IS GERMANY BECOMING THE EUROPEAN POLLUTION HAVEN? *

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December 6, 2024

Abstract

Relative prices determine competitiveness across countries. We analyse the impact of diverging implicit carbon prices – covering carbon costs, energy costs, and the shadow cost of regulations – between Germany and other EU countries on manufacturing CO_2 emissions. Using a quantitative trade and environment model with key parameters estimated from German firm-level data, we track implicit carbon prices from 2005 to 2019. Our findings reveal a sharper decline in implicit carbon prices in Germany, leading to higher emissions. In this regard, Germany appears to have emerged as a European pollution haven. We discuss whether this reallocation of emissions reflects an efficient outcome of emissions trading or is distorted by overlapping policies.

Keywords: Pollution haven, CO_2 emissions, climate policy, manufacturing, international trade
JEL-Classification: F18, H23, L60, Q56

*We thank Joseph Aldy, Beat Hintermann, Kevin R. Kaushal, Andreas Lange, Mario Larch, Thomas Niebel, Armando Rungi, Oliver Schenker, Jan Schymik, Joseph Shapiro, Jonas Teusch, Ulrich Wagner, Joschka Wanner, and Catherine Wolfram for helpful comments and discussions. We thank Jan Abrell for providing ETS data at https://www.euets.info/. We thank Claudio Rottner for technical assistance. We also thank participants at the 11^{th} and 12^{th} Mannheim Conference on Energy and the Environment, the European Trade Study Group 2023, the FSR Climate Annual Conference 2023, the AURÖ Workshop 2024, the AERE 2024 Summer Conference; the SURED 2024 conference, the 2024 Harvard Climate Economics Pipeline Workshop, the 2024 Montpellier workshop and the 29^{th} EAERE Annual Conference as well as seminar participants at the MCC-Berlin, ZEW–Leibniz-Centre for European Economic Research and the EUI-WIIW International Economics Webinar 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 Denise Henker, Stefan Seitz, Katrin Stief, Kerstin Stockmayer and Diane Zabel for their advice and technical support. Lucia Maier and Brigitta Redling from the German Federal Statistical Office provided help regarding re-exports and correspondence tables. We thank the Leibniz Association for financial support through the female professors program. Support by the German Research Foundation (DFG) through CRC TR 224 (Project B07) is gratefully acknowledged. The views expressed in this paper are those of the authors and do not necessarily represent those of the institutions mentioned above.

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1 Introduction

The European Union Emissions Trading System (EU ETS) is the cornerstone of the EU's climate policy, setting a cap on the total amount of greenhouse gas emissions across regulated sectors. While this cap limits overall emissions, it does not prescribe how emissions reductions should be distributed across industries or regions. This decentralized approach is designed to promote efficiency by allowing the market to allocate emissions reductions to the least costly abatement opportunities. However, it also creates incentives for EU member states to strategically protect their national industry, potentially shifting the burden of emissions reductions onto neighbouring countries. In response to the threat of deindustrialization, national governments may actively manage the transition process and resort to measures such as exemptions or subsidies for energy-intensive industries – particularly when they have the financial means to do so.

This paper examines how market mechanisms and overlapping policies – across nested jurisdictions and national policy portfolios – have shaped industrial emissions trends within the EU. Between 2005 and 2019, industrial CO_2 emissions in the rest of the EU declined by twice as much as in Germany, prompting the question: Is Germany becoming the European pollution haven? And if so, is this induced by the allocative efficiency of the EU ETS or the result of strategic national policies?

Evaluating the effective stringency of climate policy in the presence of overlapping and interacting regulations is inherently challenging, particularly as domestic consumption patterns evolve and international trade partners adjust their regulatory frameworks. Standard ex-post analyses of climate policies typically isolate the effects of individual policy measures, but are silent on their interactions within the broader policy landscape. In this paper, we shed light on precisely these overlooked factors, examining how the interplay of overlapping policies, foreign regulations, international trade, and general equilibrium forces shape emissions patterns in ways that traditional reduced-form approaches cannot fully capture. To do so, we employ quantitative modelling to estimate implicit carbon prices – a comprehensive measure encompassing all factors influencing CO_2 costs, including EU ETS carbon prices, national policies, fuel prices, and command-and-control measures. Our analysis then explores how divergent developments in implicit carbon prices across the EU drive shifts in production and emissions within Europe. We provide suggestive evidence that these shifts may not be due to the allocative efficiency of the EU ETS, raising concerns about the broader impact of regulatory heterogeneity on intra-European emissions distribution.

For the analysis, we apply a quantitative trade and environment model developed by Shapiro and Walker (2018), generalizing it to incorporate different assumptions on production technologies commonly used in the literature. We apply this model to a three-region world – Germany, the rest of the EU (RoEU), and the rest of the world (RoW) – allowing us to account for Germany's deep integration within the EU. This setup enables us to examine the effects of climate policy in a context where regulations overlap in a nested jurisdiction.

Using data on trade, production, and emissions, as well as key model parameters estimated from German firm-level data, we retrieve sector-specific measures of the historic development of implicit carbon prices for Germany, the rest of the EU, and the rest of the world from 2005 to 2019. These implicit carbon prices rationalise the observed outcomes in trade, production, and emissions, given the model structure we impose. We contrast the development of implicit carbon prices in Germany and the rest of the EU, and relate them to changes in energy prices and EU ETS permit prices through regression analysis. Although implicit carbon prices follow a similar trend across both regions, they declined more sharply in Germany than in the rest of the EU. Notably, we find that ETS permit prices alone do not fully explain this development in implicit carbon prices. The remaining variation across countries and sectors is consistent with overlapping national policies affecting the implicit carbon price.

Our model approach enables us to run counterfactual analyses. In a decomposition analysis in which we sequentially switch off individual emissions drivers, we show that the overall trend in implicit carbon prices – and particularly the difference between Germany and the rest of the EU – have been instrumental in shaping CO_2 emissions in German manufacturing. Finally, we demonstrate that CO_2 emissions from German manufacturing would have been substantially lower if the rest of the EU had experienced the same developments in implicit carbon prices. In this sense, Germany may indeed be evolving into a European pollution haven.

Debates about the impact of differences in regulatory stringency are high on the policy agenda. Given the shared EU climate policy under the EU ETS, these discussions have primarily focused on disparities between EU and non-EU countries. However, our analysis highlights the importance of intra-European differences in implicit carbon prices. In line with insights from the trade literature, our results indicate that trade linkages and the risk of production shifts are considerably stronger within the EU than between EU member states and non-EU countries.[1] Imposing a uniform development of implicit carbon prices in Germany and the rest of the EU changes the intra-EU allocation of emissions substantially but has little impact on emissions outside the EU.

Our findings suggest that policy discussions should not focus solely on the EU's Carbon Border Adjustment Mechanism (CBAM), which addresses the carbon footprint of imports from outside the EU; they should also consider the causes and consequences of intra-European differences in implicit carbon prices. Intra-European production shifts may be a natural consequence of the EU ETS, which induces production and emissions to relocate toward regions with less emissions-intensive production. Uniform carbon pricing makes it costlier to produce where emission intensities are high, reinforcing these shifts. The relative decline in implicit carbon prices in Germany compared to the rest of the EU may reflect convergence as other EU countries catch up with Germany's initially more stringent regulations, as Germany's industrial emission intensities were among the EU's lowest in 2005.

While such convergence likely plays a role, unilateral climate, energy, and industrial policies can also undermine the allocative efficiency of the EU ETS. Germany ranks among the top EU countries in state aid spending for "Environmental Protection," which includes support schemes such as electricity price compensation and exemptions from energy taxes, predominantly benefitting energy-intensive sectors. Against this background, the development in Germany's industrial emissions seems unlikely to reflect an efficient allocation.

With this paper, we contribute to four distinct strands of literature. First, we complement research on econometric ex-post evaluations of single climate policies (e.g., Colmer et al. 2024, Hernandez-Cortes and Meng 2023, Andersson 2019, Martin et al. 2016, or Fowlie et al. 2012). Specifically, in the context of Germany, recent studies by Gerster and Lamp (2024) and von Graevenitz and Rottner (2024) evaluate the causal effects of electricity price differences on emissions from German manufacturing firms. Our paper

[1] See, e.g., Bergstrand et al. (2015); Baier and Bergstrand (2009, 2007); Disdier and Head (2008) or Yotov (2012) on the elasticity of distance and on the effects of trade agreements in gravity equations.

extends this literature by offering a new perspective that accounts for developments in other countries, feedback effects across sectors, and macroeconomic adjustments.

Second, we contribute to the literature that employs general equilibrium models to study climate policies (see Böhringer et al. 2012 for an overview of computable general equilibrium (CGE) models). Our work also intersects with the burgeoning strand of literature in international trade that uses structural gravity models (e.g., Larch and Wanner, 2024, Caron and Fally, 2022, Shapiro, 2016, or Egger and Nigai, 2015). While structural gravity models may sacrifice some structural detail compared to typical CGE models, they offer increased tractability. Many studies in this field have quantified models for ex-ante assessment (e.g., of carbon border adjustments, such as in Campolmi et al. 2023; Sogalla 2023; Farrokhi and Lashkaripour 2022; Larch and Wanner 2017). In contrast, following the approach of Shapiro and Walker (2018), we apply this framework to understand past emissions trends, bridging the gap between reduced form ex-post analyses and model-based ex-ante evaluations.

Third, we contribute to the literature on overlapping regulation in nested jurisdictions (for instance, Goulder and Stavins, 2012 in the US context, where interactions between California's policies and federal policies raise concerns). The (welfare) effects of overlapping policies have primarily been studied using analytical models (Perino et al., 2022; Eichner and Pethig, 2019) or through ex-ante simulations with CGE models (Böhringer and Rosendahl, 2022). We show how to evaluate the importance of these overlaps and interactions ex-post using a quantitative modelling approach. Our research extends beyond analysing CO_2 emissions from German manufacturing and the role of the EU ETS. More broadly, our approach can be applied to study the interactions and overlaps of regulations in nested jurisdictions, particularly in deeply integrated regions such as the EU, the US, and China to recover underlying drivers that are not directly observable, such as implicit carbon prices.

Finally, we contribute to the literature on pollution havens, which examines how differences in environmental regulation across countries shape comparative advantages, thereby influencing the regional allocation of emissions-intensive production (see, e.g., Cherniwchan et al., 2017, Levinson and Taylor, 2008, Copeland and Taylor, 2004, or Pethig, 1976). Previous research has primarily focused on the outward shift of emissions-intensive industries from high-income, high-regulation countries to low-income, low-regulation countries (e.g., Wagner and Timmins, 2009 on outward FDI from the German manufacturing sector; Hanna, 2010 and Kellenberg, 2009 on the responses of US multinational firms to differences in environmental regulation). In contrast, we emphasize a pollution haven effect within a group of rich countries that share common regulations but where overlapping national policies interact to differing degrees with the common policy framework.

In the context of a global pollutant like CO_2, incentives to actively adopt policies that protect domestic industry are strong, as the damage caused by emissions primarily occurs in other countries. These policies can effectively transform countries into pollution havens. While such policies under an ETS do not affect overall emissions within a binding cap, they undermine the allocative efficiency of the system and have important distributional implications.

The remainder of this paper is structured as follows: In Section 2, we introduce our quantitative trade and environment model, adapted from Shapiro and Walker (2018), and discuss key model assumptions. Section 3 presents the data we use for quantifying the model and outlines our estimation of essential model parameters. In Section 4, we use the model to back out the historical development of implicit carbon prices in Germany, the rest of the EU, and the rest of the world. We examine the roles of energy prices and EU ETS permit prices. Section 5 conducts counterfactual analyses: First, we decompose the development of Germany's emissions by isolating individual emissions drivers to highlight the impact of implicit carbon price changes. Second, we assess how German emissions would have evolved if the implicit carbon prices in the rest of the EU had developed identically to those in Germany. In Section 6, we discuss whether our findings are indicative of allocative efficiency within an EU ETS or rather due to distortions from overlapping (national) policies. Section 7 concludes.

2 The model

To explain the development of CO_2 emissions in German manufacturing, we apply the quantitative trade and environment model developed by Shapiro and Walker (2018). This section offers a brief overview of the model and discusses its main assumptions. In Online Appendix A, we provide a detailed presentation of a generalized version of the model by Shapiro and Walker (2018). Specifically, we integrate two alternative formulations from the literature on incorporating firm-specific productivity into the production function (cf. Egger et al., 2021), an aspect naturally absent in traditional trade and environment model frameworks, which do not consider heterogeneous firms.[2] While the main text relies on the original Shapiro and Walker (2018) specification, we show in Online Appendix C.7 that our results remain qualitatively robust to this generalisation.

Our multi-country, multi-sector framework relies on a Melitz (2003)-type environment, where heterogeneous firms within each sector engage in monopolistic competition. Firms differ in productivity, leading to differences in emission intensities and generated emissions. The model features endogenous firm entry and exit, as well as production and export decisions. In each country, labour is the only productive factor.[3] Labour is supplied inelastically but mobile across sectors within a country. Each firm determines its production technique based on the economy-wide wage rate relative to the emission price it faces. This emission price, conceptualised as the implicit carbon price, incorporates all factors that have an impact on the costs of generating emissions.

2.1 Preferences and technology

We consider a world of $\mathcal{N}$ countries, indexed by i and j, and $\mathcal{S}$ sectors, each denoted by s.[4] The representative consumer in country i maximises utility by allocating her budget to consume $q_{ji}^s(\omega)$ of varieties $\omega \in \Omega_j^s$ from sector s produced in country j. The set of available varieties includes both imported and domestically produced varieties. We assume a two-tier utility function: a constant elasticity of substitution (CES) utility across varieties within each sector, and Cobb-Douglas utility across sectors. Accordingly,

$$U_i = \prod_{s\in\mathcal{S}} \left(\left[\sum_{j\in\mathcal{N}} \int_{\omega\in\Omega_j^s} q_{ji}^s(\omega)^{\frac{\sigma^s-1}{\sigma^s}} d\omega \right]^{\frac{\sigma^s}{\sigma^s-1}} \right)^{\beta_i^s}, \tag{1}$$

[2] A growing body of literature explores the role of firm heterogeneity at the intersection of trade and the environment, following Kreickemeier and Richter (2014). For a recent survey, see Cherniwchan et al. (2017); for empirical evidence, refer to Rodrigue et al. (2024), Kwon et al. (2023), Forslid et al. (2018), and Richter and Schiersch (2017).

[3] Alternatively, labour can be thought of as a composite of different production factors. When quantifying the modeling and estimating key model parameters, we adopt this more flexible interpretation (see Section 3).

[4] In our application, we consider a three-country world (Germany, RoEU and RoW), and ten disaggregated sectors for each region.

where $\sigma^s > 1$ represents the sector-specific elasticity of substitution across varieties, while $\beta_i^s \in (0, 1)$ denotes the expenditure share on sector s' varieties, with $\sum_{s \in \mathcal{S}} \beta_i^s = 1$. Within each sector, consumers exhibit a "love of variety".

Each variety is produced by one specific firm located in a particular country and characterised by a productivity level φ. Since each firm in country i and sector s is perfectly distinguishable by its productivity level, we simplify notation from the outset and use $\varphi = \varphi(\omega)$. To produce $q_{ji}^s(\varphi)$, destined for consumers in country i, labour l_{ji}^s is employed at the economy-wide wage rate w_j, while emissions z_{ji}^s are generated as a by-product. Emissions are costly. We assume a sector-specific emissions price of $t_j^s > 0$, which includes various cost elements related to emissions: different types of regulation, such as market-based instruments, command-and-control policies, and behavioral interventions, as well as costs associated with energy consumption leading to emissions.[5] This emissions price varies across sectors due to sector-specific regulation and differences in fuel mixes. In our application, we refer to this price as the implicit carbon price, a measure that is not directly observable empirically but which we infer from our quantitative analysis.

In line with the literature based on the seminal work by Copeland and Taylor (1994, 2003), we specify a firm's production technology as being Cobb-Douglas and treat emissions as an input. Accordingly,

$$q_{ji}^s(\varphi) = \varphi^{1-\alpha^s} (z_{ji}^s)^{\alpha^s} (l_{ji}^s)^{1-\alpha^s}, \tag{2}$$

[5] We simplify our analysis by assuming no income is generated from this emissions price. While this holds true for certain regulatory frameworks, it does not apply to emissions taxes, for instance. Thus, we assume tax revenues are lost, potentially through rent-seeking, which is not entirely implausible: As of September 2023, 29.1% of entries in the German Lobby Register concern the topic of energy (see https://www.lobbyregister.bundestag.de). According to the EU transparency register, ArcelorMittal, the world's second biggest steel producer, spends approximately 1.25-1.5 million Euros each year on activities covered by the register. For the Dow Europe GmbH (chemicals and plastics), this sum amounts to 3-3.5 million Euros. Winkler (2022) finds that lobbying for higher numbers of free emission allowances under the EU ETS was valuable and indeed successful.

where $\alpha^s \in (0,1)$ denotes the output elasticity of emissions and represents the costs share of emissions.[6] Accordingly, production in sectors with higher α^s is more emissions-intensive, all else equal.

Subject to this technology, a firm in j maximises profits from entering market i denoted by

$$\pi_{ji}^s(\varphi) = p_{ji}^s(\varphi)q_{ji}^s(\varphi) - w_j l_{ji}^s(\varphi)\tau_{ji}^s - t_j^s z_{ji}^s(\varphi)\tau_{ji}^s - w_i f_{ji}^s, \tag{3}$$

where selling in market i involves both variable iceberg trade costs $\tau_{ji}^s \geq 1$ and fixed costs $w_i f_{ji}^s$ in terms of labour of the destination market. For domestic sales, we assume $\tau_{ii}^s = f_{ii}^s = 1$. Optimal behaviour implies that a firm, facing demand as per Eq. (2), sets a price p_{ji}^s at a constant markup over marginal supply costs.

Before turning to the market entry mechanism, let us compare two firms of differing productivity, both located in the same country and each offering a unique variety within the same sector to consumers in the same destination country. For revenues, emissions intensities, and emissions, the comparison is as follows:

$$\frac{r_{ji}^s(\varphi_1)}{r_{ji}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{(\sigma^s-1)(1-\alpha^s)}, \quad \frac{i_{ji}^s(\varphi_1)}{i_{ji}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{\alpha^s-1}, \quad \frac{z_{ji}^s(\varphi_1)}{z_{ji}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{(\sigma^s-1)(1-\alpha^s)}. \tag{4}$$

The more productive firm enjoys higher revenues – and hence profits, given identical fixed costs — due to greater sales volumes, even though it charges a lower price. Moreover, the more productive firm is characterised by a lower emissions intensity but higher emissions.

2.2 Open economy equilibrium

Prospective firms based in country j learn about their productivity only after incurring initial entry fixed costs of $w_j f_j^s$, which are denominated in domestic labour. Specifically, they draw from a sector-specific Pareto productivity distribution

$$G_j^s\left(\varphi; b_j^s\right) = 1 - \left(\frac{b_j^s}{\varphi}\right)^{\theta^s}, \tag{5}$$

[6] This production technology can also be derived by assuming a specific underlying abatement technology where output is sacrificed to reduce emissions (see Shapiro and Walker, 2018). In Online Appendix A, we present a generalized version of the model by introducing the indicator $\xi \in \{0,1\}$ to define a firm's production function as: $q_{ji}^s(\varphi) = \varphi^{1-\xi\alpha^s}(z_{ji}^s)^{\alpha^s}(l_{ji}^s)^{1-\alpha^s}$. When $\xi = 1$, this specification collapses to Eq. (2) in the main text, while $\xi = 0$ represents an alternative modelling approach where labour is used for abatement. In both cases, emissions can be interpreted either as an additional production factor or as a secondary output. The Cobb-Douglas functional form is both standard in the literature and crucial for the tractability of the model (see Shapiro and Walker, 2018).

where the location parameters $b_j^s \geq 1$ defines the lower bound of the distribution and hence determines country j's productivity potential in sector s, while the shape parameter $\theta^s > (\sigma^s - 1)(1 - \alpha^s)$ describes the productivity dispersion in a sector.

In equilibrium, the fixed costs of learning about productivity are equal to the expected profits (the free entry condition). Only firms with a draw above an (endogenous) productivity threshold will find it profitable to produce their unique variety. As exporting incurs additional cost (fixed costs f_{ji}^s and iceberg transport costs τ_{ji}^s), only a subset of those firms are sufficiently productive to profit from exporting to foreign markets. For each origin-j-market-i combination, the marginal firm is determined by the so-called zero cutoff profit condition.

Labour markets clear in each country. Labour is used for five purposes: the fixed costs of the productivity draw, productive labour usage, implicit carbon prices, fixed market entry costs, and net exports. The latter is necessary because in this static model trade imbalances are represented by transfers between trading partners.

The zero cutoff profit conditions, the free entry condition, and the labour market clearing condition jointly constitute the open economy equilibrium.

2.3 Discussion of key assumptions

Before applying the model, we discuss three key assumptions. First, firm-level productivity φ is assumed to be fixed. The model abstracts from improvements in firm-level productivity induced by technological change or regulation. While restrictive, this assumption is in line with recent evidence on technology lock-in of US manufacturing plants from their first year of operation (Hawkins-Pierot and Wagner, 2022). By contrast, labour productivity as an alternative productivity measure is endogenous at the firm level, with firms adjusting in response to the wage-to-implicit-carbon-price ratio. Furthermore, the (weighted) average productivity of a country and sector changes due to the reallocation of market shares across firms.

Second, the production technology given in Eq. (2) implies constant returns to scale in emission abatement. This assumption differs from Forslid et al. (2018), who emphasise scale economies in abatement with investment costs for the most productive (exporting) firms spread over larger volumes. There is no economically viable end-of-pipe technology available to abate CO_2 emissions. Emission reductions can only be achieved through reducing output, saving energy, e.g., by increasing efficiency, or through switching fuels which does not necessarily incur high fixed cost. Given the unclear role of fixed costs for reductions of CO_2 emissions, we adhere to the commonly used emission generation and abatement process.

Third, the three key parameters – σ^s, the elasticity of substitution, α^s, the output elasticity of emissions, and θ^s, the productivity dispersion – are assumed to be sector-specific but constant across countries, and, in our application, also over time. Given the relatively short time span of our analysis from 2005 to 2019, the assumption of constancy over time does not seem controversial, whereas the assumption of constancy across countries warrants further discussion. This assumption implies *inter alia* that once technology is invented, it is available across borders. Differences in emission intensities across countries then arise from variations in average productivity, wage-to-implicit-carbon-price ratios, and country specialisations, which are further determined by trade costs. As a plausibility check, our parameter estimates using German data (see below) exhibit similar patterns across sectors and are comparable in magnitude to those reported by Shapiro and Walker (2018) for the USA and the productivity dispersion estimates from Caliendo and Parro (2015).

2.4 Defining emissions drivers

We reformulate the model using the "exact hat algebra" of Dekle et al. (2008) to facilitate quantification. This approach expresses all variables as changes from a baseline value x to a counterfactual value x', i.e. $\hat{x} \equiv x'/x$. Through this reformulation, several variables that are hard to measure drop out of the model. In our quantitative exercise, we use the year 2005 as the baseline, rewriting all variables of interest as changes relative to that year.

Our focus is on changes in emissions. Integrating over the mass of operating firms allows us to calculate aggregate country-level emissions for j as:

$$Z_j \equiv \sum_{s \in \mathcal{S}} Z_j^s \qquad \text{with} \qquad Z_j^s = M_j^s \frac{w_j}{t_j^s} f_j^s \frac{\alpha^s \theta^s}{(1-\alpha^s)}, \tag{6}$$

where M_j^s represents the mass of firms in sector s within country j that have incurred the fixed entry costs to learn about their productivity. In terms of changes, this reads as:

$$\hat{Z}_j = \sum_s \hat{Z}_j^s \frac{Z_j^s}{Z_j} \qquad \text{with} \qquad \hat{Z}_j^s = \hat{M}_j^s \frac{\hat{w}_j}{\hat{t}_j^s}. \tag{7}$$

Accordingly, emissions in sector s increase with both the mass of firms M_j^s and the wage-to-implicit-carbon-price ratio w_j/t_j^s. Given the production technology introduced in Eq. (2), each individual firm adjusts its labour input and emissions generation based on the factor price ratio, which is exogenous from the firm's perspective. Production is allocated among firms of varying emission intensities, where this allocation changes as firms enter and exit different markets and see changes in their market shares. These effects are reflected in the changes in firm entries. Considering the model's implication that changes in wages and firm entries are functions of changes in country- and sector-level revenues, it can be inferred that changes in sector-level emissions depend on three factors: the development of the implicit carbon price, the overall growth of the economy, and the relative growth of different sectors.[7]

We quantify the model to recover underlying economic drivers that impact the historical development of German emissions. The goal is to determine how these drivers must have evolved in order for the model to generate the observed trade, production, and emissions patterns across countries. Given the model structure and estimated parameters, we ask how, for example, the implicit carbon prices faced by firms in different sectors and countries must have evolved to rationalise the observed outcomes.

We follow Shapiro and Walker (2018) in defining four types of emission drivers of interest, which we allow to vary across sectors and countries.

- Changes in implicit carbon prices: $\hat{t}_j^s$. This emission driver comprises all factors that directly or indirectly influence the cost of emitting CO_2 emissions, including the carbon price under the EU ETS, national (climate) policies, fuel prices, and command-and-control measures. By rearranging Eq. (7), we obtain: $\hat{t}_j^s = \hat{M}_j^s \hat{w}_j / \hat{Z}_j^s$.

[7] Specifically, changes in wages equal changes in country-level revenues, while changes in firm entries are given by sector revenue growth relative to the average growth of the economy. This stems from the model feature of a single production factor, necessitating that all revenue changes must be reflected in wage adjustments. Real wages are determined by a country's growth relative to all other countries.

- Changes in expenditure shares: $\hat{\beta}_i^s$. This driver captures the emissions impact of changes in the allocation of expenditures across sectors, as determined by the utility function in Eq. (1).
- Changes in the competitiveness: $\hat{\Gamma}_{ji}^s$. This driver includes various factors that affect emissions through changes in a country's competitiveness, such as changes in country-j's productivity b_j^s in a given sector, in trade costs τ_{ji}^s, and fixed market entry costs f_{ji}^s. We do not separate these components but instead derive a single term that captures all these competitiveness-related variables. Specifically, the driver is defined as: $\hat{\Gamma}_{ji}^s \equiv (\hat{b}_j^s)^{\theta^s}(\hat{\tau}_{ji}^s)^{-\frac{\theta^s}{1-\alpha^s}}(\hat{f}_{ji}^s)^{1-\frac{\theta^s}{(\sigma^s-1)(1-\alpha^s)}}$.
- Changes in trade imbalances. This final emission driver allows our static framework to exactly match historical production and trade data. Conceptually, trade imbalances are represented as transfers between countries.

By plugging in production, trade, and emissions data as well as parameter estimates for σ^s, α^s, and θ^s, we can derive the historical developments of these emission drivers as implied by the model (see Section 4). We can quantify and interpret changes in implicit carbon prices, expenditure shares, and trade imbalances. Calculating the competitiveness drivers, in contrast, requires sector-specific price data which are not available. Consequently, our calculated competitiveness drivers are net of this component, making their development hard to interpret. Nonetheless, the competitiveness drivers can still be used to determine counterfactual emissions, as price indices cancel out in the equilibrium conditions where they appear.

In the next step, we disentangle the relative importance of these drivers in shaping German manufacturing emissions (see Secion 5.1). To do this, we allow all emission drivers to follow their historical path except for one, which we assume remained at its 2005 level.[8] By comparing the resulting counterfactual emissions with the actual emission development we can assess the significance of a given emission driver and the direction in which it has influenced emissions. Lastly, we use the model to examine how German

[8] Specifically, we plug these alternative values for emission drivers into the model and solve the model numerically, finding the changes in wages ($\hat{w}_j$) and firm entries ($\hat{M}_j^s$) consistent with the equilibrium conditions for all countries, sectors and years. The model is solved numerically using a trust-region-reflective algorithm, thereby constraining the endogenous variables to take on positive values. The values backed out by the algorithm can then be used to calculate emissions according to Eq. (7), associated with the endogenous firm-level decisions on emissions, entry, exit, production and exports. Importantly, those counterfactual emissions incorporate general equilibrium forces. Plugging historical values for all emission drivers into the model recreates the actual development of emissions.

industrial emissions would have developed if the implicit carbon price in the rest of the EU had followed the same trajectory as in Germany over the study period (see Section 5.2).

3 Data and parameter estimation

3.1 Data

Quantifying the model requires two ingredients: First, we need information on emissions, production values, and international trade flows. Second, we need sector-specific values for the three model parameters σ^s, α^s, and θ^s that govern fundamental model relationships. These data inputs enable us to back out the values of the various emissions drivers necessary for the model to replicate actual patterns of trade, production and CO_2 emissions. In the following, we briefly describe the data sets used, while Section 3.2 provides a detailed discussion of the estimation procedure for the three key model parameters.

Sector-level emissions are taken from the IEA (2022a) for the period 2005 to 2019. These emissions data include indirect emissions from electricity consumption.[9,10] Accurate sector-level emissions data are available for Germany and the rest of the EU, but unfortunately not for the entire rest of the world. Many countries report all their industrial emissions under the industry category "non-specified". Therefore, we define RoW as those countries in which only a reasonable share of emissions is categorised as non-specified.[11] This choice limits RoW to 22 countries, which collectively account for roughly 70% of German trade flows outside of the EU.[12] The development of emissions relative

[9] We can calculate sector-level emissions from German manufacturing using Census data. There are some differences in sector-level emissions for Germany between the two data sets, notably in the varying trends observed since 2005: According to the Manufacturing Census, CO_2 emissions increased between 2005 and 2017, whereas they exhibit a slightly decreasing trend according to the IEA. We further elaborate on these differences in Online Appendix B.3. Qualitatively, we obtain similar results from quantifying the model with either of the two data sources, as shown in Online Appendix C.8.

[10] We limit our main analysis to CO_2 emissions from combustion. In Online Appendix C.9, we show that additionally including process emissions does not substantially alter our results. This is because emissions developments were similar for combustion and process emissions, resulting in comparable outcome in terms of changes, although emissions levels naturally differ when process emissions are included.

[11] Specifically, we require countries to report less than 15% of emissions in the non-specified industry category for at least 10 out of 15 years (which corresponds to the 90th percentile of this share in the EU), or to report less than 27% of emissions in the non-specified category in every year (which corresponds to the 95th percentile of this share in the EU).

[12] Our RoW covers the following countries: Albania, Australia, Azerbaijan, Belarus, Bosnia, Brazil, Chinese Taipei, Colombia, Japan, South Korea, Norway, China, Philippines, North Macedonia, Russia, Switzerland, Thailand, Ukraine, US, Bahrain, Canada, Costa Rica. The covered world regions are visualised in Online Appendix B.1. Among the world's largest CO_2 emitters, India is absent from the analysis because it reports between one-third and two-thirds of its industrial emissions in the non-

to 2005 is depicted in Figure 1. To ensure that our results are robust to this limited country coverage, we conduct our decomposition analysis with the full RoW comprising all countries as well. In this additional analysis, due to the lack of emissions data for the entire RoW, we cannot distinguish changes in implicit carbon prices from the competitiveness driver for RoW, as we do for Germany and RoEU. Qualitatively, our results remain unchanged when broadening the set of RoW-countries (see Online Appendix C.10).

Production data in manufacturing are taken from the United Nations Industrial Development Organization (2022). The INDSTAT database provides output (in million dollars) disaggregated at the 2-digit sector-level of the International Standard Industrial Classification of All Economic Activities (ISIC) for 174 countries, though the exact coverage varies across years. Data are available from 1963 to 2020, but we focus on the years 2005 to 2019 according to the availability of other datasets. To ensure consistency across the different data sets, we merge very small sectors and use sector combinations. This procedure yields 10 different manufacturing sectors for our analysis. Their respective NACE sector codes and short descriptions are detailed in Table 1.[13] Given the European focus of our analysis, we convert dollar values to Euros using exchange rates from the OECD (2022). Lastly, we aggregate production data to our three world regions.[14]

TABLE 1: Analysed NACE 2 sectors

NACE 2 Code	Description
10 to 12	Food, tobacco and beverages
13 to 15	Textiles, wearing apparel, fur, leather and footwear
16	Wood products
17 and 18	Paper, paper products, printing and publishing
20 and 21	Chemicals, chemical products and pharmaceuticals
22, 31 and 32	Rubber and plastic products, furniture, manufacturing n.e.c.
23	Non-metallic mineral products
24	Basic metals
25 to 28, 33	Fabricated metals, electronic products, electric equipment, machinery and installation
29 and 30	Vehicles, vehicle components, other transport

specified industry category. In total, we lose approximately 12% of world production by limiting our country sample in this manner.

[13] The respective concordance table from ISIC Rev. 3 to NACE 2 sector codes is provided in Online Appendix B.2.

[14] We assign countries to only one group, either RoEU or RoW, disregarding changes through EU accessions. In our analysis, the UK is considered part of RoEU, as Brexit was only implemented after the end of our period of analysis.

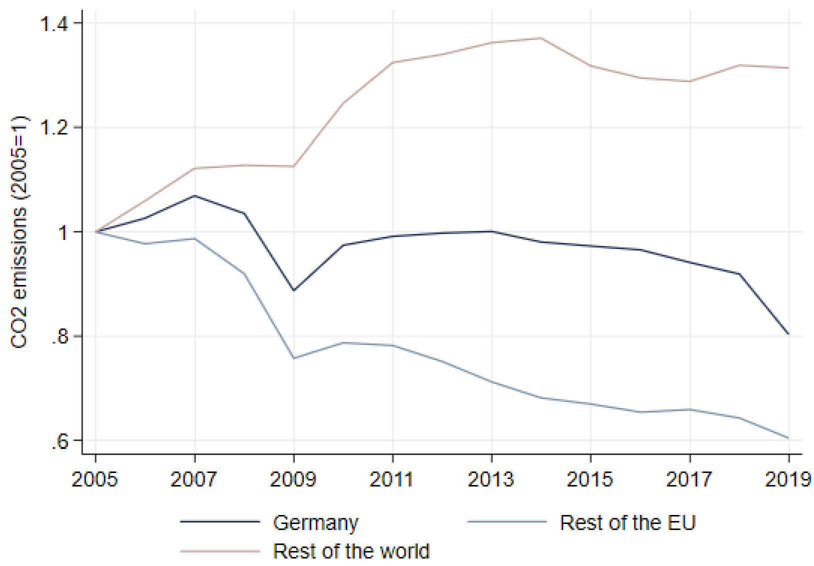


Figure 1: Development in industrial CO_2 emissions, 2005-2019.

Notes: Industrial CO_2 emissions from combustion, including emissions from electricity use, by world region. Source: Own calculation based on IEA (2022a).

Trade data are provided by Eurostat (2023a). Specifically, we obtain German and EU-level import and export data in Euros.[15] To correct for re-exports (i.e., exports where the goods were not originally produced in the exporting country), we use information on annual imports that are subsequently re-exported, obtained from input-output tables for Germany and the EU (Eurostat, 2023b). These re-export values are subtracted from the import and export data for Germany, RoEU, and RoW.[16,17]

Moreover, to better understand the factors driving the development of implicit carbon prices, we collect data on country-level fuel prices and fuel mixes from the IEA (IEA

[15] While combining trade and production data at the sectoral level is inherently difficult due to fundamentally different underlying classifications, the Eurostat data is reported in a classification that can be directly linked to NACE codes.

[16] The issue is that while re-exports are reflected in trade data both as imports and as exports, they are not included in production data. Re-exports can be substantial. Quantifying the model requires us to calculate the shares of worldwide production that are produced and consumed domestically, produced domestically but exported, and consumed domestically but imported. To ensure these measures are accurate and prevent exports from exceeding production, we adjust trade flows downward by accounting for re-exports. Details on the correction we apply can be found in Online Appendix B.4.

[17] We cross-check trade and production data in Germany against figures from the German Manufacturing Census. Levels and trends are similar, as shown in Online Appendix B.5. Additionally, we compare the gross output data from INDSTAT with country-level manufacturing GDP from the World Bank. The countries included in the INDSTAT data account for approximately 94-96% of global GDP as reported by the World Bank, depending on the year. Therefore, the coverage of our analysis is extensive. The ratio of manufacturing GDP (from the World Bank) to gross output (from INDSTAT) is generally around 30% at the median, aligning well with the range reported by Dekle et al. (2008) at the country-level.

2022c and IEA 2022b), on ETS coverage of different sectors from the European Union's transaction log, and on ETS future prices from the EEX. In addition, data on the state aid expenditures from EU members are taken from the EU's State Aid Scoreboard.[18] All these data are available for the period between 2005 and 2019.

The data and their level of aggregation have important implications for the scope of the analysis, warranting a detailed discussion. First, unlike Shapiro and Walker (2018), we treat the quantitative model as a three-country world, distinguishing between Germany, RoEU, and RoW. We do so to account for Germany's deep integration within the EU, with its single market and common (climate) policies, such as the EU ETS. This distinction allows us to recover separate developments of implicit carbon prices in each region. Despite the EU having a common climate policy instrument with the EU ETS, substantial national autonomy remains in setting the stringency of climate regulation for each country, a topic we will explore in greater detail in Section 4. By contrasting implicit carbon prices for Germany and RoEU, we can highlight the extent of differences and assess whether there is truly a single climate policy within the EU. Overall, by separating all German trading partners into groups of countries that are either highly integrated with Germany or not, we can evaluate the significance of market and policy integration with other countries for the development of German CO_2 emissions.

Second, our sector classification has important implications for identifying and specifying the separate emission drivers in our quantitative model. Specifically, the model focuses on within-sector changes and does not account for endogenous substitution across sectors. Changes in the relative importance of different sectors are reflected as changes in the Cobb-Douglas exponents β_i^s (expenditure share driver). Using a rather broad sector classification implies that composition shifts within sectors are not treated as changes in expenditure shares. Instead, any emission development coming from within-sector composition shifts is captured by one of the other emission drivers.[19] Conducting the analysis at a more disaggregated sectoral level would provide a more accurate picture but would also introduce more noise. For instance, using a finer sector classification would allow for more variation in production technologies and impose fewer restrictions on the responsive-

[18] The data can be downloaded under the following address: https://competition-policy.ec.europa.eu/state-aid/scoreboard/scoreboard-state-aid-data_en (last accessed on July 22, 2024).

[19] In a decomposition analysis with German data, Rottner and von Graevenitz (2024) show that even within narrowly defined 3-digits sectors, there may be substantial composition shifts giving rise to aggregation bias when working with aggregate data.

ness of output to emissions within 2-digit sectors. However, production and trade data at the 3-digit sector-level, although available, are substantially more volatile. Even at the 2-digit level, small sectors such as tobacco production or printing and publishing display unreasonably large variation in their production and trade patterns. Additionally, emissions data are not available at the 3-digit level from the IEA. Given these considerations, we conduct our analysis at the 2-digit sector level.

All parameters are estimated using firm-level data from the official German Manufacturing Census, which mandates participation. The Census generally covers all German manufacturing plants with at least 20 employees, though different thresholds apply to specific modules. We use data from our base year 2005.[20] To estimate the three parameters, we use information on firm-level revenues, energy use, CO_2 emissions, capital stocks, and costs.[21]

3.2 Parameter estimation

Parametrizing the model requires estimating three distinct sets of parameters at the sector level: the output elasticity of emissions, α^s, the elasticity of substitution, σ^s, and the Pareto shape parameter, θ^s. In the following, we briefly describe the estimation of each parameter, with further details provided in Online Appendix B.6.

To recover the sector-specific output elasticity of emissions, α^s, we proceed in two steps. First, we compute the output elasticity of energy by applying the factor share approach, taking the energy cost share from revenues (Syverson, 2011). Second, we divide this elasticity by an estimate of the elasticity of CO_2 emissions to energy use,

[20] Choosing 2005, the year the EU ETS was introduced, as a base year might seem an odd choice. An earlier base year could potentially allow us to analyse the increase in climate policy stringency due the EU ETS. Recovering this effect is challenging, however: First, firms' expectations about future carbon prices might have already influenced their emissions and abatement behaviour even before the EU ETS took effect. Secondly, grandfathering of free permits under the EU ETS might have induced firms to increase their emissions prior to its introduction. Additionally, the input-output tables we use are not available prior to 2005, and the energy statistics in the German Manufacturing Census are less reliable before 2005 due changes in reporting. Given these challenges, we chose 2005 as our base year.

[21] While the Census itself does not contain information on plant-level CO_2 emissions, it requires plants to report their consumption of 14 different fuels plus electricity. We use these fuel consumption data along with emission factors provided by the German Federal Environmental Agency (Umweltbundesamt, 2008, 2020a,b) to convert fuel consumption into CO_2 emissions. Capital stocks are calculated using the perpetual inventory method, as described by Lutz (2016).

converting the energy output elasticity to an emissions output elasticity. Formally, the two steps are summarised by

$$\alpha^s = \frac{\partial q^s}{\partial z^s}\frac{z^s}{q^s} = \frac{\partial q^s}{\partial e^s} \times \frac{\partial e^s}{\partial z^s}\frac{z^s}{q^s} = \frac{\frac{\partial q^s}{\partial e^s}}{\frac{\partial z^s}{\partial e^s}}\frac{e^s}{q^s}\frac{z^s}{q^s}\frac{q^s}{e^s} = \frac{\frac{\partial q^s}{\partial e^s}\frac{e^s}{q^s}}{\frac{\partial z^s}{\partial e^s}\frac{e^s}{z^s}}, \tag{8}$$

where e^s denotes energy input.

The factor share approach to retrieve the output elasticity of energy – the numerator of the last term in Eq. (8) – follows from static cost minimisation. Generally, such simple index measures of output elasticities have been found to perform well (Biesenbroeck, 2007), but output elasticities obtained from this approach may be misspecified if there are factor adjustment costs, as discussed in de Loecker and Syverson (2021). While these costs are typically low for energy (as compared to labour, for instance), we mitigate any potential bias by taking sector-level averages to smooth out idiosyncratic misalignments arising from firms operating away from their long-run (desired) input level. We then adjust the calculated output elasticity of energy by the emission intensity of sector-level fuel mixes. For that purpose, we estimate the elasticity of CO_2 emissions to energy use separately for each sector in 2005 using log-log regressions of emissions on energy use at the firm level – the denominator of the last term in Eq. (8).

To obtain sector-level elasticities of substitution between varieties, σ^s, we adopt an approach from previous literature, measuring markups by calculating the ratio of revenues to variable costs (see, e.g., Shapiro and Walker 2018, Antras et al. 2017 or Hsieh and Ossa 2016). Specifically, we follow Blaum et al. (2018) and use firm-level total revenues and the sum of materials and labour expenditure plus 0.2 times the capital stock as a proxy for the user cost of capital.[22] Subsequently, we back out the elasticity of substitution that rationalises these markups, given the imposed market structure: $\sigma^s = (1-\alpha^s)/(1-\alpha^s-\mu^s)$, where μ^s represents the markup. Using this methodology, we calculate markups averaging approximately 38% across German industrial sectors in 2005 (unweighted), which is well in line with the estimate of 35% for Germany by de Loecker and Eeckhout (2018).

[22] This approach helps to operationalise the model relation $w_j L_j^{s,p} = (1-\alpha^s)(\sigma^s-1)/\sigma^s R_j^s$, with $L_j^{s,p}$ denoting labour used in production and R_j^s being revenues in sector s and country j, by eliminating cost components from the measurement of total input cost that are clearly not productive, such as marketing cost.

To estimate the Pareto shape parameter, θ^s, we leverage the fact that a Pareto distribution of firm productivities implies that firm revenues also follow a Pareto distribution with a shape parameter $\theta^s/(\sigma^s - 1)$. Thus, we infer the underlying shape parameter of the productivity distribution by studying the revenue distribution of firms. Following Gabaix (2009), we estimate the shape parameter of the revenue distribution in each sector by regressing the log of a firm's revenue rank on the log of its revenues. We then calculate θ^s by multiplying the estimate with $(1 - \sigma^s)$. Firm-level revenues are taken from the German Manufacturing Census and our regressions are conducted for 2005. To mitigate bias due to selection into exporting, following di Giovanni et al. (2011), we include only domestic revenues in the regression. Moreover, consistent with previous research (Gabaix, 2009; di Giovanni et al., 2011), we restrict our sample to firms in the top decile of the revenue distribution, as the Pareto distribution best fits the right tail of firm distributions.[23] To further mitigate biases, we adjust the sales rank by subtracting one-half before taking the log, as proposed by Gabaix and Ibragimov (2011). Typically, estimates from the rank-revenue regression are close to minus unity, as predicted from Zipf's law.

Our parameter estimates are summarised in Table 2. Basic metals, non-metallic mineral products, paper products and chemical products exhibit the highest output elasticity of emissions, α^s. As expected, elasticities of substitution σ^s are generally lower for sectors with arguably differentiated products (such as food, chemicals) and higher for sectors in which products are more homogeneous (like printing and reproduction of media, basic metals). Related to that, the estimates of θ^s, describing the dispersion of productivity within each sector, show that sectors like food and chemicals are relatively heterogeneous (small θ^s), whereas the sectors paper products, basic metals, and textiles & apparel are relatively homogeneous (large θ^s).

Our findings generally show similar patterns and are fairly similar in magnitude to other estimates found in the literature, though some sectors are not directly comparable due to different sector aggregations. For α^s, our estimates resemble those of Shapiro and Walker (2018) despite their focus on local pollutants, whereas we specifically concentrate on CO_2 emissions.[24] Our productivity dispersion parameters are similar in magnitude

[23] We conduct visual checks to ensure that, indeed, for these firms, the relationship between firm rank and size is approximately linear.

[24] Even if local pollutants and CO_2 are co-pollutants, similar parameter values do not necessarily occur. For local pollutants, end-of-pipe technologies such as filters reduce emissions without an impact on CO_2

TABLE 2: Parameter values

NACE 2 Code	**Description**	α_s	σ_s	θ_s
10 to 12	Food, tobacco, beverages	0.020	2.512	2.102
13 to 15	Textiles, wearing apparel, leather	0.019	4.442	7.124
16	Wood products	0.038	4.767	6.442
17 and 18	Pulp, paper, publishing	0.058	10.270	16.871
20 and 21	Chemicals, pharmaceuticals	0.041	3.101	2.605
22, 31 and 32	Rubber, plastics, and n.e.c.	0.024	4.323	5.483
23	Non-metallic minerals	0.078	4.563	6.841
24	Basic metals	0.063	7.396	8.187
25 to 28, 33	Metal products, electronics, machinery	0.010	6.194	7.063
29 to 30	Vehicles, other transport, n.e.c.	0.008	6.133	5.147

Notes: All parameter values are estimated using data from the German Manufacturing Census for the year 2005. α_s denotes the output elasticity of emissions. σ_s represents the elasticity of substitution between varieties, and θ_s the shape parameter from the Pareto distribution from which firms draw their productivity. DOIs: 10.21242/43531.2018.00.03.1.1.0; 10.21242/42111.2021.00.01.1.1.0; 10.21242/42221.2021.00.01.1.1.0

and display similar sectoral patterns as those reported by Caliendo and Parro (2015) which are widely used in the literature.

emissions. In contrast, the abatement options for CO_2 (energy savings, output reductions) also reduce local pollutant emissions.

4 Implicit carbon prices in Germany and the EU

4.1 Historical developments of emission drivers

Quantifying the model allows us to recover the historical developments of the derived emission drivers. In the following discussion, we focus on the development of implicit carbon prices.[25]

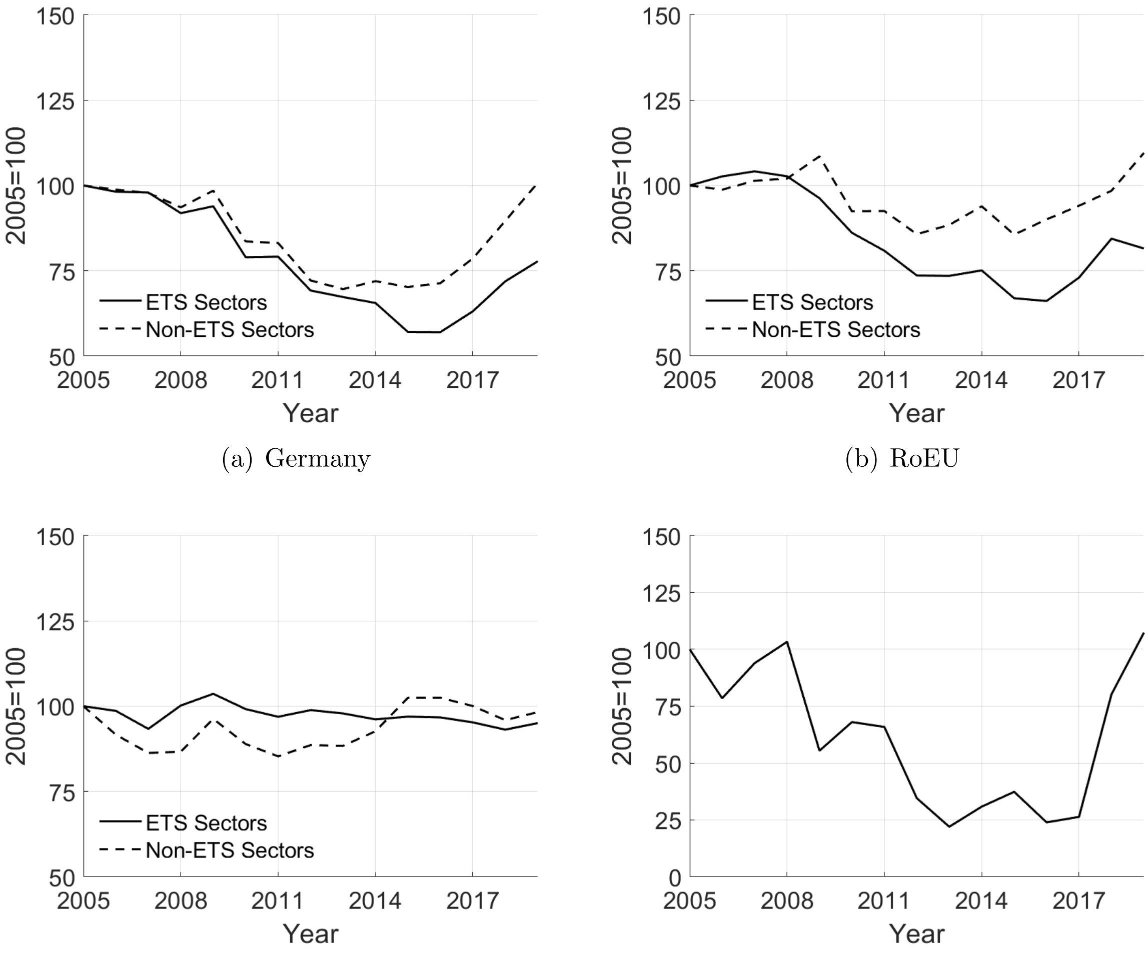
Figure 2 shows the development of implicit carbon prices in the considered regions as compared to base year 2005. Obtaining sector-specific implicit carbon prices, the graph presents revenue-weighted averages across two types of sectors: those mostly covered by the EU ETS and the remaining non-ETS sectors.[26] Revenue weights are assigned based on the base year 2005 and differ across regions.

The upper left panel, Figure 2(a), illustrates the development for German manufacturing. The implicit carbon price in both sector types follows similar trends; between 2005 and 2015, however, it decreased more substantially in ETS sectors (by 42.9%) than in non-ETS sectors (by 29.8%). By the end of our study period in 2019, the implicit carbon price for non-ETS sectors was slightly higher than in 2005, whereas for ETS sectors, it remained considerably lower. The upper right panel, Figure 2(b), shows a qualitatively similar pattern in the RoEU, though with a weaker downward trend and with an initial increase in implicit carbon prices for ETS sectors. In contrast, the lower left panel, Figure 2(c), reveals that implicit carbon prices in RoW have changed little since 2005. There is some movement in the less emission-intensive sectors without a clear trend, while implicit carbon prices in the more emission-intensive sectors have barely changed at all.

A key advantage of our approach is that we can infer implicit carbon prices from our quantitative analysis without the need to separately quantify all individual effects that comprise the direct and indirect costs of emitting CO_2. This feature, however, also prevents us from isolating all key drivers behind the development of implicit carbon prices. Nevertheless, we discuss driving forces of these developments in implicit carbon prices carefully in the following. For both Germany and the RoEU, the decline in implicit carbon

[25] The historical developments of expenditure shares are shown in Online Appendix C.1, whereas, as mentioned earlier, the historical values of the competitiveness drivers are not meaningful for interpretation.

[26] Sectors mostly covered by the EU ETS are NACE 17+18: pulp, paper and publishing; NACE 20+21: chemicals and pharmaceuticals; NACE 23: other non-metallic mineral products and NACE 24: metal production. Changes in implicit carbon prices for individual sectors are reported in Online Appendix C.2.



(a) Germany (b) RoEU

(c) RoW (d) ETS futures

Figure 2: Development of the Implicit Carbon Price and ETS Future Prices

Notes: ETS sectors comprise NACE codes 17, 18, 20, 21, 23 and 24. Non-ETS sectors comprise NACE codes 10-16, 22, and 25-33. Sector-level implicit carbon price developments are aggregated using 2005, country-specific revenue-weights. Annual averages of one year ETS futures are calculated using transaction volume weights. Sources: own calculations based on INDSTAT, IEA, and EEX data.

prices for ETS sectors visibly mirrors the development of EU ETS futures, as shown in the lower right panel, Figure 2(d). This correlation holds true for both the initial decline – with EU ETS futures falling by 73.6% from 2005 to 2017 – and the increase in the last years of our study period. While this link to the EU's main climate policy instrument is unsurprising and reassuring, it is notable for two reasons.

First, the decrease in implicit carbon prices is reflected not only in sectors covered by the EU ETS but also in less emission-intensive sectors, particularly pronounced in Germany and also evident in the RoEU. This similarity across sectors may stem from firms covered by the EU ETS passing on costs, as suggested by Hintermann et al. (2020) for manufacturing or Hintermann (2016) for the power sector, indirectly affecting firms in non-ETS sectors. For instance, the pass-through of costs in electricity generation exposes manufacturing firms using electricity to the ETS price.

Second, carbon prices under the EU ETS are not the only factor captured. The implicit carbon prices also reflect the evolution of energy prices and various command-and-control regulation, such as the promotion of renewable energies and combined heat and power (CHP), technology standards under directives like the large combustion plant directives (LCPD), emission reporting requirements introduced by the E-PRTR, and mandates for energy management systems or energy audits for large companies.

In the following sections, we investigate the role of the EU ETS, energy prices, and other factors using descriptive regression analysis. We further discuss the underlying reasons for differences in implicit carbon prices between Germany and RoEU.

4.2 Explaining developments in implicit carbon prices

To what extent is the initial decrease in implicit carbon prices in Germany and RoEU associated with declining prices under the EU ETS, as opposed to changes in fuel prices and command-and-control measures? To disentangle the relative importance of these factors, we employ a simple regression analysis and focus on the implicit carbon price developments within the EU, with $i \in \{DE, RoEU\}$.[27] Specifically, we estimate the following equations:

$$\hat{t}^{s}_{i,y} = \beta_f \hat{p}^{s,energy}_{i,y} + \beta_{ets}\hat{p}^{s,ets}_{i,y} + \mu_{i,y} + \epsilon^{s}_{i,y} \tag{9}$$

$$\mu_{i,y} = \gamma_{ets}\hat{p}^{ets}_{i,y} + \psi_{i,y}, \tag{10}$$

where the subscript y denotes the years of the sample between 2005 and 2019. The explanatory variable $p^{s,energy}_{i,y}$ reflects the energy prices faced by sector s in country i at time y. While industrial fuel prices do not vary across sectors within a given country-year combination, variation across sectors is introduced by the different fuel mixes used. Sectors that more heavily rely on natural gas, e.g., are more exposed to gas price developments than other sectors.

Similarly, $p^{s,ets}_{i,y}$ captures the effective sector-specific carbon price expectation under the EU ETS. Since the EU constitutes a single carbon market, the ETS-price only displays variation over time. However, sector- and country-level variation emerges from sectors and countries using fuel mixes with varying emission intensities, as well as from sectors being covered to different extents under the EU ETS in different countries and at different times. Due to the installation-specific inclusion threshold of 20 MW in the industrial sector, not all emissions from a given sector are regulated. These differences are captured by $p^{s,ets}_{i,y}$, which reflects the effective average price in EUR/kWh in a sector, country, and year, given the emission intensity of the fuel mix and the ETS coverage.

To capture the perceived stringency of climate policy, we use ETS price expectations instead of spot market prices. These expectations are more influential in driving firms' adjustment responses than spot market prices. Some ETS price developments over the period are merely artefacts of regulatory design (e.g., the drop to zero in 2007 due to banking restrictions across ETS phases). We use a transaction volume-weighted average of one-year future prices from the EEX.[28] Both the development of energy prices and effective ETS-prices for different sectors are shown in Online Appendix B.7 and B.8.

General developments in EU ETS and energy prices, as well as national cross-sectoral command-and-control measures, are captured by the country-by-year fixed effects $\mu_{i,y}$.

[27] RoW is comprised of very heterogeneous countries for which the estimation of average effects in such a regression is less meaningful.

[28] In Online Appendix C.3, we report regression results using ETS spot prices instead. The point coefficient estimates and R^2 value are substantially smaller when using spot market prices.

We decompose this fixed effect in a second regression, Eq. (10), to separate the EU ETS from national regulation ($\psi_{i,y}$). Any other command-and-control measures that vary by country, sector, and year are included in the error term $\epsilon^s_{i,y}$. We abstain from clustering standard errors at the sector level due to the low number of clusters (see Cameron and Miller, 2015). Since the dependent variable is an index (equal to 1 in base year 2005), we also transform our explanatory variables $p^{s,energy}_{i,y}$ and $p^{s,ets}_{i,y}$ into indices. Thus, we correlate the *development* in implicit carbon prices with the *development* in energy and carbon prices. This transformation has a similar, albeit not identical, effect to using sector fixed effects.

The results are shown in Table 3. As indicated in column (1), energy prices strongly correlate with implicit carbon prices: A doubling of energy prices compared to 2005 (i.e., an increase in a sector's energy price index by 1) is associated with a 49 percentage point increase in implicit carbon prices. In contrast, carbon prices under the EU ETS exhibit a small negative correlation when identified from sectoral variation. This suggests that the EU ETS is mostly captured by the country-by-year fixed effects.

TABLE 3: DETERMINANTS OF THE DEVELOPMENT OF IMPLICIT CARBON PRICES

	$\hat{t}^s_{i,y}$ (1)	$\mu_{i,y}$ (2)
$\hat{p}^{s,energy}_{i,y}$	0.491***	
	(0.106)	
$\hat{p}^{s,ets}_{i,y}$	-0.055***	0.473***
	(0.019)	(0.025)
N	300	300
R^2	0.37	0.55

Notes: The regressions include observations from 2005–2019. Dependent variables are indexed and are 1 in 2005. The regression in column (1) is run with country by year fixed effects. Column (2) explains the fixed effect estimated in column (1). Standard errors are displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

This is confirmed in Column (2), which shows a highly significant relationship between the ETS price and the fixed effects. Carbon prices under the EU ETS exhibit a correlation with implicit carbon prices similar to that of energy prices. This coefficient captures both the direct regulation under the EU ETS and the indirect regulation through rising electricity prices, to the extent permit prices might have been passed on by the power sector, as suggested by Fabra and Reguant (2014) and Hintermann (2016). Approximately half of the country-by-year variation in implicit carbon prices is explained by the EU ETS, indicating that other policies, e.g., command-and-control measures, also play a substantial role.

During our observation period, permit prices under the EU ETS did not increase or decrease monotonically. Therefore, it is reassuring in terms of the informative value of our model that we observe a strong relationship between the country-by-year fixed effects and permit prices. This relationship is not merely driven by both factors moving continuously up or down. In fact, plotting the estimated $\mu_{i,y}$ from the regression reveals a pattern over time that closely mirrors the development of permit prices under the EU ETS, as illustrated in Figure 3.

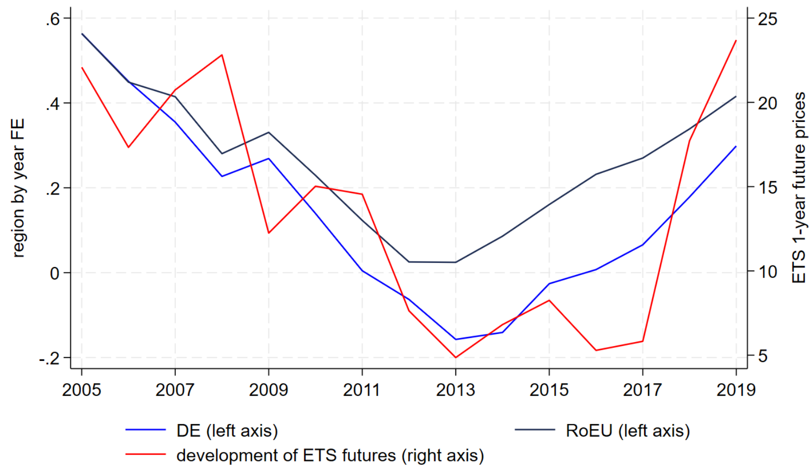


FIGURE 3: Development of Estimated Country-by-Year Fixed Effects from Explaining the Historical Implicit Carbon Prices, and of One-Year ETS Future Prices

4.3 Differences in implicit carbon prices across regions

We have seen in Figure 2 that the implicit carbon prices we back out from the model exhibit a similar trend in Germany and RoEU. This similarity extends to the non sector-specific country-by-year component, depicted in Figure 3. The common trends are reasonable given the common policy framework within the EU: The EU ETS applies to all member states, as do many command-and-control measures. For instance, the Large Combustion Plant (LCP) Directive (2001/80/EC) sets technology standards and emission limits (for local pollutants) for large combustion plants with a capacity of more than

50 MW across the EU. Similarly, emissions reporting requirements under the E-PRTR must be met by all member states (regulation no. 166/2006).

Yet, our findings indicate that the German implicit carbon price has declined at a steeper rate than in the rest of the EU compared to its 2005 level. This trend is observed in both ETS and non-ETS sectors.[29] Are such differing developments reasonable given the many common policies in place in the EU? At least four explanations come to mind:

First, the common European policy framework allows member states some leeway in the exact policy implementation. For example, in case of the EU ETS, member states decided on the amount and rules for allocating emission allowances through national allocation plans prior to phase 1. While the plans were reviewed by the European Commission, this decentralised approach arguably led to cross-country differences in climate policy stringency within the EU. Additionally, member states have the opportunity to compensate firms in certain sectors for electricity price increases due to the EU ETS. While most member states take advantage of this opportunity, the exact implementation of the compensation scheme (and the size of eligible sectors) differs across member states. In 2018, Germany had by far the largest number of beneficiaries in terms of installations (891), followed by France (296) and Spain (151) (EC, 2019).[30] Generally, countries are not restricted from exceeding the requirements set by the EU. The UK, for instance, has supplemented the EU ETS with a price floor since 2013.

Second, even if EU member states follow a common policy, the *impact* of that policy may differ across countries. For example, the LCP Directive sets common emission limits for local pollutants (SO_2, NO_x, dust) from large combustion plants. Before the LCP, there was substantial variation in the emission intensity of individual plants across Europe, with plants especially in Eastern European countries being substantially more emission-intensive than, for instance, German plants. The LCP Directive led to large emission reductions in local pollutants, especially in the most emission-intensive countries (e.g., Cyprus, Estonia, Greece, Romania, Slovenia, Spain), while having a very small impact in Germany over the period from 2004 to 2015 (EEA, 2019). These reductions

[29] We are silent on the absolute level of regulatory stringency, however. It is possible that Germany started out with more stringent climate policies than other EU countries, e.g., in form of higher energy prices or environmental standards. In that case, our results imply a convergence of German policy toward the climate policy stringency of the rest of the EU. We return to this point in section 6.

[30] In 2018, Germany spent about 18% of allowance auction revenues on indirect cost compensation, compared to almost 20% in the Netherlands, 32% in France and 29% in Finland. The UK, in contrast, spent less than 4%, whereas Spain spent 12% of auction revenues in the same year.

were partly achieved through the shutdown of the most inefficient plants and reduced coal usage, also contributing to reduced CO_2 emissions. The LCP requirements became binding between 2010 and 2014, consistent with a smaller decline in implicit carbon prices for RoEU compared to Germany, where most facilities were already compliant.

Third, member states can adopt unilateral policies. A prominent example is Germany's heavy subsidies for the expansion of renewable energies under the Renewable Energy Act since 1990. This expansion has reduced the CO_2 emissions intensity of the power sector in Germany and thus indirect CO_2 emissions in manufacturing. The feed-in tariffs used in this scheme were financed through a surcharge on electricity prices.[31] To mitigate any adverse impact on the competitiveness of German industrial firms, exemptions from paying the Renewable Energy Surcharge were introduced for electricity-intensive firms and expanded over the period under study. Exemptions from paying electricity grid charges were also expanded for large electricity users in 2011. These exemptions primarily affect sectors regulated under the EU ETS. Therefore, this policy development – and especially the increase in the Renewable Energy Surcharge over the period – is consistent with the growing divergence in implicit carbon prices between ETS and non-ETS sectors in Germany after 2012. The expansion of exemptions from different policy instruments also aligns with the stronger decrease in implicit carbon prices in Germany as compared to RoEU.

Fourth, industrial energy and electricity prices differ across countries due to fundamentally different energy mixes in the industrial and power sectors: France relies more on nuclear power than Germany, Poland more on coal, Estonia on oil, Denmark on renewables, etc. Against this background, the difference in the development of implicit carbon prices between Germany and the rest of the EU seems plausible.

5 Counterfactual analysis

5.1 Decomposing CO_2 emissions from German manufacturing

How important has the decrease in the implicit carbon prices been for the emissions development in German manufacturing? How significant is the divergence in the development

[31] The German Renewable Energy Surcharge increased from 2 ct/kWh in 2010 to 6.2 ct/kWh in 2014, peaking at 6.9 ct/kWh in 2017.

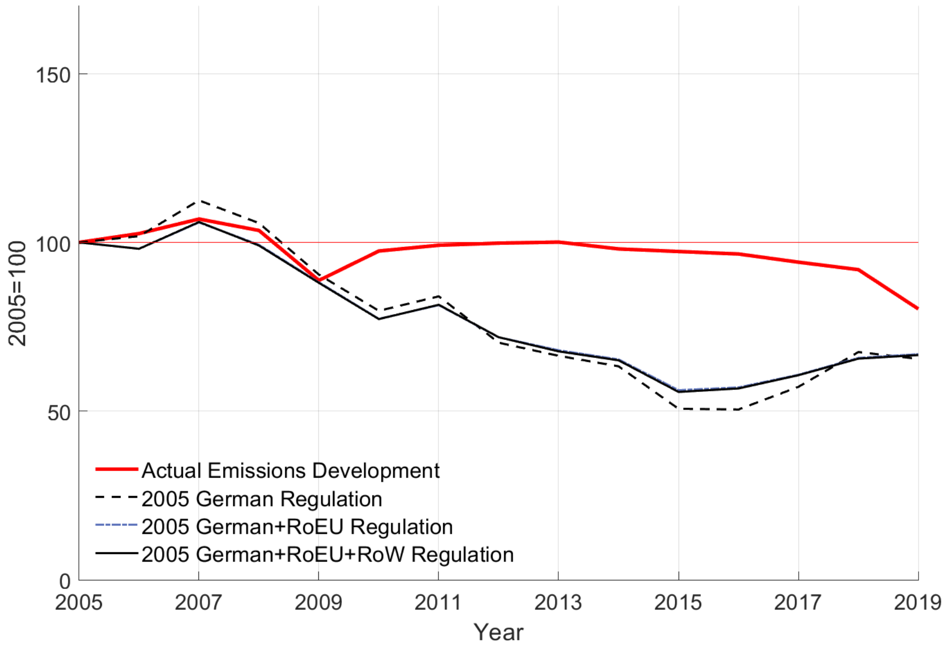
between RoEU and German (and RoW) implicit carbon prices in shaping German industrial emissions? Are changes in competitiveness a major driver of emissions in German industry? To understand the relative contributions of different driving forces, we run counterfactuals where we allow all determinants of emissions in the model to follow their historical paths except one. By isolating and shutting off each driver of German industrial emissions one by one, we can assess the contribution of each driver to the actual emission development.

The results of this exercise are shown in Figure 4.[32] The red line represents the actual development in German industrial CO_2 emissions, indexed to base year 2005. All other lines depict counterfactual emissions where one emission driver is held constant at its 2005 value. The upper panel, Figure 4(a), focuses on the roles of the implicit carbon price developments, while the lower panel, Figure 4(b), examines the role of the development in competitiveness and expenditure shares. If counterfactual emissions are higher than actual emissions, it indicates that the development of the emission driver held constant has contributed to a decline in emissions. Conversely, if counterfactual emissions are lower than the actual ones, it suggest that the development of the respective emission driver has contributed to an increase in emissions.

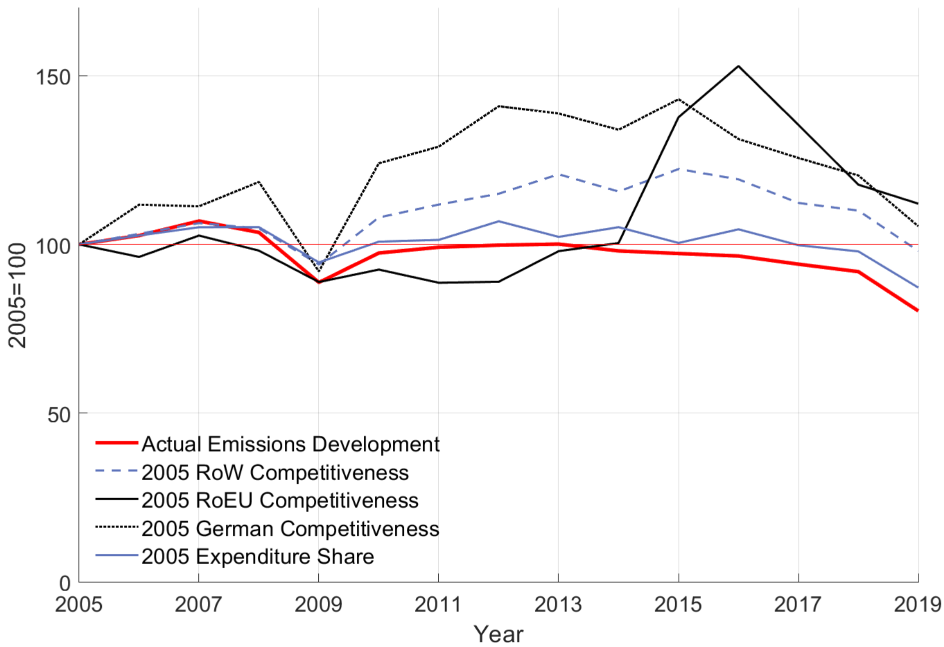
Mimicking the decline in implicit carbon prices documented in the previous subsections, the dashed black line in Figure 4(a) shows that, except in the early years, German industrial emissions would have been lower than they actually were if everything had followed its historical path except for German implicit carbon prices ($\hat{t}^s_{GER,y} = 1 \; \forall \; y$). By 2019, in the counterfactual, German emissions would have been 35% lower than in 2005, while in reality they declined by about 20%. Thus, the development in German implicit carbon prices has contributed to an increase in industrial emissions.

The difference between the counterfactual with a constant implicit carbon price and actual emissions is not driven by strong differences in growth, but rather by the German sector composition. In the counterfactual, Germany would have grown less in very emission-intensive sectors (specifically metals, and pulp and paper, where the elasticity of substitution is large, as well as chemicals). Conversely, labour would have been shifted toward less emission-intensive sectors (like machinery, cars, and textiles).

[32] We check the residuals from running the trust-region-reflective algorithm and find them to be extremely small throughout. When setting all emission drivers to their historic values, the model accurately recreates the actual emission development.



(a) The role of implicit carbon prices



(b) The role of competitiveness and expenditure shares

FIGURE 4: Decomposition of the Actual German Industrial CO_2 Emissions Development

Notes: One by one the driving forces are held constant at their 2005 values while the other driving forces follow their historical paths

Given the single market in the EU, policy developments in other EU member states might significantly impact German emissions development. The blue line in Figure 4(a) (which is covered almost entirely by the black line) shows that this is indeed the case. Holding constant the RoEU's implicit carbon prices in addition to Germany's ($\hat{t}^s_{RoEU,y} = \hat{t}^s_{GER,y} = 1 \ \forall \ y$) results in a smaller decrease in emissions compared to holding constant only German implicit carbon prices. In 2015 and 2016, the difference amounts to roughly 7 percentage points.

The fact that RoEU's implicit carbon prices decreased simultaneously mitigates the emission-increasing effect of the German development in implicit carbon prices. However, in terms of magnitude, the development in RoEU's implicit carbon prices is markedly less important than the development in German implicit carbon prices. In contrast, additionally holding constant the implicit carbon price development in RoW barely changes counterfactual emissions, as shown in the solid black line in Figure 4(a). In Online Appendix C.6, we demonstrate that this is not due to a lack of significant changes in implicit carbon prices in RoW (as shown in Figure 2). Rather, it is because developments in implicit carbon prices in RoW generally matter less for German emissions, given the lower level of market integration.

Our finding suggests that the differences in implicit carbon prices within the EU, documented in the last section, are significant for the emissions development. Given the small distance between EU countries and the high degree of market integration, even comparatively small regulatory differences might have large effects on production shifts, especially in sectors producing relatively homogeneous products. In the next subsection, we examine how German industrial emissions would have developed had the implicit carbon price in RoEU followed exactly the same path as in Germany.

The developments of the different competitiveness drivers (net of implicit carbon prices) also play an important role, as shown in Figure 4(b). Specifically, our results indicate that German competitiveness decreased over time. Without that loss in competitiveness, German production and hence German emissions would have increased, as shown by the dotted black line. Accordingly, part of German production has been replaced by foreign production, thereby reducing the emissions occurring in Germany.

The impact of competitiveness developments in RoEU is also important for the development of industrial emissions in Germany. From 2013 onward, increased RoEU competitiveness has contributed to decreasing German industrial emissions, as visible in the solid black line. The competitiveness of RoW generally increased as well. In a counterfactual where only RoW competitiveness is held constant at 2005 values, German emissions would have increased due to production shifting toward Germany, as shown in the dashed blue line.

Finally, the counterfactual scenario focusing on the role of the expenditure share development (solid blue line) suggests that worldwide consumer spending shifts have barely affected German emissions.

5.2 Equating German and EU implicit carbon prices

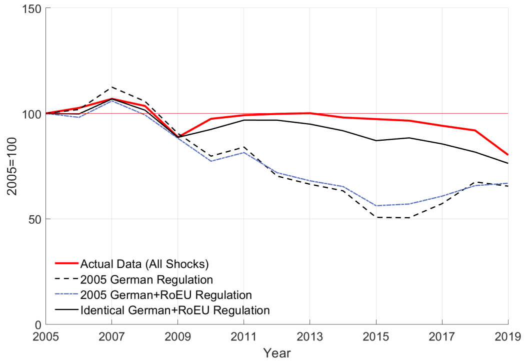
To understand the importance of intra-European differences in the development of regulatory stringency captured by the implicit carbon prices, we run a counterfactual scenario where the implicit carbon prices in Germany and RoEU follow identical paths, $\hat{t}^s_{RoEU,y} = \hat{t}^s_{GER,y}$. In principal, this scenario can impact German emissions through two channels: First, there is no change in the relative difference of implicit carbon prices anymore; a harmonisation occurs. Second, there is a change in stringency in one region. To focus on the first channel and isolate the effect of relative price differences on German emissions, we assume that RoEU's implicit carbon price would have followed the same trajectory as that in Germany.[33] For RoEU, the counterfactual conflates the harmonisation of climate policies with a decline in climate policy stringency.

Results for this scenario are shown in Figure 5. Figure 5(a) depicts the counterfactual emissions in Germany, Figure 5(b) in RoEU, and Figure 5(c) in RoW.[34]

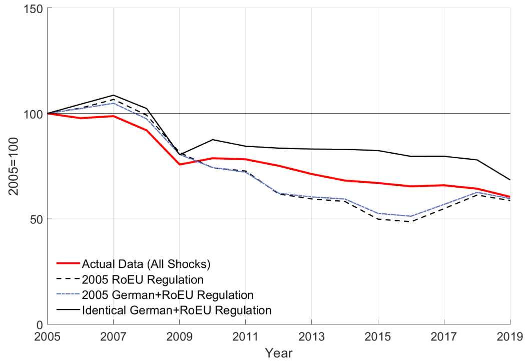
In the years prior to 2009, equating the implicit carbon price developments makes little difference to German emissions since developments in implicit carbon prices were very similar in RoEU and Germany during this period. However, in subsequent years, German emissions would have been up to 9 percent lower compared to base year 2005 (most notably in 2015 and 2018), if the RoEU experienced the same changes in implicit carbon prices as Germany. In this scenario, the metals sector in Germany would have

[33] In Online Appendix C.5, we present results for the alternative counterfactual scenario where German implicit carbon prices follow the path of those in RoEU.

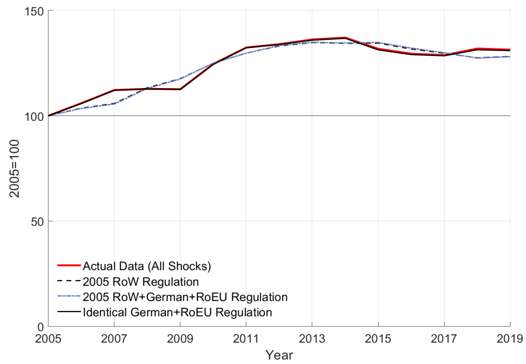
[34] Online Appendix C.4 provides the according counterfactual scenario separately for the metals and paper sectors.



(a) Emissions in Germany



(b) Emissions in RoEU



(c) Emissions in RoW

Figure 5: Counterfactual with RoEU Implicit Carbon Prices Following the German Path with all other Emission Drivers Taking on their Historical Values

Notes: All driving forces take on their historical value, except the implicit carbon prices whose development varies over counterfactuals.

contracted substantially more than it actually did by 2019, driving much of the decline in emissions.

The EU displays opposite patterns: Had the RoEU experienced the same change in implicit carbon prices as Germany, emissions would have been higher than they actually were. The relative difference between actual and counterfactual emissions is larger than for Germany, amounting to up to 17 percent in 2015. Therefore, at the EU-level, harmonising the development of implicit carbon prices would have led to more emissions. RoEU emissions would have increased by more than German emissions would have decreased. This is because the RoEU is larger in terms of emissions, which are affected by the implicit carbon prices, and because German emission intensity in many sectors, including metals and non-metallic minerals, was lower than the EU average in 2005.[35]

For the emissions of RoW, the implicit carbon price equality in Germany and RoEU hardly matters.

6 Discussion

Our findings show that changes in relative implicit carbon prices, alongside changes in competitiveness, significantly influence the evolution of CO_2 emissions. Specifically, implicit carbon prices have decreased in Germany compared to RoEU.

In the title, we ask whether Germany is becoming the European pollution haven. Our results are consistent with such a scenario. However, our analysis rests on the effect of changes in implicit carbon prices and is silent on the absolute levels in each region.

The steeper decline in implicit prices in Germany compared to RoEU could be attributed to a "catching up" effect if Germany initially had higher implicit carbon prices. This interpretation holds some truth, as Germany has historically had higher electricity prices than the EU average and stricter policies on co-pollutants from burning fossil fuels, such as SO_2 and particulate matter, harmonised with the LCP Directive. Indeed, at the beginning of the study period, Germany was less emission-intensive than the EU average in several energy-intensive sectors (see Figure 6).

With this interpretation, our results may illustrate the "first-mover-advantage" often cited by policymakers aiming to develop green lead markets. In a world where climate policies become more common across countries over time, countries with low emission intensity in production have a stronger initial position and can benefit from these early policy steps. Consequently, our findings are relevant beyond the EU context in global markets. They may reflect the allocative efficiency properties of an ETS, as production shifts to locations where emission intensities are lower.

The allocative efficiency of an ETS, which implies that emission reductions occur where they are cheapest (or production takes place where it is associated with the least emissions), is a feature that makes it popular among economists. As discussed in Sec-

[35] In Online Appendix B.9, we provide information on sector-level emission intensities across regions. The net increase in EU emissions would, of course, also have impacted the ETS price, which would likely have mitigated the increase in emissions.

tion 4.3, however, there are overlapping policies affecting implicit carbon prices that can undermine this allocative efficiency.

When assessing the development of emission intensity by sector and region over time, we observe in Figure 6 that while Germany initially had low emission intensities compared to the RoEU average, Germany's emission intensities, e.g., in the metals sector (NACE 24), were higher than in RoEU at the end of the period. Additionally, emission intensities declined faster in several sectors in the RoEU than in Germany.

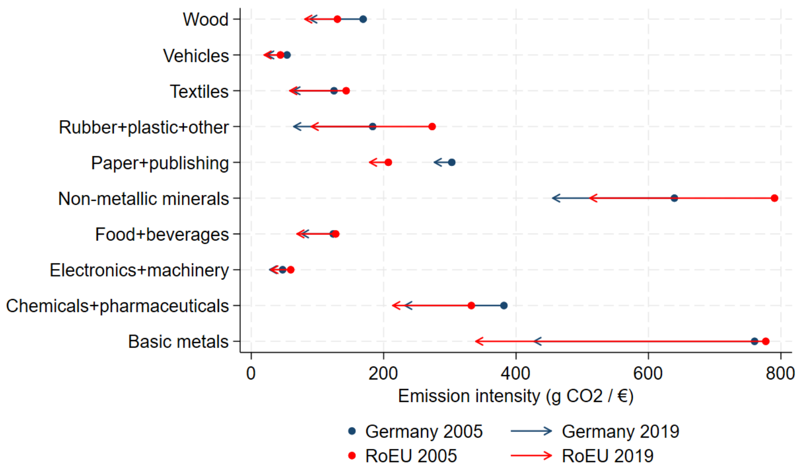


FIGURE 6: Developments from 2005 to 2019 in Emission Intensity by Region and Sector

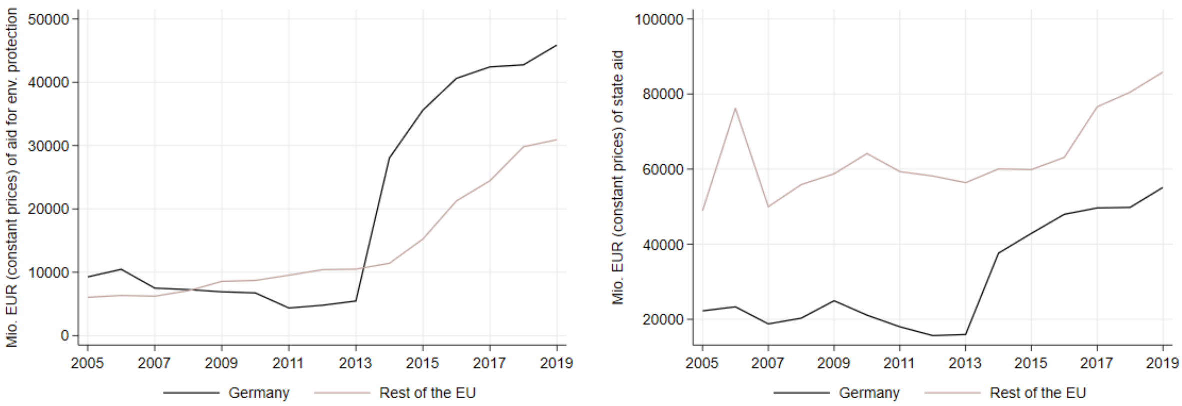
Notes: The figure displays emission intensities in $gCO_2/€$ of output by sector and region for the years 2005 and 2019. The figure is based on data from the IEA (emissions) and UNIDO (output).

Ideally, through the ETS, we would expect emission intensities across countries to converge as inefficient production sites reduce activities. Overlapping policies can interfere with this development by providing heterogeneous marginal incentives across countries and sectors.[36]

Germany has a history of compensating particularly energy-intensive industries for rising energy prices due to climate policy. The EU Commission's state aid scoreboard consistently places Germany among the top five spenders on programs labelled as "Aid for Environmental Protection".[37] Figure 7(a) demonstrates that between 2014 and 2019, Germany's state aid expenditures in this category exceeded the combined expenditures

[36] In Online Appendix B.9, we separate RoEU countries into individual EU member states and show that manufacturing emission intensities have indeed become less heterogeneous over time. However, Germany's position in the ranking has declined, which is consistent with interference with the ETS through unilateral policies.
[37] This data source defines the EU excluding the UK.

of RoEU. These programs include support schemes such as electricity price compensation and exemptions from renewable energy surcharges over the study period, predominantly benefiting the energy-intensive sectors. Such programs are motivated by concerns about competitiveness and demonstrate Germany's commitment to maintaining its position as an industrial hub. By supporting stringent common climate policies while having the fiscal ability to provide relief to domestic industry, Germany's approach could be viewed as a "beggar-thy-neighbour" industrial policy within the EU context.



(a) Environmental protection & energy savings

(b) Total

FIGURE 7: State aid in constant prices in Germany and RoEU.

Notes: The figure shows the development of state aid expenditures from Germany and the rest of the EU, excluding the UK. Panel (a) collects information on the state aid measures with the objective of environmental protection, including energy savings, panel (b) on all state aid measures. Constant prices adjust for the effects of inflation. Source: EU State Aid Scoreboard.

Also in terms of total expenditures, Germany holds a substantial and growing share. As shown in Figure 7(b), total state aid granted by Germany increased by a factor of roughly 2.5 between 2005 and 2019 (in constant prices), compared to growth factor of roughly 1.8 in the rest of the EU.

Our results highlight that the impact of inner-European differences in implicit carbon prices on production allocation is important. With substantial heterogeneity in the fiscal capability of member states, the distortionary effects of such policies could undermine the cohesion of the EU, challenging the "Just Transition" (EU Commission). Against this background, it is unlikely that the increase in German industrial emissions is efficient. Similar effects are conceivable in other regions of the world where countries are closely integrated yet heterogeneous in their fiscal capabilities.

7 Conclusion

In contrast to the broader EU trend, Germany's industrial CO_2 emissions have declined at a significantly slower rate, raising questions about the underlying drivers. Using a quantitative trade and environment model, we show that this disparity is partly driven by regional differences in the development of implicit carbon prices – a comprehensive measure that includes all factors influencing CO_2 costs. Specifically, our findings indicate that Germany's implicit carbon price declined significantly from 2005 to 2017 before rising again toward the end of our study period. While implicit carbon prices also declined in the rest of the EU, the decrease was less pronounced than in Germany. These trends generally follow the EU ETS permit prices and correlate with fluctuations in fuel prices, with the remaining variation suggesting a role for overlapping national policies. We demonstrate that this divergence in implicit carbon prices has significantly impacted the allocation of industrial CO_2 emissions. Had firms across the EU faced the same development of implicit carbon prices as in Germany, German emissions would have been substantially lower, while industrial emissions in the rest of the EU would have been higher.

Our analysis suggests that Germany's relatively steeper decline in implicit carbon prices has attracted more CO_2 emission-intensive production, potentially making it a European pollution haven. However, since our approach does not reveal absolute levels of implicit carbon prices, it remains unclear whether Germany reduced implicit carbon prices more from a comparable baseline or if it sought to level the playing field by lowering carbon prices more steeply from a higher initial level. The answer is likely a combination of both. In 2005, German industrial production was generally less carbon-intensive than in most other EU member states, reflecting earlier stringent regulation. Thus, the stronger decrease in implicit carbon prices in Germany may partly reflect convergence induced by the ETS and other EU regulation, granting Germany a first-mover advantage. At the same time, we also document Germany's stronger use of state aid programs to exempt and compensate energy-intensive industries. By 2019, German emission intensity in several sectors had declined less than the EU average, suggesting that overlapping national policies within the EU can undermine the allocative efficiency of the EU ETS.

Previous research on EU climate policy has largely focused on the risk of carbon leakage and the countermeasures such as carbon border adjustments. In contrast, our analysis highlights that strong trade ties and spatial proximity among EU member states make intra-EU production shifts highly likely in response to regulatory differences – perhaps even more so than shifts to distant, less integrated economies. Therefore, closer coordination of climate policies within the EU – including the alignment of state aid schemes – is essential to fully realize the efficiency gains that make the EU ETS a cost-minimizing policy tool. Such coordination would also enhance transparency and support a just transition.

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Online Appendix for

"IS GERMANY BECOMING THE EUROPEAN POLLUTION HAVEN?"

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September 6, 2024

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Appendix

A The quantitative trade and environment model

This section of the Appendix provides details on our quantitative trade and environment model, including the derivations of key relationships not covered in the main text. Specifically, we extend the model of Shapiro and Walker (2018) by allowing for the more general firm-specific production function:

$$q^s_{ji}(\varphi) = \varphi^{1-\xi\alpha^s} (z^s_{ji})^{\alpha^s} (l^s_{ji})^{1-\alpha^s}, \tag{A.1}$$

where $\xi \in \{0, 1\}$ denotes an indicator, while the remaining notation follows as introduced in the main text. As in Shapiro and Walker (2018) and Anouliès (2017), we assume $\xi = 1$ in the main text and specify the corresponding production function in Eq. (2). An often-used alternative with $\xi = 0$ (e.g. Egger et al., 2021) is included in the following generalized model presentation.[1]

We show that the choice of ξ does not qualitatively alter any key theoretical or numerical results, which is reassuring given the different model choices in the literature. However, it does have implications for the trade elasticity, as this includes α^s when $\xi = 1$.

A.1 Optimal firm behaviour subject to entry

Given utility in Eq. (1), an individual firm with productivity φ located in country j faces demand for its unique variety within sector s from country i as

$$q^s_{ji}(\varphi) = \frac{p^s_{ji}(\varphi)^{-\sigma^s}}{(P^s_i)^{1-\sigma^s}} E^s_i, \tag{A.2}$$

where $E^s_i (P^s_i)^{\sigma^s-1}$ is the market size of country i with P^s_i denoting the standard CES-price index of sector s in country i and E^s_i country-i's total expenditures on varieties in sector s. Country-sector-specific expenditures are determined as a constant share β^s_i of total revenues R_i net of transfers for trade deficits NX_i, i.e. $E^s_i = \beta^s_i (R_i - NX_i)$.

Subject to Eqs. (A.1), (A.2) and firm profits in Eq. (3), we derive the profit-maximising price of this firm as

$$p^s_{ji}(\varphi) = \frac{\sigma^s}{\sigma^s - 1} \tau^s_{ji} c^s_j(\varphi), \tag{A.3}$$

where (destination-independent) marginal production costs are denoted by:

$$c^s_j(\varphi) = \frac{c^s_0 (t^s_j)^{\alpha^s} (w_j)^{1-\alpha^s}}{\varphi^{1-\xi\alpha^s}} \qquad \text{with} \qquad c^s_0 \equiv (\alpha^s)^{-\alpha^s} (1-\alpha^s)^{-(1-\alpha^s)} > 0. \tag{A.4}$$

Making use of Eqs. (A.2)-(A.4), we can specify sold quantities as:

$$q^s_{ji}(\varphi) = \frac{\left[\frac{\sigma^s}{\sigma^s-1} \tau^s_{ji} c^s_0 (t^s_j)^{\alpha^s} (w_j)^{1-\alpha^s}\right]^{-\sigma}}{(P^s_i)^{1-\sigma^s}} E^s_i \varphi^{\sigma(1-\xi\alpha^s)} \tag{A.5}$$

and can express firm revenues as:

$$r^s_{ji}(\varphi) \equiv p^s_{ji}(\varphi) q^s_{ji}(\varphi) = \left(\frac{p^s_{ji}(\varphi)}{P^s_i}\right)^{1-\sigma^s} E^s_i. \tag{A.6}$$

Firm profits given by Eq. (3) can be rewritten as

$$\pi^s_{ji}(\varphi) = r^s_{ji}(\varphi) - \tau^s_{ji} c^s_j(\varphi) q^s_{ji}(\varphi) - w_i f^s_{ji} = \frac{r^s_{ji}(\varphi)}{\sigma^s} - w_i f^s_{ji}. \tag{A.7}$$

[1] Rationalizing the production technology in Eq. (A.1) based on a specific abatement technology (see Copeland and Taylor, 1994, 2003), $\xi = 1$ corresponds to the assumption that output is sacrificed to reduce emissions. In contrast, $\xi = 0$ corresponds to using labour input for abatement.

Profit maximisation leads to optimal variable labour input demand of:

$$l_{ji}^s(\varphi) = (1-\alpha^s)c_0^s \left(\frac{t_j^s}{w_j}\right)^{\alpha^s} \varphi^{-(1-\xi\alpha^s)} q_{ji}^s(\varphi), \tag{A.8}$$

while generated emissions are determined as:

$$z_{ji}^s(\varphi) = \alpha^s c_0^s \left(\frac{w_j}{t_j^s}\right)^{1-\alpha^s} \varphi^{-(1-\xi\alpha^s)} q_{ji}^s(\varphi). \tag{A.9}$$

From Eq. (A.9), we can finally compute emissions intensity (per physical quantity) as:

$$i_{ji}^s(\varphi) \equiv \frac{z_{ji}^s(\varphi)}{q_{ji}^s(\varphi)} = \alpha^s c_0^s \left(\frac{w_j}{t_j^s}\right)^{1-\alpha^s} \varphi^{-(1-\xi\alpha^s)}. \tag{A.10}$$

From these expressions, we can compare two firms of different productivity levels, generalizing Eq. (4) in the main text as follows:

$$\frac{p_{ji}^s(\varphi_1)}{p_{ij}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{-(1-\xi\alpha^s)}, \quad \frac{q_{ji}^s(\varphi_1)}{q_{ji}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{\sigma^s(1-\xi\alpha^s)} \tag{A.11}$$

$$\frac{r_{ji}^s(\varphi_1)}{r_{ji}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{(\sigma^s-1)(1-\xi\alpha^s)}, \quad \frac{i_{ji}^s(\varphi_1)}{i_{ji}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{\xi\alpha^s-1}, \tag{A.12}$$

$$\frac{z_{ji}^s(\varphi_1)}{z_{ji}^s(\varphi_2)} = \left(\frac{\varphi_1}{\varphi_2}\right)^{(\sigma^s-1)(1-\xi\alpha^s)}. \tag{A.13}$$

Since $\alpha^s \in (0,1)$, the choice of ξ does not qualitatively alter the comparison, and the statements from the main text generally apply.

A.2 The equilibrium conditions

In equilibrium, firm selection into destination markets is determined via *zero cutoff profits conditions*, while two additional conditions need to be satisfied: the *free entry condition* and the *labour market clearing condition*.

A.2.1 Zero cutoff profits conditions

Given knowledge of productivity φ, an individual firm decides to enter a specific market whenever it can earn non-negative profits. The marginal firm located in j, entering market i and characterised by cutoff productivity φ_{ji}^s, is implicitly determined by the *zero cutoff profit condition* $\pi_{ji}^s(\varphi_{ji}^s) = 0$. Using Eqs. (A.3)-(A.7), we can compute

$$\varphi_{ji}^s = \left[\frac{\sigma^s}{\sigma^s-1} \frac{\tau_{ji}^s c_0^s (t_j^s)^{\alpha^s}(w_j)^{1-\alpha^s}}{P_i^s} \left(\frac{\sigma^s w_i f_{ji}^s}{E_i^s}\right)^{\frac{1}{\sigma^s-1}}\right]^{\frac{1}{1-\xi\alpha^s}}, \tag{A.14}$$

where every firm with $\varphi \geq \varphi_{ji}^s$ enters.

A.2.2 Free entry condition

The *free entry condition* requires that, within each sector, the fixed cost of drawing a productivity in terms of labour equals the expected profits of doing so:

$$w_j f_j^s = \sum_i \int_{\varphi_{ji}^s}^{\infty} \pi_{ji}^s(\varphi) g(\varphi) d\varphi. \tag{A.15}$$

This can be rewritten using the expression for firm profits in Eq. (A.7), the specified Pareto distribution in Eq. (5), the firm comparison in Eq. (A.12), and the relationship $r^s_{ji}(\varphi^s_{ji}) = \sigma^s w_i f^s_{ji}$ as:

$$w_j f^s_j = \frac{(\sigma^s - 1)(1 - \xi\alpha^s)}{\theta^s - (\sigma^s - 1)(1 - \xi\alpha^s)} \sum_i \left(\frac{b^s_j}{\varphi^s_{ji}}\right)^{\theta^s} w_i f^s_{ji}. \tag{A.16}$$

We can further simplify this condition by substituting φ^s_{ji} using an alternative expression to Eq. (A.14). To do so, we first need to define sector-specific bilateral expenditures, which satisfy $E^s_i = \sum_j X^s_{ji}$. This yields

$$\begin{aligned} X^s_{ji} &\equiv [1 - G^s_j(\varphi^s_{ji})] M^s_j \int_{\varphi^s_{ji}}^{\infty} r^s_{ji}(\varphi) \frac{g(\varphi)}{1 - G^s_j(\varphi^s_{ji})} d\varphi & \text{(A.17)} \\ &= M^s_j w_i f^s_{ji} \frac{\sigma^s \theta^s}{\theta^s - (\sigma^s - 1)(1 - \xi\alpha^s)} \left(\frac{b^s_j}{\varphi^s_{ji}}\right)^{\theta^s}, & \text{(A.18)} \end{aligned}$$

where the second equality follows from the specified Pareto distribution in Eq. (5), firm comparison in Eq. (A.12), and the relationship $r^s_{ji}(\varphi^s_{ji}) = \sigma^s w_i f^s_{ji}$. Reformulating this, we obtain an alternative expression for the cutoff productivity level:

$$\left(\varphi^s_{ji}\right)^{\theta^s} = \frac{\sigma^s \theta^s}{\theta^s - (\sigma^s - 1)(1 - \xi\alpha^s)} \frac{M^s_j \left(b^s_j\right)^{\theta^s} w_i f^s_{ji}}{X^s_{ji}}. \tag{A.19}$$

Finally, by inserting Eq. (A.19) in Eq. (A.16), we arrive at the rewritten free entry condition

$$w_j f^s_j = \frac{1 - \xi\alpha^s}{\theta^s} \frac{\sigma^s - 1}{\sigma^s} \frac{R^s_j}{M^s_j}, \tag{A.20}$$

where $R^s_j = \sum_i X^s_{ji}$ denotes the total revenues from sector s in country j. Note that sector-level revenues and expenditures do not necessarily coincide; we define $NX^s_j \equiv R^s_j - E^s_j$ as the net exports of country j in sector s.

A.2.3 Labour market clearing condition

The *labour market clearing condition* states that

$$L_j = L^d_j \qquad \text{with} \qquad L^d_j = \sum_s L^{s,e}_j + L^{s,p}_j + L^{s,t}_j + L^{s,m}_j + L^{nx}_j, \tag{A.21}$$

where L_j and L^d_j denote country j's total labour supply and demand, respectively. Here, $L^{s,e}_j$ represents the labour input used to pay the fixed entry cost, $L^{s,p}_j$ the labour input for production, $L^{s,t}_j$ the labour used to pay the carbon tax, $L^{s,m}_j$ the labour for market entry costs,[2] and L^{nx}_j accounts for labour to pay for trade deficits.

In detail, we can derive the individual components of labour demand as follows, occasionally utilizing the free entry condition from Eq. (A.20) and the specified Pareto distribution in Eq. (5).

First, the labour input used to pay the fixed entry cost can be directly computed as:

$$L^{s,e}_j \equiv M^s_j f^s_j = \frac{1 - \xi\alpha^s}{\theta^s} \frac{\sigma^s - 1}{\sigma^s} \frac{R^s_j}{w^s_j}. \tag{A.22}$$

Second, using Eq. (A.8), we calculate the aggregate labour input for production as

$$L^{s,p}_j \equiv M^s_j \sum_i \int_{\varphi^s_{ji}}^{\infty} \tau^s_{ji} l^s_{ji} g^s_j(\varphi) d\varphi = (1 - \alpha^s) \frac{\sigma^s - 1}{\sigma^s} \frac{R^s_j}{w^s_j}. \tag{A.23}$$

[2] Both domestic firms *and* foreign exporters pay these fixed costs. Country j exporting firms, in turn, pay fixed costs in foreign country i, which is accounted for in L^{nx}_i.

Third, and similarly to $L_j^{s,p}$, the labour used for emission tax payments is computed as:

$$L_j^{s,t} = \frac{t_j^s Z_j^s}{w_j} = \alpha^s \frac{\sigma^s - 1}{\sigma^s} \frac{R_j^s}{w_j^s}, \tag{A.24}$$

where we make use of Eq. (A.10) to derive aggregate sector-level emissions:

$$Z_j^s \equiv M_j^s \sum_i \int_{\varphi_{ji}^s}^{\infty} \tau_{ji}^s z_{ji}^s g_j^s(\varphi) d\varphi = M_j^s \frac{w_j}{t_j^s} f_j^s \frac{\alpha^s \theta^s}{1 - \xi \alpha^s} \tag{A.25}$$

Setting $\xi = 1$ gives Eq. (6) in the main text.

Fourth, we derive aggregate labour use for market entry using Eq. (A.18) and the relationship $E_j^s = \sum_k X_{kj}^s$ as

$$L_j^{s,m} \equiv \sum_k [1 - G(\varphi_{kj}^s] M_k^s f_{kj}^s = \frac{\theta^s - (\sigma^s - 1)(1 - \xi \alpha^s)}{\sigma^s \theta^s} \frac{E_j^s}{w_j} \tag{A.26}$$

Fifth, we derive labour for transfer payments for trade deficits as residuum labour demand component. To do so, we collect the four derived components of labour demand, employ labour market clearing from Eq. (A.21) and use the following relationships $R_j = L_j w_j$, $NX_j^s = R_j^s - E_j^s$, and $NX_j = R_j - \sum_s E_j^s$. This yields:

$$L_j^{nx} = \frac{NX_j}{w_j} - \sum_s \frac{NX_j^s}{w_j} \frac{(\sigma^s - 1)[\theta^s + (1 - \xi \alpha^s)]}{\sigma^s \theta^s}. \tag{A.27}$$

Given Eqs. (A.21)-(A.27), we can finally express the labour market clearing condition as

$$L_j = \sum_s \frac{1}{1 - \frac{\theta^s - (\sigma^s - 1)(1 - \xi \alpha^s)}{\sigma^s \theta^s} \beta_j^s} \frac{1}{w_j} \left[R_j^s \frac{(\sigma^s - 1)[\theta^s + (1 - \xi \alpha^s)]}{\sigma^s \theta^s} + \eta_j \right], \tag{A.28}$$

with $\eta_j \equiv \sum_s \left[- \frac{\theta^s - (\sigma^s - 1)(1 - \xi \alpha^s) - \sigma^s \theta^s}{\sigma^s \theta^s} \beta_j^s NX_j - NX_j^s \frac{(\sigma^s - 1)[\theta^s + (1 - \xi \alpha^s)]}{\sigma^s \theta^s} \right]$.

A.3 Model formulation in changes

In the following, we express the equilibrium in terms of changes using the "exact hat algebra" by Dekle et al. (2008). Consistent with Shapiro and Walker (2018), we assume throughout that $\hat{f}_j^s = 1$.

A.3.1 Equilibrium conditions in changes

We can express the free entry condition from Eq. (A.20) in terms of changes as

$$\hat{w}_j = \frac{\hat{R}_j^s}{\hat{M}_j^s}. \tag{A.29}$$

To operationalize this, following Shapiro and Walker (2018), we rewrite Eq. (A.29) by replacing $\hat{R}_j^s$. To do so, we use $R_j^s = \sum_i X_{ji}^s = \sum_i \lambda_{ji}^s E_i^s$, with $\lambda_{ji}^s \equiv X_{ji}^s / E_i^s$ denoting the sector-specific expenditure share of country i for country j's products in sector s, computed from Eq. (A.18) as:

$$\lambda_{ji}^s = \frac{M_j^s \left(b_j^s\right)^{\theta^s} \left(\tau_{ji}^s\right)^{\frac{-\theta^s}{1 - \xi \alpha^s}} \left(w_j\right)^{\frac{-(1 - \alpha^s)\theta^s}{1 - \xi \alpha^s}} \left(t_j^s\right)^{\frac{-\alpha^s \theta^s}{1 - \xi \alpha^s}} \left(f_{ji}^s\right)^{\frac{(\sigma^s - 1)(1 - \xi \alpha^s) - \theta^s}{(\sigma^s - 1)(1 - \xi \alpha^s)}}}{\sum_k M_k^s \left(b_k^s\right)^{\theta^s} \left(\tau_{ki}^s\right)^{-\frac{\theta^s}{1 - \xi \alpha^s}} \left(w_k\right)^{-\frac{(1 - \alpha^s)\theta^s}{1 - \xi \alpha^s}} \left(t_k^s\right)^{-\frac{\alpha^s \theta^s}{1 - \xi \alpha^s}} \left(f_{ki}^s\right)^{\frac{(\sigma^s - 1)(1 - \xi \alpha^s) - \theta^s}{(\sigma^s - 1)(1 - \xi \alpha^s)}}}, \tag{A.30}$$

where $k \in \mathcal{N}$ is an alias for i and j. Expressing this in terms of changes, we derive the envisaged alternative to Eq. (A.29) as:

$$\hat{w}_j = \sum_i \frac{\zeta_{ji}^s (\hat{b}_j^s)^{\theta^s} (\hat{\tau}_{ji}^s)^{-\frac{\theta^s}{1-\xi\alpha^s}} (\hat{t}_j^s)^{-\frac{\alpha^s\theta^s}{1-\xi\alpha^s}} (\hat{w}_j)^{-\frac{(1-\alpha^s)\theta^s}{1-\xi\alpha^s}} (\hat{f}_{ji}^s)^{1-\frac{\theta^s}{(\sigma^s-1)(1-\xi\alpha^s)}}}{\sum_k \lambda_{ki}^s \hat{M}_k^s (\hat{b}_k^s)^{\theta^s} (\hat{\tau}_{ki}^s)^{-\frac{\theta^s}{1-\xi\alpha^s}} (\hat{t}_k^s)^{-\frac{\alpha^s\theta^s}{1-\xi\alpha^s}} (\hat{w}_k)^{-\frac{(1-\alpha^s)\theta^s}{1-\xi\alpha^s}} (\hat{f}_{ki}^s)^{1-\frac{\theta^s}{(\sigma^s-1)(1-\xi\alpha^s)}}} \cdot \hat{\beta}_i^s \frac{R_i' - NX_i'}{R_i - NX_i}, \tag{A.31}$$

where $\zeta_{ji}^s \equiv X_{ji}^s / \sum_i X_{ji}^s$ denotes the share of country j's production in sector s that is exported to country i, and where we incorporate the relationship

$$\hat{E}_i^s = \hat{\beta}_i^s \hat{E}_i = \hat{\beta}_i^s \frac{R_i' - NX_i'}{R_i - NX_i}. \tag{A.32}$$

We can express the labour market clearing condition from Eq. (A.28) in terms of changes as:

$$1 = \frac{1 - \sum_s \frac{\theta^s - (\sigma^s-1)(1-\xi\alpha^s)}{\sigma^s\theta^s} \beta_j^s}{1 - \sum_s \frac{\theta^s - (\sigma^s-1)(1-\xi\alpha^s)}{\sigma^s\theta^s} \beta_j^{s'}} \left(\frac{\sum_s \hat{M}_j^s R_j^s \frac{(\sigma^s-1)[\theta^s + (1-\xi\alpha^s)]}{\sigma^s\theta^s} + \frac{1}{\hat{w}_j} \eta_j^{s'}}{\sum_s R_j^s \frac{(\sigma^s-1)[\theta^s + (1-\xi\alpha^s)]}{\sigma^s\theta^s} + \eta_j^s} \right), \tag{A.33}$$

noting that $R_j^{s'} / \hat{w}_j = \hat{M}_j^s R_j^s$ from Eq. (A.29).

A.3.2 Emissions drivers

In addition to changes in implicit carbon prices $\hat{t}_j^s$, as shown in the main text, we can specify the changes in expenditure shares as

$$\hat{\beta}_i^s = \frac{\hat{E}_i^s}{\hat{E}_i} = \frac{\hat{E}_i^s}{\frac{R_i' - NX_i'}{R_i - NX_i}}, \tag{A.34}$$

essentially reformulating Eq. (A.32). The changes in competitiveness, in turn, are computed based on $\hat{\lambda}_{ji}^s = \hat{X}_{ji}^s / \hat{E}_i^s$, together with Eqs. (A.14), (A.18), and(A.32), as:

$$\begin{aligned} \hat{\Gamma}_{ji}^s &\equiv (\hat{b}_j^s)^{\theta^s} (\hat{\tau}_{ji}^s)^{-\frac{\theta^s}{1-\xi\alpha^s}} (\hat{f}_{ji}^s)^{1-\frac{\theta^s}{(\sigma^s-1)(1-\xi\alpha^s)}} \\ &= (\hat{t}_j^s)^{\frac{\alpha^s\theta^s}{1-\xi\alpha^s}} \frac{\hat{\lambda}_{ji}^s}{\hat{M}_j^s \hat{w}_j^{-\frac{(1-\alpha^s)\theta^s}{1-\xi\alpha^s}}} (\hat{P}_i^s)^{-\frac{\theta^s}{1-\xi\alpha^s}} \left(\frac{\hat{\beta}_i^s}{\hat{w}_i} \frac{R_i' - NX_i'}{R_i - NX_i} \right)^{1-\frac{\theta^s}{(\sigma^s-1)(1-\xi\alpha^s)}} \end{aligned} \tag{A.35}$$

While destination-specific price index data are generally not available, counterfactuals can be analysed without measuring $\hat{P}_i^s$. This is because, in the free entry conditions in changes in Eq. (A.31), the price indices cancel out. Consequently, counterfactual emissions calculated using competitiveness measures that omit price indices are equivalent to those obtained by incorporating accurate measures of competitiveness drivers that include price indices. However, historical measures of domestic and foreign competitiveness that exclude the price index information are not informative, and thus, we refrain from interpreting them.

B Data details

This part of the Appendix provides more details on the data used and evaluates data accuracy, where possible. The Appendix also contains more details on the estimation of central model parameters and additional summary statistics.

B.1 World regions in the analysis

Given the lack of reliable emissions data at the sector level, our analysis does not cover the full set of countries around the world. The countries included in the analysis are visualised in Figure B.1.

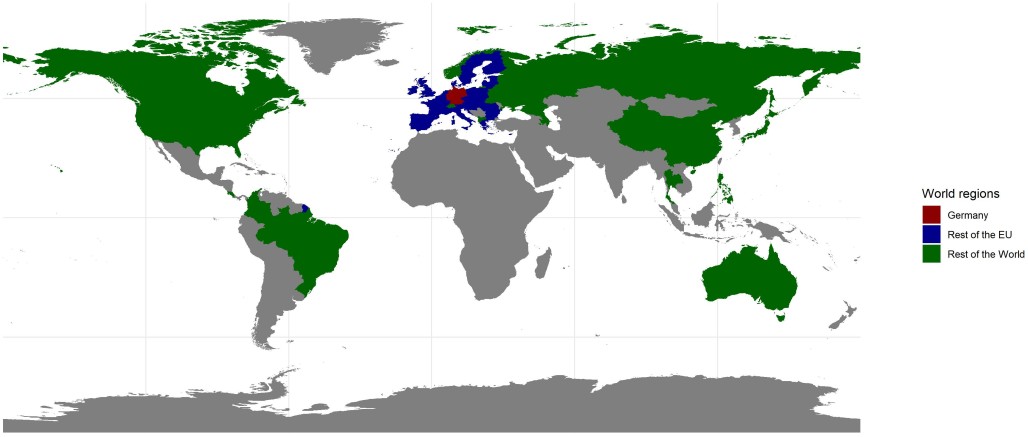


FIGURE B.1: World Regions in the Analysis

B.2 Concordance tables ISIC Rev. 3 – NACE 2

TABLE B.1: Concordance ISIC Rev. 3 – NACE 2

ISIC Rev. 3 Code	Description	NACE 2 Code
15	Food and beverages	10 and 11
16	Tobacco products	12
17	Textiles	13
18	Wearing apparel, fur	14
19	Leather, leather products and footwear	15
20	Wood products (no furniture)	16
21	Paper and paper products	17
22	Printing and publishing	18
23	Coke, refined petroleum products, nuclear fuel	19
24	Chemicals and chemical products	20 and 21
25	Rubber and plastic products	22
26	Non-metallic mineral products	23
27	Basic metals	24
28	Fabricated metal products	25
29	Machinery and equipment	28 and 33
30	Office, accounting and computing machinery	26
31	Electrical machinery and apparatus	27
32	Radio, television and communication equipment	26
33	Medical, precision and optimal instruments	26
34	Motor vehicles, trailers, semi-trailers	29
35	Other transport equipment	30
36	Furniture; manufacturing n.e.c.	31 and 32

Taken from the INDSTAT 2 metadata

B.3 Comparing IEA emissions data to emissions computed with the German manufacturing Census

We take sector-level emissions from the IEA database "CO_2 Emissions from Fuel Combustion Statistics: Greenhouse Gas Emissions from Energy". We use total CO2 emissions, i.e., including scope 2 emissions from electricity and heat generation. The IEA computes CO_2 emissions based on the IEA energy data (i.e., the World Energy Balances and World Energy Statistics) and methods and emission factors from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.[3] This method does not take into account more detailed country-specific information, e.g., on different technologies or processes, even though the emission factor for electricity varies across countries. The general approach of combining energy consumption data with emission factors however is the same we follow for calculating emissions from the German Manufacturing Census. For more information, the reader is referred to the database documentation.

Table B.2 shows the average and median percentage deviation between German CO_2 emissions from IEA and manufacturing Census over the years 2005 to 2017 (for which both data sources are available). Percentage deviations are calculated by subtracting the Census emissions from the IEA emissions and dividing by the Census values.

As can be seen, in most sectors, the deviations are below 5%. Generally, the emissions data from the IEA are a bit too small. However, there is a larger deviation in sector 24 (metal production) in which IEA emissions data are tremendously smaller. Metal production involves energy consumption in transformation for coke ovens and blast furnaces, where allocation of emissions might be challenging.

Figure B.2 shows the aggregate development of CO_2 emissions according to both data sources over time. As can be seen, while emission paths generally are similar, over the last years of the sample, emissions diverge: According to the IEA, emissions by 2017 were lower than in 2005, while (the more accurate) manufacturing Census shows an increase in emissions.

[3] In the case of Germany, e.g., the information on energy use in the Energy Balances comes from the Federal Ministry for Economic Affairs and Energy.

TABLE B.2: Percentage deviation between emissions from IEA and German manufacturing Census across sectors

NACE 2 Code	Average deviation	Median deviation
10 to 12	-0.032	-0.038
13 to 15	-0.052	-0.044
16	-0.042	-0.044
17 and 18	0.008	0.006
20 and 21	-0.036	-0.062
22, 31 and 32	0.121	0.042
23	0.077	0.051
24	-0.369	-0.390
25 to 28, 33	-0.043	-0.025
29 and 30	-0.048	-0.054

The Table shows the average and median deviation from emissions data over time from the IEA and the German Manufacturing Census by sector. Positive numbers indicate that IEA emissions are larger, negative numbers indicate that Census emissions are larger.

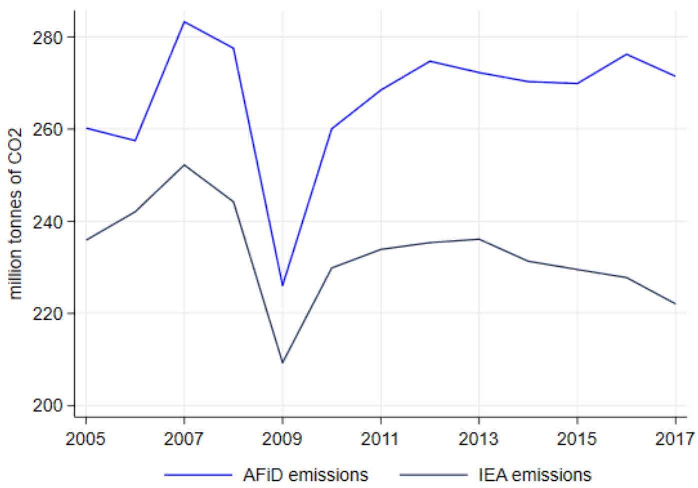


Figure B.2: Aggregate Emissions Development in German Manufacturing according to IEA and Manufacturing Census

Our analysis does not rely on emissions data in levels, but in changes as compared to our base year. As long as sector-level emission paths develop similar in the different data sets, the (partly substantial) differences across data sets do not matter. For robustness, however, we also run the analysis using the emissions from the manufacturing census for Germany which limits the analysis window to the time period between 2005 and 2017. Qualitatively, the results are unchanged, as reported in Appendix C.

B.4 Correction of trade data to account for re-exports

Re-exports are a well-known challenge encountered in combining production and trade data. Intuitively, the problem occurs because exports not produced in the exporting country are counted as exports, but not as production – which means that exports of a given good can exceed actual production. The issue becomes larger the smaller the unit analysed: For a single country, all exports which have been imported previously constitute re-exports; if country groups are analysed, only the exports that have been imported from third countries outside of the country group itself, and additionally are exported to third countries are re-exports. Everything that would represent re-exports from the perspective of a single country, but stays within the country group, constitutes intra-group trade.

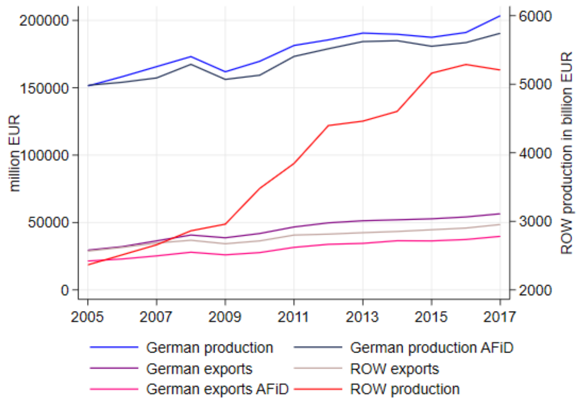
We use data from Eurostat input-output tables to correct for re-exports, specifically from the import use matrix. For Germany and the EU28 (including Germany), we compute the share of imports that are exported to the EU and to the rest of the world, respectively. For Germany, in 2016, the share of imports exported again gets as large as 43% for the pharmaceuticals sector (NACE 21). With about 3%, the share is smallest in the coke and petroleum sector (NACE 19). For the EU28, numbers are generally lower, due to intra-group trade not being counted as re-exports. Note that for the rest of the EU in our model, we use the values of the EU28, that include Germany (which it strictly speaking should not, in our context). However, the error is likely to be small. Computing shares for the EU without Germany from country-level input-output tables would require knowledge to where exactly imported goods are exported to, in order to accurately distinguish within-group versus out-of-group exports. These data are not available to us.

As we treat our model as a three-country world, for Germany, we calculate separate shares (of imports that are exported again) for the rest of the world and the EU. That is necessary because shares can differ widely: In the car industry (NACE 29), e.g., only about 5% of total imports are re-exported to other EU countries, but 24% to countries outside of the EU.

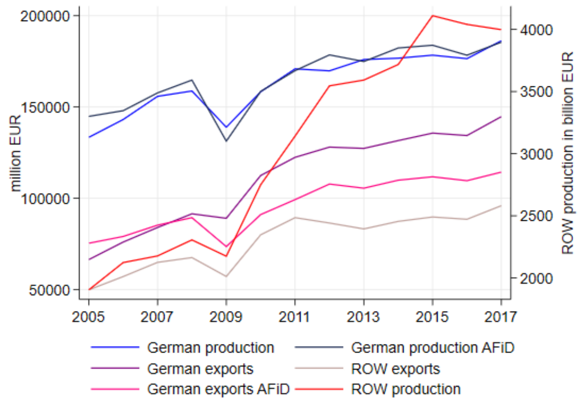
We multiply the calculated re-export shares of imports with total imports to obtain a measure of total re-exports that differ by country, sector and year. Then we subtract these re-exports from both the import and export numbers such that trade patterns of each country only reflect trade in own production. Note that we do not need any input-output table for the rest of the world, as trade is symmetric (i.e., German imports from RoW are equal to RoW exports to Germany). Therefore, RoW trade patterns are automatically adjusted by correcting EU and German trade flows.

B.5 Comparing German export and production data from different data sources

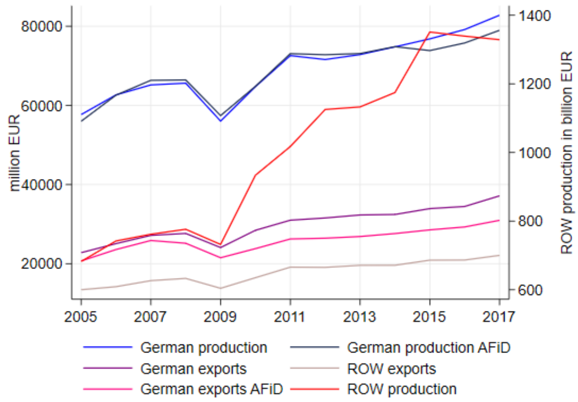
The following graphs compare production (dark blue, dark red) and export (green, yellow) from aggregate data sources (UNIDO and Eurostat) versus the German Manufacturing Census (AFiD). The comparison is exemplary depicted for sectors 10/11, 20/21, 22 and 29, but generally the patterns hold across all sectors. As can be seen, numbers are generally similar and follow similar trends, even though levels are not always identical. Differences between the data sources can be explained by inaccurate sector recodings, different exact measurements as well as the manufacturing Census not covering very small plants (below 20 employees).



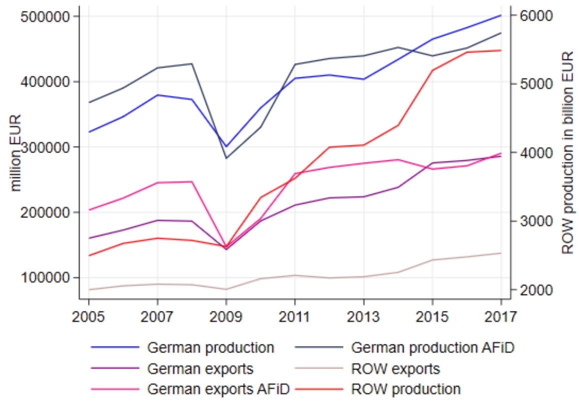
(a) 10, 11 and 12 (food, beverages and tobacco)



(b) 20 and 21 (chemicals and pharmaceuticals)



(c) 22 (rubber and plastics)



(d) 29–32 (vehicles, other transport, other)

FIGURE B.3: Production and Trade Data for Germany and RoW from Different Data Sources for Selected Sectors.

B.6 Details on parameter estimation

We estimate the Pareto shape parameter θ_s by regressing log firm sales on log firm's sales rank, as described in the main text. The shape parameter is recovered by combining the estimated coefficient, shown in column (1) of Table B.3, with the elasticity of substitution.

Column (2) of Table B.3 reports the estimated multiplicative markups that are needed to back out the elasticity of substitution σ_s. Column (3) reports the estimated energy output elasticities (i.e., energy cost shares from revenues), and column (4) contains the elasticity of emissions to energy input, retrieved from log-log regressions. All numbers are for 2005.

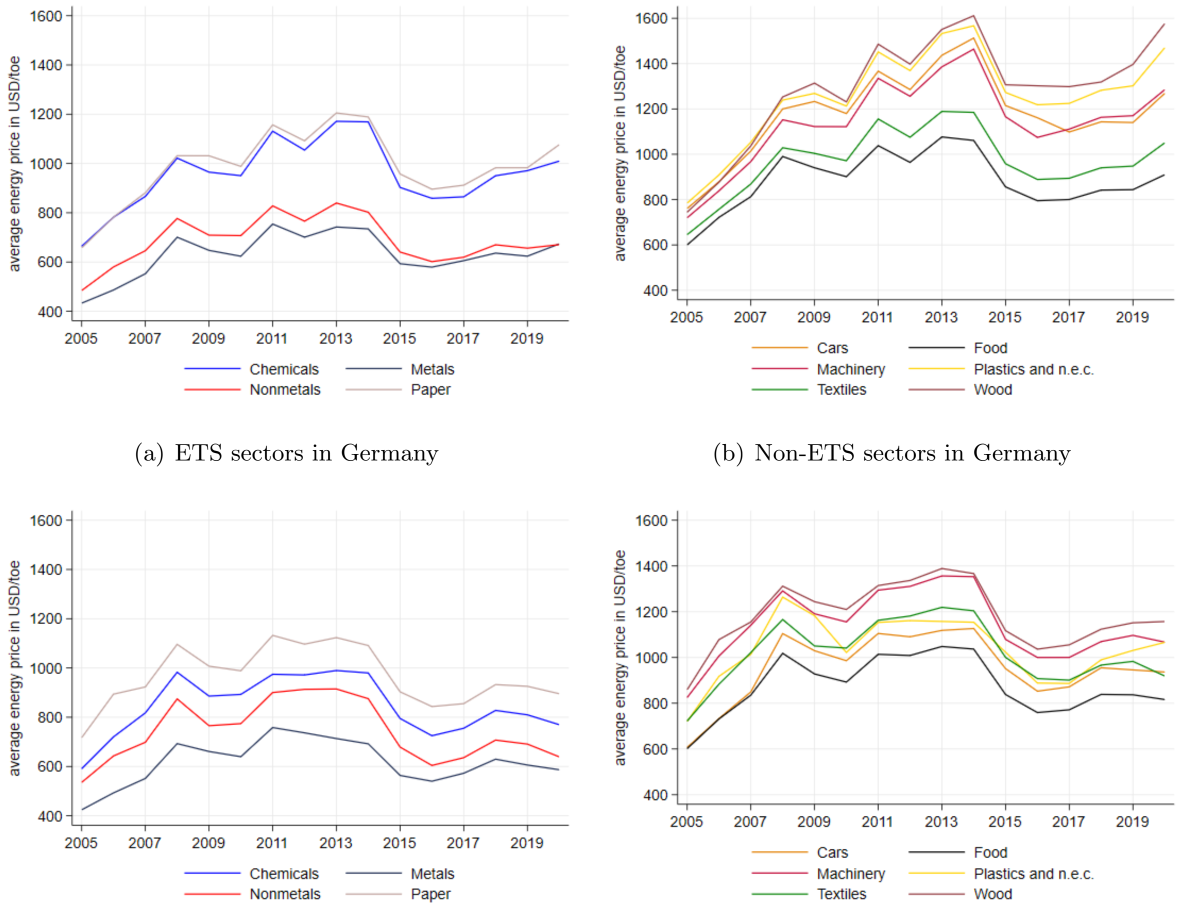
TABLE B.3: INTERMEDIATE RESULTS FOR THE PARAMETER ESTIMATION

NACE 2 Code	Coefficient estimate for θ_s	Markups	Energy output elasticity	Emissions elasticity
	(1)	(2)	(3)	(4)
10 to 12	-1.391	1.695	0.016	0.974
13 to 15	-2.065	1.316	0.018	1.002
16	-1.708	1.316	0.031	0.873
17 and 18	-1.825	1.177	0.059	0.962
20 and 21	-1.239	1.539	0.034	0.993
22, 31 and 32	-1.652	1.333	0.022	1.012
23	-1.924	1.389	0.065	0.946
24	-1.277	1.235	0.061	0.993
25 to 28, 33	-1.363	1.205	0.010	1.011
29 to 30	-0.936	1.205	0.008	1.001

Column (1) of the Table shows the estimated coefficient from log sales – log sales rank regressions. Column (2) of Table B.3 reports the estimated multiplicative markups from taking the ratio of variable to total cost. Column (3) reports the ratio of energy cost to revenues, and column (4) the estimated coefficient from log-log regressions of emissions on energy use. All regressions are based on data for our base year 2005 from the German Manufacturing Census.

B.7 Energy price data

We take energy price data from the IEA (2022b). Time-varying fuel prices for industry are weighted by a sector's fuel mix in each year to compute one average energy price. Country-level prices are aggregated to the EU-level by taking a weighted average of prices, where weights are given by the country's energy consumption relative to total EU energy consumption in a given sector. Missings (especially for coal prices) are filled in by averages of other reporting countries in a given year. Figure B.4 shows the development of the computed average energy prices for different sectors in Germany and the rest of the EU, respectively.



(a) ETS sectors in Germany

(b) Non-ETS sectors in Germany

(c) ETS sectors in RoEU

(d) Non-ETS sectors in RoEU

FIGURE B.4: Average Energy Prices in Different Sectors in USD/toe.

The Figure shows the development of average energy prices by sector and region. Data are taken from the IEA. Energy price data vary by country, and sectoral variation comes from differences in fuel mixes.

B.8 ETS price data

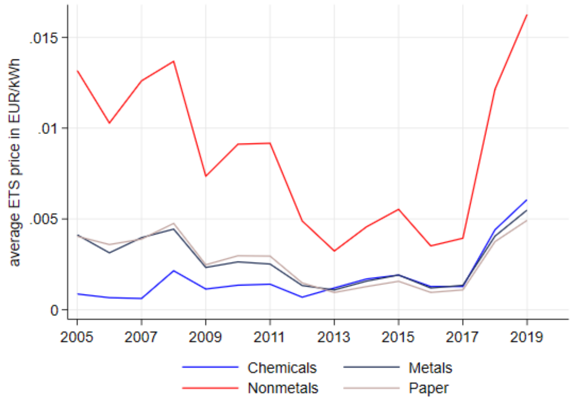
We calculate the EU ETS permit prices for different sector/country/year combinations, taking into account the sector's coverage under the EU ETS, as well as sector-level fuel mixes.

Transaction weighted averages of one year future ETS prices are taken from the EEX. These permit prices are multiplied with a sector-country-year specific emission intensity. We obtain this emission intensity by dividing verified emissions under the EU ETS from the EU's transaction log by the sector's fossil energy use in a given country and year (taken from the IEA 2022a).[4] This emission intensity reflects both the sector's fuel mix (i.e., verified emissions per kWh of energy use are higher with a dirtier fuel mix) and the sector's coverage under the EU ETS (i.e., sectors in which many installations are subject to the EU ETS have higher verified emissions). Note that generally, a sector's average permit price calculated this way is too high, as verified emissions also contain process emissions. Unfortunately, however, the EUTL data does not allow us to separate process from combustion emissions. The error however is likely to be small, as we only make use of the development in average ETS prices, not their levels.

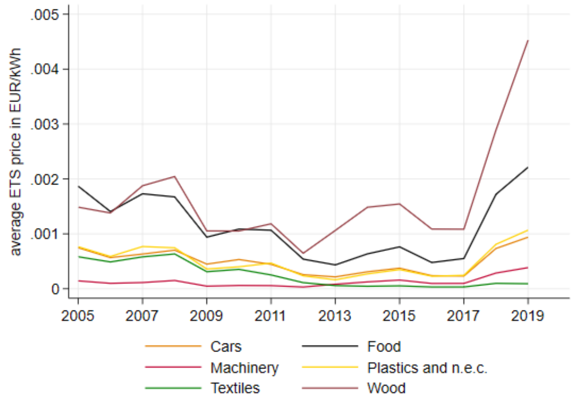
The development of the resulting permit prices is shown in Figure B.5. As can be seen, prices across sectors generally follow the same trend, namely the trend of future permit prices. Still, there is

[4] Implicitly, we are assuming that the ETS covered installations in any sector use the same fuel mix as those firms not directly regulated under the EU ETS.

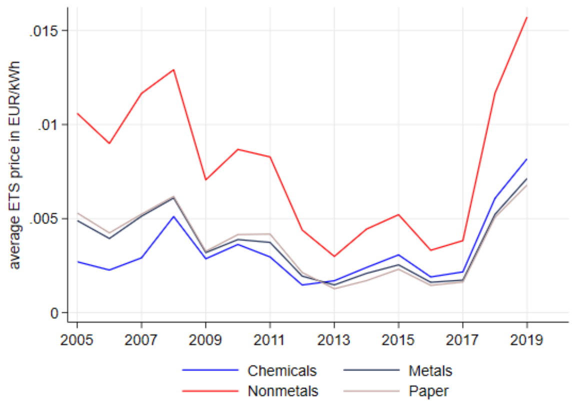
substantial variation as some sectors (such as textiles or machinery) are barely directly regulated under the EU ETS.



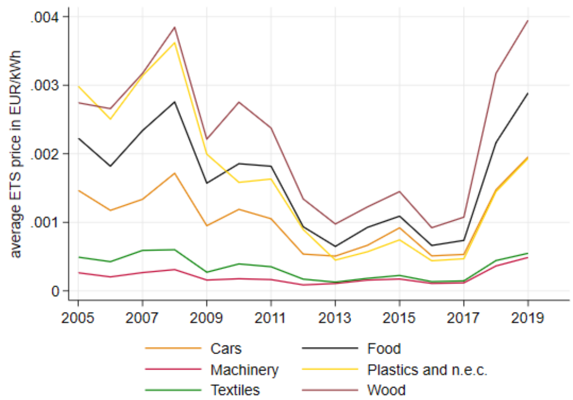
(a) ETS sectors in Germany



(b) Non-ETS sectors in Germany



(c) ETS sectors in RoEU



(d) Non-ETS sectors in RoEU

Figure B.5: Average Permit Prices in Different Sectors in EUR/kWh.

The Figure shows the development of average ETS permit prices. Permit prices are taken from the EEX and constitute one year ahead prices. Permit prices vary over time, and sectoral variation comes from differences in fuel mixes and ETS coverage. Information on these variables comes from the IEA and the EUTL.

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B.9 Development of emission intensities of production in different sectors

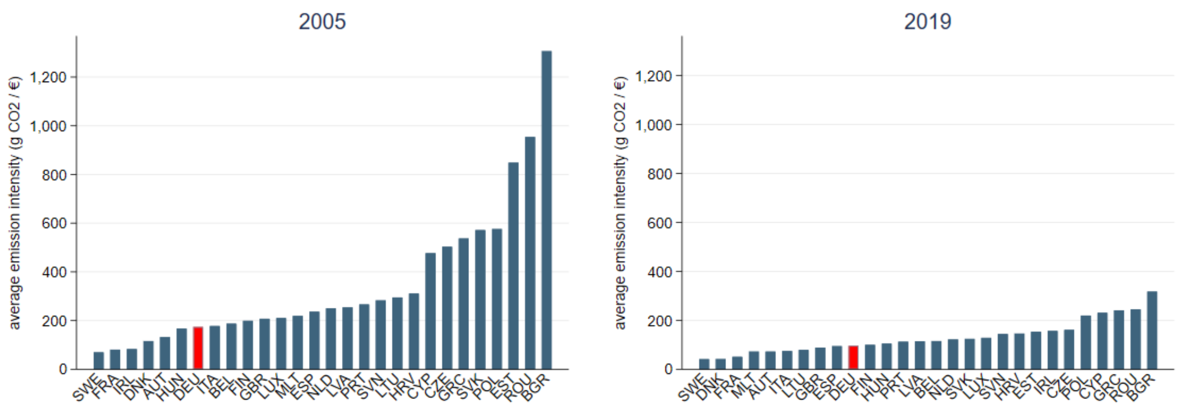
Table B.4 shows sector-level emission intensities of production in the different world regions over time. Emission intensities are calculated by dividing IEA sector-level emissions by the (non-deflated) UNIDO production values in EUR. Emission intensities are expressed as grams of CO_2 per EUR of output.

Figure B.6 shows the average emission intensity of production (i.e., gram of CO_2 per Euro of output) in manufacturing per EU member state. Output values are not adjusted for inflation. Germany is marked in red.

TABLE B.4: Emission intensities of production

NACE 2 Code	region	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
10 to 12	DE	123.8	118.8	117.1	107.7	111.5	106.1	101.8	102.6	99.6	99.0	98.1	98.6	89.9	89.3	76.0
	RoEU	127.6	117.2	111.2	104.2	100.5	98.1	91.8	88.2	82.4	79.1	81.1	80.2	76.4	97.8	69.2
	RoW	275.1	277.3	277.6	258.3	231.9	198.2	181.1	154.2	152.8	140.9	118.3	118.4	120.2	128.4	120.0
13 to 15	DE	125.0	111.7	112.9	107.4	106.3	110.5	97.7	107.3	94.4	83.6	93.6	84.1	78.6	77.1	63.2
	RoEU	143.4	130.2	116.3	111.6	110.2	97.8	88.5	89.1	84.5	73.2	69.7	67.5	66.3	65.1	58.3
	RoW	547.7	538.5	558.9	492.8	445.1	366.4	339.3	292.0	274.5	240.5	196.7	202.7	224.3	264.9	243.1
16	DE	169.0	155.7	156.4	163.3	168.3	158.2	146.3	144.3	146.3	123.3	120.1	126.0	125.6	112.6	88.6
	RoEU	130.1	124.3	117.4	116.6	127.8	120.6	116.1	112.0	108.1	94.1	94.6	98.6	99.4	93.3	81.1
	RoW	364.9	379.1	402.4	442.3	460.1	387.9	326.8	267.0	242.9	225.5	178.4	182.3	181.0	212.5	203.0
17 and 18	DE	302.9	279.6	290.2	386.2	407.2	379.4	360.2	382.3	390.1	386.2	374.3	357.7	333.2	321.9	276.7
	RoEU	207.1	203.6	196.3	199.9	292.6	276.2	256.8	257.6	257.6	238.4	217.8	215.2	210.1	193.6	178.8
	RoW	644.9	626.0	674.6	657.4	649.0	564.3	545.0	467.7	456.5	438.3	369.4	368.8	374.0	384.2	344.5
20 and 21	DE	381.7	367.8	373.1	353.1	358.0	348.1	323.3	339.1	328.4	326.3	330.4	333.4	308.1	267.7	232.0
	RoEU	332.4	294.4	281.2	277.4	297.8	263.4	267.4	256.6	249.2	233.0	243.7	244.1	220.0	200.9	213.9
	RoW	945.4	890.4	908.9	813.5	809.0	715.3	644.2	559.9	552.2	532.7	484.0	480.4	517.1	565.3	530.0
22, 31 and 32	DE	183.4	183.7	202.4	139.0	120.7	114.7	101.4	104.2	104.3	99.3	94.2	91.9	83.1	73.1	64.3
	RoEU	273.3	252.3	247.8	257.1	235.6	224.8	166.7	168.9	155.9	145.0	135.5	117.4	112.2	101.7	90.8
	RoW	837.5	788.0	680.2	666.7	656.6	612.2	535.4	514.0	480.4	428.3	341.4	327.6	328.1	377.8	375.2
23	DE	639.2	603.0	629.7	657.7	658.8	642.3	574.3	563.5	548.0	528.4	539.9	517.1	497.0	505.5	455.5
	RoEU	790.4	695.7	664.0	656.0	657.9	669.9	657.8	655.0	646.7	622.4	610.6	617.0	569.2	565.5	511.5
	RoW	2809.5	2552.6	2554.6	2377.8	2355.6	1920.0	1795.5	1462.3	1346.3	1281.5	1042.3	1018.1	1001.5	1132.7	1054.3
24	DE	760.3	672.4	544.9	531.0	612.9	587.3	498.7	498.6	536.9	527.1	552.7	568.2	492.7	468.0	427.2
	RoEU	777.2	624.0	564.0	530.0	626.1	524.5	473.0	481.5	477.6	452.0	440.0	457.7	406.9	350.1	339.3
	RoW	1952.1	1739.8	1700.0	1481.3	1748.7	1388.7	1306.0	1230.0	1275.6	1321.6	1175.6	1208.9	1188.0	1251.6	1201.1
25 to 28, 33	DE	47.4	43.5	41.8	51.2	52.5	50.7	47.3	49.6	50.8	49.0	41.3	40.0	37.0	33.3	27.9
	RoEU	59.7	54.5	50.0	47.2	50.1	48.2	44.8	42.4	41.4	36.8	36.7	35.9	34.8	33.1	29.8
	RoW	153.7	153.8	162.7	158.6	161.1	144.3	141.8	120.3	121.2	113.1	88.3	90.2	94.4	100.3	94.3
29 to 30	DE	54.0	48.9	45.7	42.2	46.4	43.2	37.9	39.3	41.4	35.9	32.6	32.3	29.5	27.7	23.6
	RoEU	44.1	42.7	40.1	40.0	43.2	39.1	36.2	35.8	34.1	29.4	25.9	23.0	22.5	21.9	19.6
	RoW	107.3	108.6	112.8	111.5	111.3	94.5	91.7	79.9	79.6	72.3	57.0	54.4	55.9	63.3	55.4

Emission intensities are in grams of CO_2 per Euro of output. Emissions include scope 2 emissions from electricity consumption. Source: own calculation, based on data from UNIDO and the IEA.



(a) Emission intensities in 2005 (b) Emission intensities in 2019

Figure B.6: Average CO_2 Emission Intensity in Manufacturing by EU Member State in 2005 and 2019

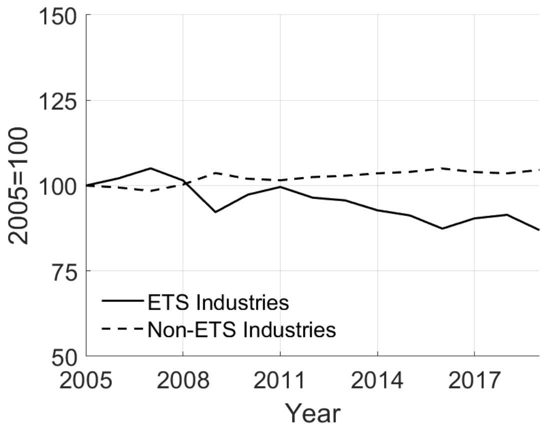
Note: Emissions include scope 2 emissions from electricity consumption. Emission intensities are calculated for the manufacturing sector as a whole. Based on data from UNIDO and the IEA.

C Additional results

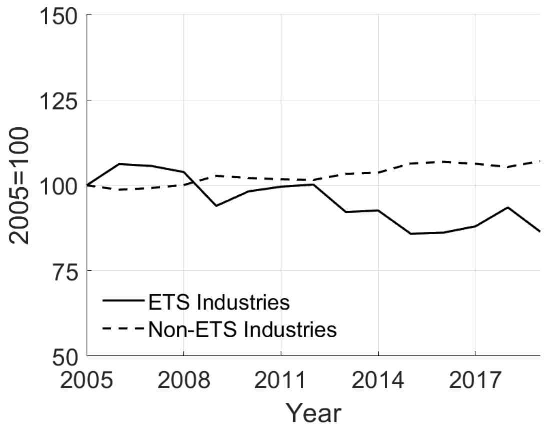
This part of the Appendix reports additional results and robustness checks not discussed in the main text.

C.1 Historical developments of emission drivers and the accompanying development of endogenous variables

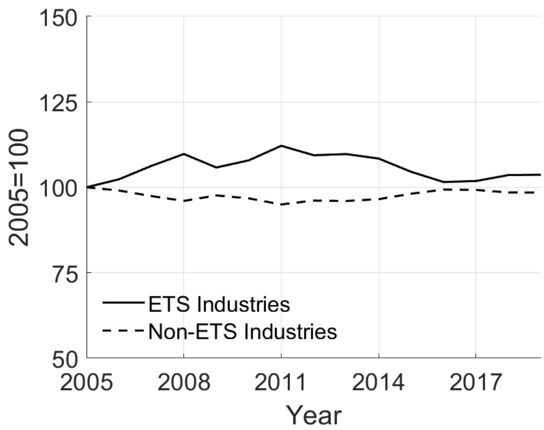
The following graphs show the historical development of the domestic and foreign expenditure share drivers, as well as the development of endogenous variables (firm entries, wages) in the different countries. Historical competitiveness drivers are not shown as they are not informative due to the omission of price index data. Note that real wages are not sector-specific and hence, for real wages, results are not split across ETS- and non-ETS-sectors. For all other depicted variables, the results are simple arithmetic averages across sectors.



(a) Germany



(b) RoEU



(c) RoW

Figure C.1: Development of the Expenditure Share Driver.

Own calculations. Based on data from UNIDO.

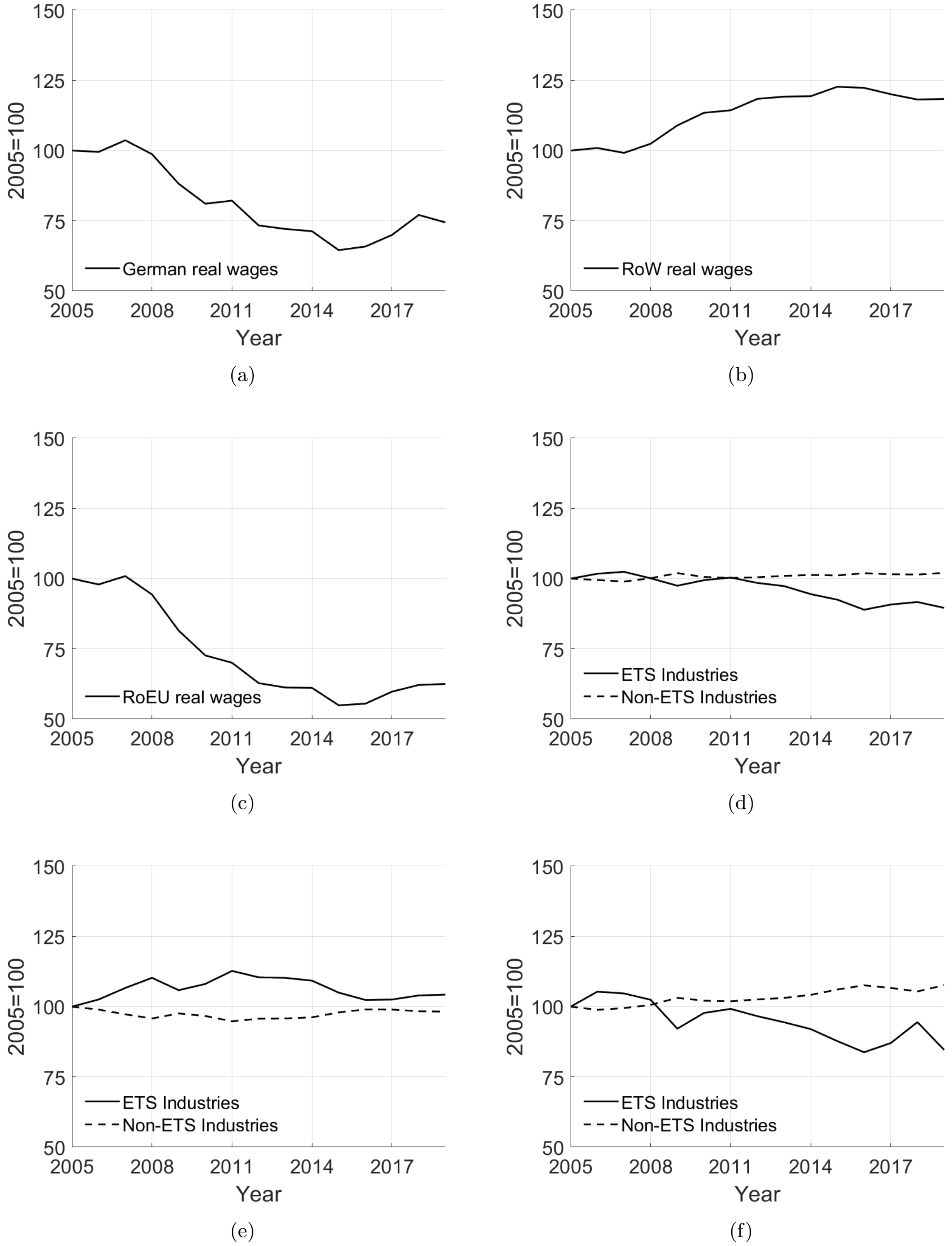


FIGURE C.2: Development of Endogenous Variables when all Emission Drivers take on Historical Values: (a) German Real Wages (b) RoW Real Wages (c) RoEU Real Wages (d) German Firm Entries (e) RoW Firm Entries (f) RoEU Firm Entries

Own calculations. Based on data from UNIDO.

C.2 Development of implicit carbon prices by sector

Here we report the development of implicit carbon prices separately by region and by NACE sector.

TABLE C.1: Implicit carbon prices by sector

NACE 2 Code	region	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
10 to 12	DE	1	0.95	0.93	0.98	1.02	0.87	0.82	0.73	0.74	0.72	0.64	0.63	0.70	0.75	0.84
	RoEU	1	1.00	1.01	1.04	1.17	0.97	0.94	0.88	0.92	0.92	0.80	0.80	0.85	0.70	0.95
	RoW	1	0.91	0.87	0.91	1.09	1.03	1.03	1.08	1.07	1.12	1.18	1.17	1.17	1.15	1.18
13 to 15	DE	1	1.02	0.97	0.99	1.08	0.84	0.86	0.71	0.79	0.86	0.68	0.75	0.81	0.87	1.01
	RoEU	1	1.01	1.08	1.09	1.20	1.09	1.09	0.98	1.01	1.12	1.04	1.07	1.11	1.18	1.26
	RoW	1	0.93	0.86	0.95	1.13	1.11	1.09	1.14	1.19	1.30	1.41	1.37	1.25	1.11	1.16
16	DE	1	0.99	0.95	0.88	0.93	0.80	0.78	0.71	0.69	0.77	0.71	0.68	0.69	0.81	0.98
	RoEU	1	0.96	0.97	0.95	0.94	0.80	0.76	0.70	0.72	0.79	0.70	0.67	0.67	0.75	0.82
	RoW	1	0.88	0.80	0.70	0.73	0.70	0.75	0.83	0.90	0.93	1.04	1.01	1.03	0.92	0.92
17 and 18	DE	1	0.99	0.92	0.67	0.69	0.59	0.57	0.48	0.46	0.45	0.41	0.43	0.46	0.51	0.56
	RoEU	1	0.93	0.93	0.88	0.65	0.56	0.54	0.49	0.48	0.50	0.48	0.49	0.50	0.57	0.59
	RoW	1	0.94	0.84	0.83	0.92	0.85	0.80	0.84	0.83	0.84	0.88	0.88	0.88	0.90	0.96
20 and 21	DE	1	0.95	0.90	0.92	0.98	0.82	0.80	0.68	0.69	0.67	0.59	0.58	0.63	0.77	0.84
	RoEU	1	1.03	1.04	1.02	1.03	0.94	0.84	0.79	0.79	0.82	0.69	0.69	0.77	0.89	0.80
	RoW	1	0.97	0.91	0.99	1.08	0.98	0.99	1.02	1.02	1.02	0.99	0.99	0.93	0.90	0.91
22, 31 and 32	DE	1	0.91	0.79	1.12	1.40	1.19	1.22	1.07	1.05	1.06	0.99	1.01	1.13	1.35	1.46
	RoEU	1	0.99	0.97	0.90	1.07	0.91	1.11	0.98	1.05	1.08	1.02	1.18	1.24	1.45	1.54
	RoW	1	0.97	1.08	1.07	1.18	1.02	1.06	0.99	1.04	1.12	1.24	1.29	1.30	1.19	1.14
23	DE	1	0.97	0.89	0.83	0.89	0.74	0.75	0.69	0.70	0.69	0.60	0.62	0.66	0.68	0.72
	RoEU	1	1.04	1.04	1.02	1.11	0.88	0.81	0.73	0.73	0.73	0.66	0.65	0.71	0.75	0.79
	RoW	1	1.01	0.96	1.00	1.10	1.09	1.06	1.17	1.24	1.26	1.37	1.39	1.43	1.33	1.37
24	DE	1	1.03	1.22	1.22	1.14	0.96	1.03	0.93	0.84	0.83	0.70	0.68	0.79	0.87	0.91
	RoEU	1	1.14	1.21	1.25	1.14	1.10	1.11	0.98	0.97	0.98	0.89	0.86	0.97	1.19	1.17
	RoW	1	1.03	1.01	1.12	1.03	1.05	1.01	0.96	0.91	0.85	0.84	0.82	0.83	0.84	0.83
25 to 28, 33	DE	1	1.00	0.99	0.79	0.83	0.70	0.68	0.58	0.55	0.55	0.58	0.60	0.65	0.76	0.87
	RoEU	1	1.00	1.05	1.07	1.10	0.92	0.90	0.85	0.86	0.93	0.82	0.84	0.88	0.97	1.03
	RoW	1	0.91	0.83	0.82	0.88	0.79	0.73	0.78	0.76	0.78	0.88	0.86	0.83	0.82	0.84
29 to 30	DE	1	1.01	1.04	1.09	1.07	0.93	0.96	0.83	0.78	0.86	0.84	0.84	0.93	1.05	1.17
	RoEU	1	0.94	0.97	0.94	0.94	0.84	0.82	0.75	0.77	0.86	0.86	0.97	1.00	1.08	1.15
	RoW	1	0.90	0.83	0.82	0.89	0.85	0.79	0.81	0.80	0.85	0.95	1.00	0.98	0.91	0.99

Sources: own calculations based on INDSTAT and IEA data

C.3 Explaining the implicit carbon price development using ETS spot market prices

We here run the same regression as in the main text (shown in Table III), but refer to ETS spot market prices instead of ETS futures. While this does not qualitatively change results, the explanatory power of spot market prices is substantially lower, owing to the drop in ETS prices in 2007.

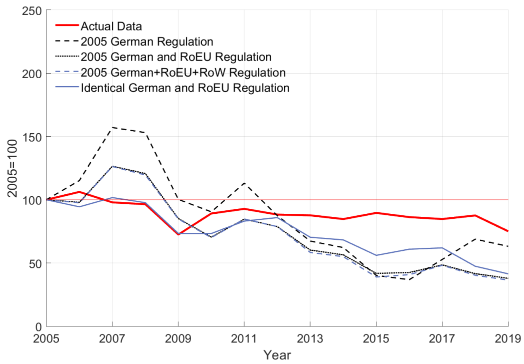
TABLE C.2: Determinants of the development of implicit carbon prices

	$\hat{t}^s_{i,y}$ (1)	$\mu_{i,y}$ (2)
$\hat{p}^{s,energy}_{i,y}$	0.491***	
	(0.106)	
$\hat{p}^{s,ets}_{i,y}$	-0.055***	0.358***
	(0.019)	(0.028)
N	300	300
R^2	0.37	0.36

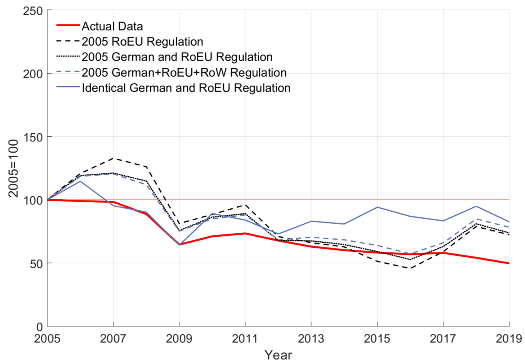
Notes: The regressions include observations from 2005–2019. Dependent variables are indexed and are 1 in 2005. The regression in column (1) is run with country by year fixed effects. Column (2) explains the fixed effect estimated in column (1). Standard errors are displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

C.4 Counterfactual emissions for specific sectors

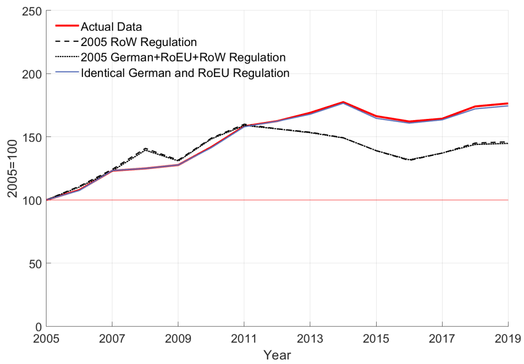
In the main text, we only report counterfactual emissions on aggregate. We here show counterfactuals exemplary for two emission intensive sectors, namely metals (NACE 24) and pulp, paper and publishing (NACE 17+18).



(a) Germany



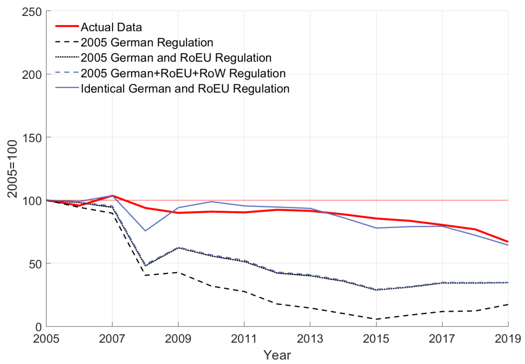
(b) RoEU



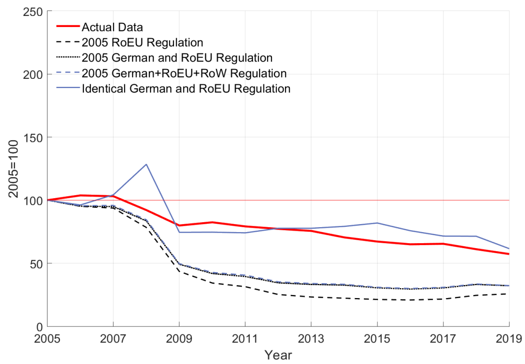
(c) RoW

FIGURE C.3: Counterfactual in the Metals Sector under Different Scenarios.

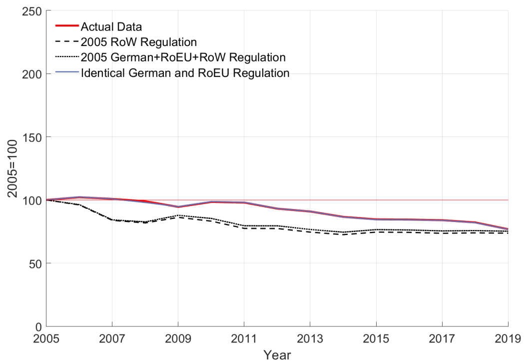
Notes: One by one the driving forces are held constant at their 2005 values while the other driving forces follow their historical paths



(a) Germany



(b) RoEU



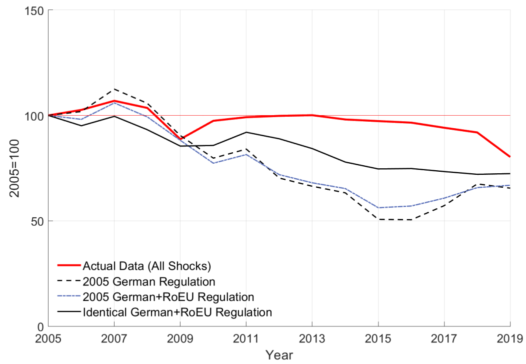
(c) RoW

FIGURE C.4: Counterfactual in the Pulp, Paper, and Publishing Sector under Different Scenarios.

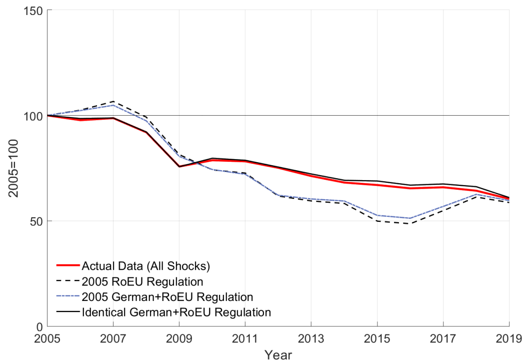
Notes: One by one the driving forces are held constant at their 2005 values while the other driving forces follow their historical paths

C.5 Counterfactual analysis with German implicit carbon prices taking on EU values

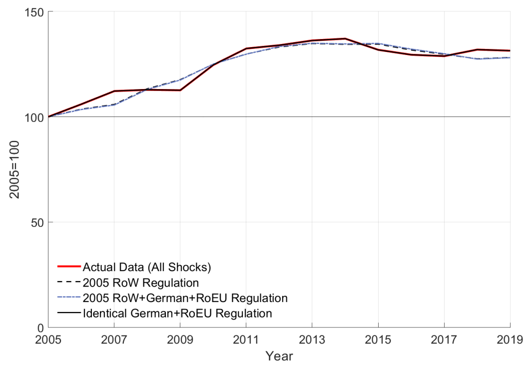
In this subsection, we run a counterfactual in which the German implicit carbon prices do not follow their historical path, but take on the values from the rest of the EU. Regulatory differences in the EU are hence shut off. In this counterfactual, German emissions would have decreased by more than with EU implicit carbon prices taking on German values, as not only regulatory differences are shut off, but also German regulation is rendered more stringent. In the rest of the EU (and RoW), the counterfactual leads to an emission increase.



(a) Germany



(b) RoEU



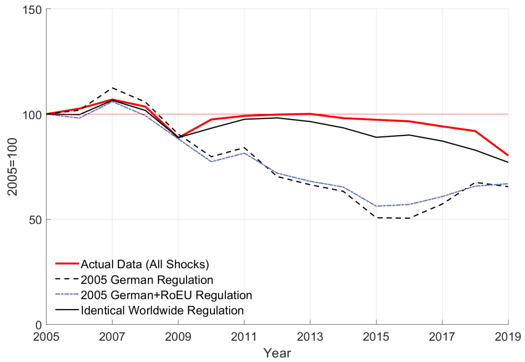
(c) RoW

FIGURE C.5: Counterfactual Emissions with the German Implicit Carbon Prices taking on EU Values with all other Emission Drivers taking on their Historical Values.

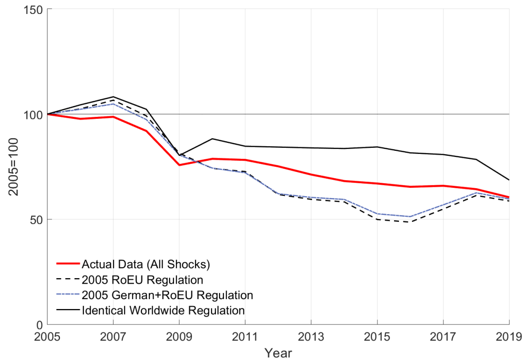
Notes: All driving forces take on their historical value, except the implicit carbon prices whose development varies over counterfactuals.

C.6 Counterfactual analysis with all world regions following the German implicit carbon price development

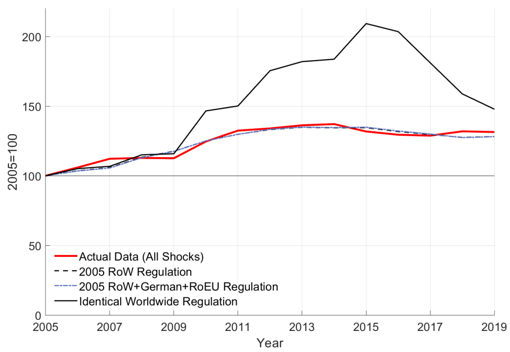
In this subsection, we try to better understand the role played by developments in implicit carbon prices in the rest of the world for German industrial emissions. As implicit carbon prices haven't changed strongly in the rest of the world, it is not clear from the decomposition in Section 5 whether the small impact from RoW implicit carbon prices is due to the lack of variation in these prices or due to the lack of relevance of the rest of the world for German emissions. Here, we conduct a counterfactual analysis in which all world regions follow the German development in implicit carbon prices. As can be seen in Figure C.6, this yields hardly different results than just equating German and EU implicit carbon prices as done in Figure IV.



(a) Germany



(b) RoEU



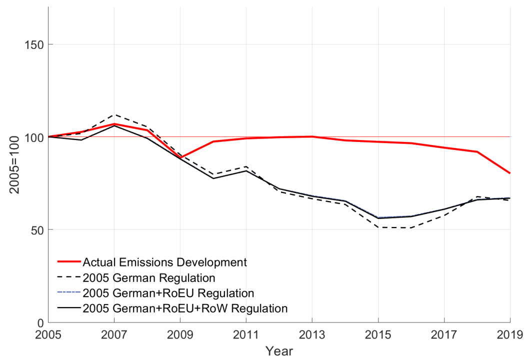
(c) RoW

FIGURE C.6: Counterfactual Emissions with Identical German, EU and RoW Carbon Price Developments with all other Emission Drivers taking on their Historical Values.

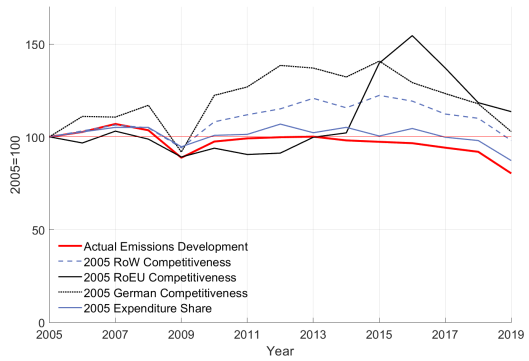
Notes: All driving forces take on their historical value, except the implicit carbon prices whose development varies over counterfactuals.

C.7 Analysis with a more generalised production technology

In this Appendix, we show that decomposing the emissions development into the different drivers yields qualitatively the same results when using a more generalised production technology where ξ takes on a value of zero. The results are very similar to the results with $\xi = 1$ shown in Figure III in the main text.



(a)



(b)

FIGURE C.7: Decomposition of Actual German Industrial Emissions Development where Selective Driving Forces are held constant at their 2005 Values while the other Driving Forces follow their Historical Paths using the German Manufacturing Census. The Value of ξ is set equal to Zero.

Notes: One by one the driving forces are held constant at their 2005 values while the other driving forces follow their historical paths

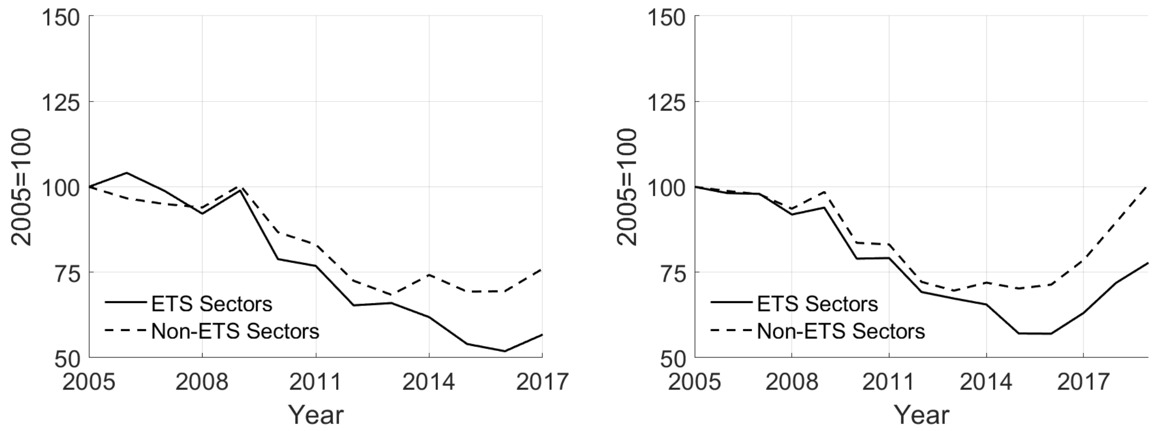
C.8 Analysis using emissions data from the German Manufacturing Census

In light of the difference in German industrial carbon emissions across data sources reported in Appendix B, In this section, we report results using, for Germany, emission data from the German Manufacturing Census instead of the IEA. As we have Census data available only up to 2017, the time frame of this analysis differs from the main results. We report both developments in historical implicit carbon prices if retrieved from the Census data, and counterfactual emissions.

TABLE C.3: DETERMINANTS OF THE DEVELOPMENT OF IMPLICIT CARBON PRICES

	$\hat{t}_{i,t,s}$ (1)	$\mu_{i,t}$ (2)
$\hat{p}^{energy}_{i,s,t}$	0.371***	
	(0.095)	
$\hat{p}^{ets}_{i,(s),t}$	-0.017	0.462***
	(0.031)	(0.028)
N	260	260
R^2	0.53	0.52

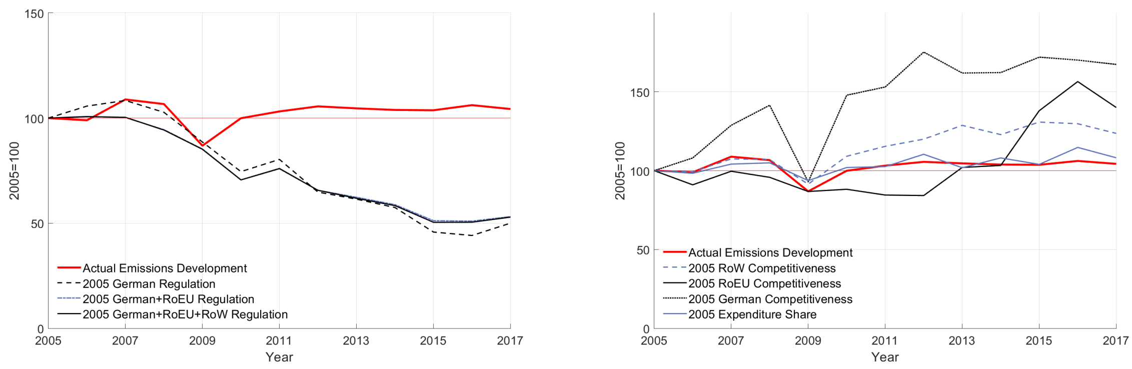
Notes: The regressions include observations from 2005–2017. Dependent variables are indexed and are 1 in 2005. The regression in column (1) is run with country by year fixed effects. Column (2) explains the fixed effect estimated in column (1). Standard errors are displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.



(a) (b)

FIGURE C.8: Development of Implicit Price on CO_2 Emissions in Germany (a) using Data from the German Manufacturing Census (b) using Data from the IEA (right) on German Industrial CO_2 Emissions

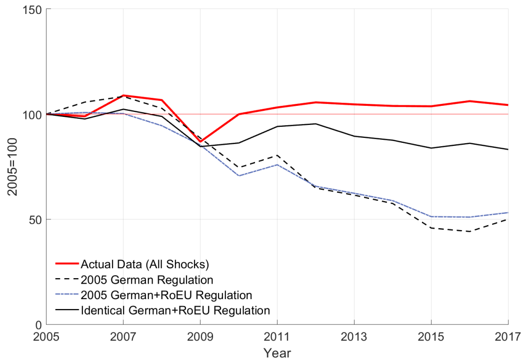
Source: own calculations, based on data from INDSTAT, the IEA, and the German Manufacturing Census.



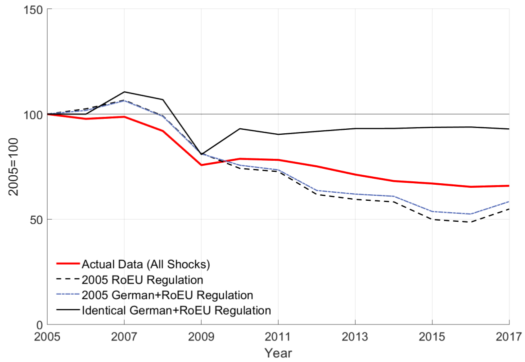
(a) (b)

FIGURE C.9: Decomposition of Actual German Industrial Emissions Development where Selective Driving Forces are held constant at their 2005 Values while the other Driving Forces follow their Historical Paths using the German Manufacturing Census

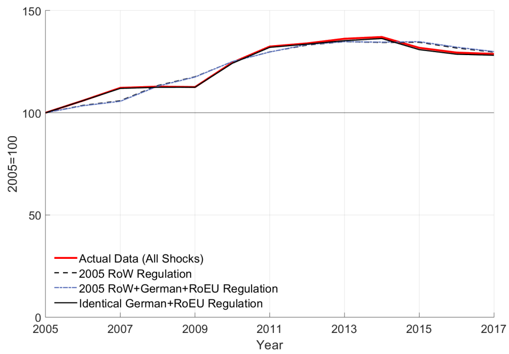
Notes: One by one the driving forces are held constant at their 2005 values while the other driving forces follow their historical paths



(a) Germany



(b) RoEU



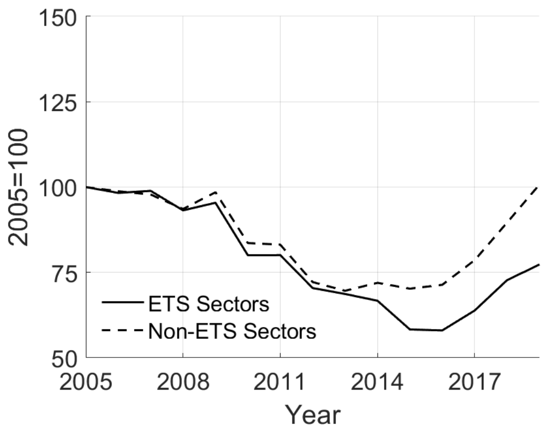
(c) RoW

FIGURE C.10: Counterfactual Emissions with Identical German and EU Carbon Price Developments with all other Emission Drivers taking on their Historical Values.

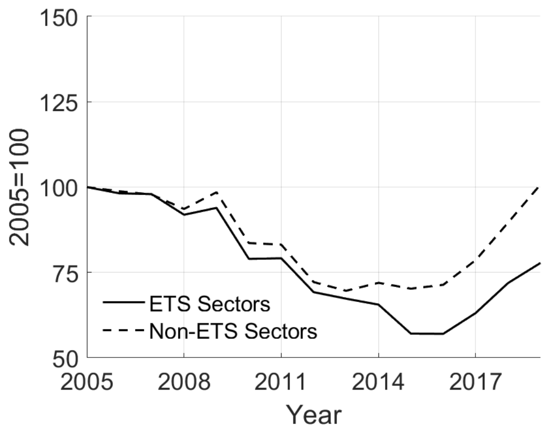
Notes: All driving forces take on their historical value, except the implicit carbon prices whose development varies over counterfactuals.

C.9 Analysis with process emissions

In the main text, our measure of emissions by the IEA is limited to combustion emissions. In this section, we additionally consider process emissions. For that purpose, we complement the IEA emissions data with process emissions from EDGAR (2023). Process emissions occur in the chemicals sector (NACE 20), the non-metallic minerals sector (NACE 23) and the metals sector (NACE 24). While, especially in the non-metallic minerals sector, process emissions make up a considerable share of total emissions (roughly half), in changes, total emissions developments are very similar to the case of combustion emissions only. It is therefore not surprising that including process emissions does not substantially alter results, as shown below.



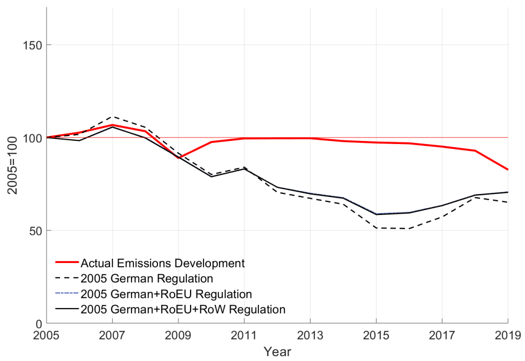
(a)



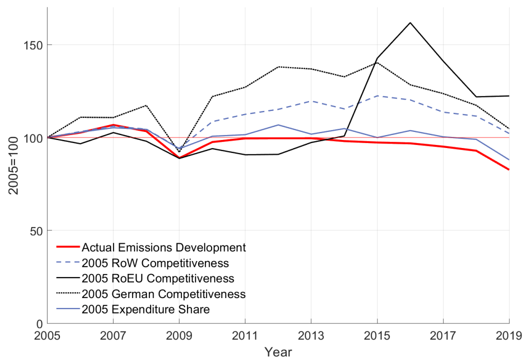
(b)

FIGURE C.11: Development of Implicit Price on CO_2 Emissions in Germany (a) adding Data on Process Emissions from EDGAR (b) using only Combustion Emissions Data from the IEA (right) on German Industrial CO_2 Emissions

Source: own calculations, based on data from INDSTAT, the IEA, and EDGAR.



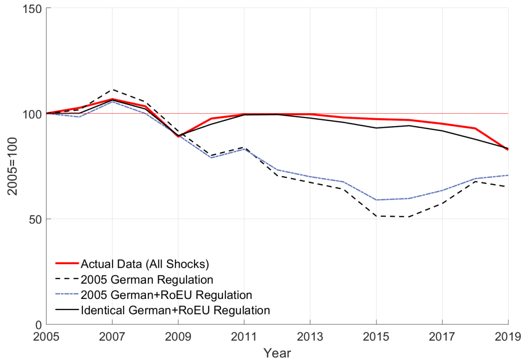
(a)



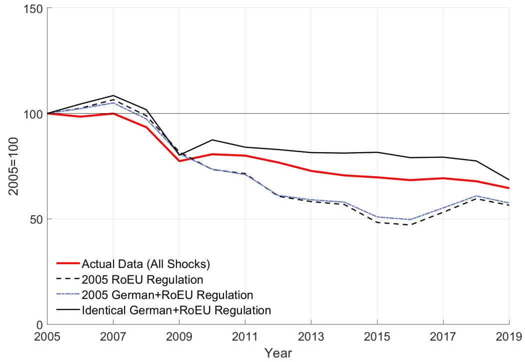
(b)

Figure C.12: Decomposition of Actual German Industrial Emissions Development (including Process Emissions) where Selective Driving Forces are held constant at their 2005 Values while the other Driving Forces follow their Historical Paths

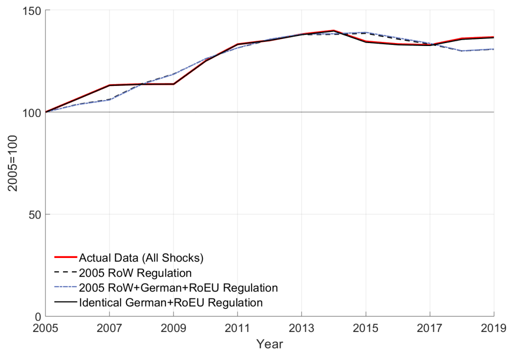
Notes: One by one the driving forces are held constant at their 2005 values while the other driving forces follow their historical paths



(a) Germany



(b) RoEU



(c) RoW

FIGURE C.13: Counterfactual Emissions (including Process Emissions) with Identical German and EU Carbon Price Developments with all other Emission Drivers taking on their Historical Values.

Notes: All driving forces take on their historical value, except the implicit carbon prices whose development varies over counterfactuals.

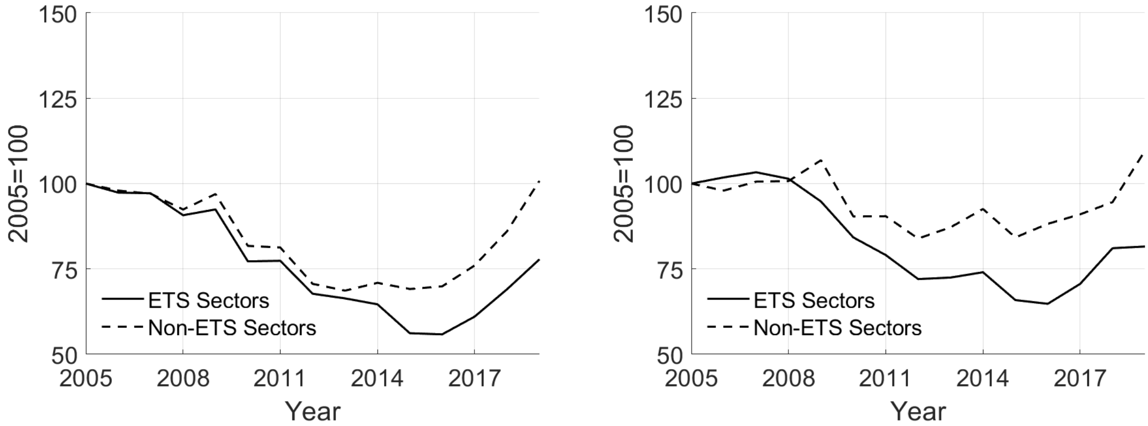
C.10 Analysis using data on the full set of RoW countries

In this section, we use trade flow and production data for the full set of RoW (including countries for which no reliable emissions data are available) to show that our results are not driven by sample selection. As we do not have emissions data for the full set of rest of the world countries, in this analysis, we cannot compute the implicit carbon price for RoW. Instead, in the counterfactual analyses, the change in implicit carbon prices for RoW is subsumed under the competitiveness driver and not separated as in Eq. (A.35). The adjusted competitiveness driver, which includes the implicit carbon price, is defined as:

$$
\begin{aligned}
\hat{\Gamma}_{ji}^{s,t} &\equiv (\hat{b}_j^s)^{\theta^s} (\hat{\tau}_{ji}^s)^{-\frac{\theta^s}{1-\alpha^s}} (\hat{f}_{ji}^s)^{1-\frac{\theta^s}{(\sigma^s-1)(1-\alpha^s)}} (\hat{t}_j^s)^{-\frac{\alpha^s\theta^s}{1-\alpha^s}} \\
&= \frac{\hat{\lambda}_{ji}^s}{\hat{M}_j^s \hat{w}_j^{-\theta^s}} (\hat{P}_i^s)^{-\frac{\theta^s}{1-\alpha^s}} \left(\frac{\hat{\beta}_i^s}{\hat{w}_i} \frac{R_i' - NX_i'}{R_i - NX_i} \right)^{1-\frac{\theta^s}{(\sigma^s-1)(1-\alpha^s)}}
\end{aligned}
\tag{C.1}
$$

for $j = RoW$. For the other two regions, we sill employ $\hat{\Gamma}_{ji}^s$ from Eq. (A.35).

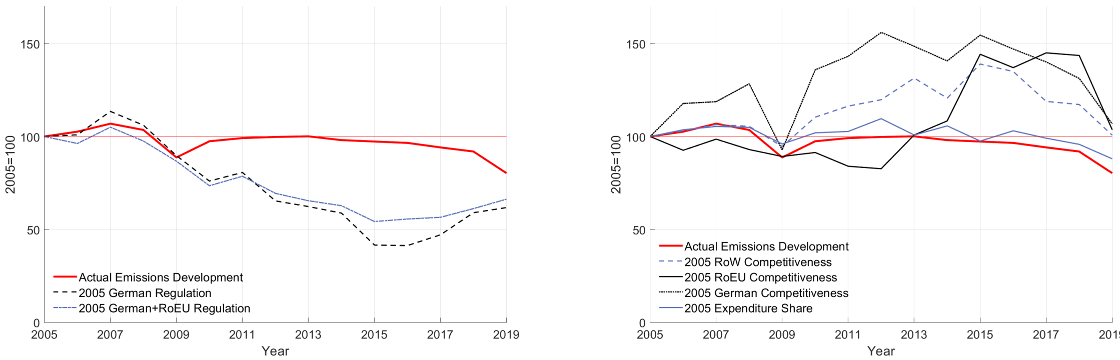
As Figures C.14 and C.15 show, our results are barely affected by this change in the sample.



(a) Germany (b) RoEU

FIGURE C.14: Development of Implicit Price on CO_2 Emissions with a Full Set of RoW Countries.

Source: own calculations, based on data from INDSTAT and the IEA.



(a) (b)

FIGURE C.15: Decomposition of Actual German Industrial Emissions Development where Selective Driving Forces are held constant at their 2005 Values while the other Driving Forces follow their Historical Paths using a Full Set of RoW Countries

Notes: One by one the driving forces are held constant at their 2005 values while the other driving forces follow their historical paths

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