb}_i = \sum_j \frac{\zeta_j}{t_j} M_{ji}. \tag{C.8}$$

D Shift-share diagnostics

We follow the exogenous shocks identification approach, which relies on having a large number of quasi-random shocks. To ensure that we have a high enough number of sufficiently variable shocks, that shocks are not too correlated, and that shock exposure is not too concentrated, we conduct several diagnostic checks suggested by Borusyak et al. (2022).

Firms with similar exposure shares have correlated $Z_{f,t}$ and may also be exposed to similar unobserved shocks leading to correlated error terms (Borusyak et al. (2025)). Borusyak et al. (2022) show that valid standard errors that take into account this correlation of the error terms can be produced by running a shock-level 2SLS-regression. This regression is run on a transformed shock-level dataset which contains the transformed outcome, the transformed treatment and the shocks. The outcome and treatment are transformed by first residualizing them on the firm-level controls and then calculating their shock-level exposure-share-weighted averages.[32] The 2SLS-regression on this transformed shock-level dataset, takes the transformed outcome as the dependent variable, the transformed treatment as the endogenous treatment variable, and directly takes the shocks $\Delta X_{cp,t}$ as instruments (instead of the shift-share instrument $Z_{f,t}$ which is used as an instrument in a traditional individual- or firm-level shift-share estimation). The shock-level regression then also makes it possible to account for potential clustering of the shocks by clustering the standard errors at the adequate level. To identify potential correlations in the shocks and to determine the adequate level of clustering of standard errors in the shock-level regression, we again follow Borusyak et al. (2022).

We regress the shocks on time fixed effects, μ_t, and random effects for each level of product categorization in the Harmonized System (HS), i.e. HS-Section, HS-2-digit-code, HS-4-digit-code and HS-6-digit-code:

$$\Delta X_{cp,t} = \mu_t + a_{HSSection,(p),t} + b_{HS4,(p),t} + c_{HS2,(p),t} + d_{HS6,t}. \tag{D.1}$$

From the estimated random effects coefficient, we can compute the intra-class-correlation (ICC) at each level of the HS-product categorization. The estimated ICCs in Appendix Table D.1 are all below 0.01, and, thus, reveal that there is only very little clustering of shock-residuals at the different product-category-levels. To be on the safe side, we nevertheless cluster standard errors at the HS6-level.

In addition, we present several descriptive statistics on the distribution of the shocks in the shock-level dataset in Table D.2. With more than 1,000,000 product-country-year specific shocks, we can be highly confident that we have enough shocks for the large-N asymptotics of the exogenous shocks identification approach. There is also sufficient variation in the shocks as the shocks' standard deviation (0.31) and inter-quartile range (0.29) are much larger than the shocks' mean (-0.01). Furthermore, we need to ensure that the firms' exposure shares are not too concentrated, meaning that there is not too much exposure to some product-country specific demand shocks. We therefore compute the inverse of the exposure shares' Herfindahl-Hirschmann index (HHI), $1/\sum s^2_{pc,t_0}$. With an inverse HHI of 20,621.22, we have a very low concentration of exposure shares.

32. We generate the shock-level dataset using the Stata *ssaggregate* command by Borusyak et al. (2020). For more details on the transformation of the firm-level dataset to the shock-level dataset see Borusyak et al. (2022).

Table D.1: Shock Intra-Class Correlations

	Shock ICCs
HS Section	0.001
	(0.001)
HS2	0.001
	(0.005)
HS4	0.007
	(0.002)
HS6	0.002
	(0.000)
# of product-country-year shocks	1,044,364

Notes: The table reports ICC-coefficients of the export demand shocks $\Delta X_{cp,t}$. The ICC-coefficients are calculated based on the random effects coefficients, which are estimated using the mulit-level model described in Eq. D.1. Robust standard errors are given in parentheses.

Table D.2: Shock summary statistics

	(1)	(2)
Mean	-0.01	0.00
Standard deviation	0.31	0.28
Interquartile range	0.29	0.21
Specification		
Residualizing on year fixed effects		✓
Effective sample size ($1/HHI$ of s_{pc,t_0} weights)		
Across products, countries and years	20,621.22	20,621.22
Across HS4 product categories	184.43	184.43
Observation counts		
# of product-country-year shocks	1,044,364	1,044,364
# of HS6 product categories	4,446	4,446
# of HS4 product categories	1,161	1,161

Notes: The table shows several statistics describing the distribution the export demand shocks $\Delta X_{cp,t}$. All statistics are weighted by the average shock-level exposure shares s_{pc,t_0}. Column 1 presents descriptive statistics on the original shock-level dataset. In column 2, shocks are residualized on year fixed effects. We additionally report the inverse of the HHI of the s_{pct_0} weights, which provides information on the effective sample size.