

Rottner, Elisa; von Graevenitz, Kathrine

Article — Published Version

What Drives Carbon Emissions in German Manufacturing: Scale, Technique or Composition?

Environmental and Resource Economics

Provided in Cooperation with:

Springer Nature

Suggested Citation: Rottner, Elisa; von Graevenitz, Kathrine (2024) : What Drives Carbon Emissions in German Manufacturing: Scale, Technique or Composition?, Environmental and Resource Economics, ISSN 1573-1502, Springer Netherlands, Dordrecht, Vol. 87, Iss. 9, pp. 2521-2542, <https://doi.org/10.1007/s10640-024-00894-7>

This Version is available at:

<https://hdl.handle.net/10419/315258>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by/4.0/>



What Drives Carbon Emissions in German Manufacturing: Scale, Technique or Composition?

Elisa Rottner¹ · Kathrine von Graevenitz²

Accepted: 20 June 2024 / Published online: 16 July 2024
© The Author(s) 2024

Abstract

Emissions of local pollutants from industry have declined across many developed countries over the last decades. For carbon emissions such reductions have yet to materialize. Using German administrative micro-data at the product level, we apply the workhorse model for decomposing emission changes into scale, composition (changes in the mix of goods produced) and technology (emission factors of production) effects. We find that the production composition in German manufacturing shifted towards less CO₂ intensive goods, while emission intensities of production increased. We show that data aggregation matters. Both effects are substantially underestimated when using data at the sector level as compared to the product level. A complementary plant level decomposition reveals that emission intensities of production increased both within plant, and due to a reallocation of production to more emission intensive plants.

Keywords Carbon emissions · Climate policy · Statistical decomposition · Manufacturing

We are grateful to two excellent referees who helped us improve the paper substantially. We thank Sylwia Bialek, Claire Brunel, Andreas Gerster, Arti Grover, Beat Hintermann, Arik Levinson, Dominik Schober, Bodo Sturm and Ulrich Wagner for suggestions and insightful comments. We also thank seminar participants at the ZEW–Leibniz-Centre for European Economic Research, the 9th Mannheim Conference on Energy and the Environment, the European Association of Environmental and Resource Economists, the annual meeting of the Association of Germanspeaking Economists (VfS), the AURÖ junior workshop and the World Bank brown bag series Greening Private and Financial Sector. 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, Kerstin Stockmayer and Diane Zabel for their advice and technical support. We thank the Federal Ministry of Education and Research (BMBF) for the financial support through the Project TRACE (Grant number 01LA1815A). The views expressed in this paper are those of the authors and do not necessarily represent those of the institutions mentioned above.

✉ Kathrine von Graevenitz
vongraevenitz@zew.de

Elisa Rottner
rottner@zew.de

¹ ZEW - Leibniz Centre for European Economic Research and University of Basel, P.O. Box 10 34 43, 68034 Mannheim, Germany

² ZEW - Leibniz Centre for European Economic Research and University of Mannheim, P.O. Box 10 34 43, 68034 Mannheim, Germany

JEL Classification D22 · L60 · Q41 · Q48

1 Introduction

Environmental policy to improve air quality has been remarkably effective. Local pollutant emissions have been regulated in many countries since the 1970s and 1980s. In contrast, we have yet to make substantial progress on the reduction of CO₂ emissions. Regulation of CO₂ emissions is much more recent, and not as widespread even among developed economies. For an individual country, the direct benefits of reducing carbon emissions are less clear than the benefits of reducing local pollutants, since damages depend on emissions globally and vary across countries. Perhaps in consequence of less stringent regulation, end-of-pipe technologies for CO₂ removal are not yet commercially viable, and emissions remain closely linked to activity levels increasing the perceived costs of regulation.

The industrial sector accounts for the lion's share of global greenhouse gas emissions, together with the power sector (IPCC 2014). In this sense, carbon emissions are similar to the case of local pollutants. Electricity generation has become cleaner over time through expansion of renewable electricity generation from wind and solar installations. For industry, a reduction in greenhouse gas emissions, and, most prominently, CO₂ has not materialized, even in countries where climate policies are implemented and are comparatively strict from a global point of view: In Germany, carbon emissions from manufacturing have increased in recent years and were about 32 million tonnes higher in 2017 than in 2003 (von Graevenitz and Rottner 2023). The lack of progress in absolute terms, even in such an industrialized economy with climate policies in place, is problematic—especially if countries like Germany are to serve as a blueprint for decarbonization without deindustrialization in other countries.

What drives the development of CO₂ emissions in the German manufacturing sector? Answering this question is crucial to determine appropriate countermeasures. Are emission increases solely grounded in a rising production scale? Do we have to worry about the outsourcing of dirty products and carbon leakage (production composition)? Are there technological improvements that might be exported to other countries and facilitate emission reductions there as well (production technique)? Decomposition methods are a useful tool to disentangle these emission drivers and have been widely used for local pollutants in the environmental community (Brunel 2017; Levinson 2009, 2015; Najjar and Cherniwchan 2021; Shapiro and Walker 2018).

Due to limited data availability, past research has conducted Levinson-style statistical decompositions at the sectoral level. Using fine-grained data at the product level distinguishing between more than 4600 9-digit products, we decompose the development of carbon emissions in German manufacturing. We show that data aggregation matters: Generally, we find that the German manufacturing sector has been shifting towards a cleaner product composition between 2005 and 2017. The clean up due to compositional change is 9.4% in our 9-digit baseline decomposition, but only 6.8% in the 3-digit decomposition (71%). Conversely, emission intensities of German manufacturing (production technique) have increased between 2005 and 2017. At the 9-digit level, this increase amounts to 4.5%, but only 2.3% at the 3-digit level (51%). The increase in production scale and the positive technique effect combined are the reasons why carbon emissions in German industry have not decreased.

The detailed micro-data available from the German Manufacturing Census allow us to combine the Levinson-style decomposition with a plant level decomposition in the style of Foster et al. (2008). In doing so we follow Barrows and Ollivier (2018). Conducting decomposition analyses using different units of observation (product versus plant), we can exploit the respective merits of each method and obtain a fuller picture of the channels through which emission intensities of production have increased. Our results show that selection (plant entry and exit) had negligible effects on the emission intensity of German industry. Emission intensities of production increased within plant. Re-allocation of production between plants has also led to an increase in emission intensity. The cross effect is large and negative indicating that emission intensity of plants with initially high intensities has grown relatively less, dampening the net impact on emission intensity of the manufacturing sector.

With our paper, we contribute to the literature using decomposition tools as a means to understand the drivers of emission developments (e.g. Shapiro and Walker 2018; Levinson 2009, 2015, 2021; Brunel 2017; Najjar and Cherniwchan 2021). First, we contribute by characterizing the aggregation bias. Prior work by Lyubich et al. (2018) show that emission intensities in the US vary substantially within 375 narrowly defined NAICS industries. The German manufacturing sector displays similar heterogeneity (von Graevenitz and Rottner 2023). Part of this heterogeneity is due to different emission intensity of products within industries, i.e., the within industry composition. In decompositions of emissions conducted at the industry level, technique effects are calculated as within sector changes in emission intensity. Changing composition of products within an industry gives rise to aggregation bias in the technique and composition effect. The direction of bias depends on the sign of the “true” technique and composition effects. With negative composition effects and positive technique effects as in our case, both effects are underestimated. When both effects are negative, the technique effect would tend to be overestimated in absolute terms: Emission reductions attributed to the technique effect in reality stem from within sector compositional shifts. Whenever the true composition effect is negative, the bias works towards predicting a technique effect that is too clean. Either, it is positive but too small, or negative and too large. These findings suggest that the clean-up attributed to the technique effect in prior analyses at a less granular level is likely overstated.

Second, we contribute to the decomposition literature by providing evidence on carbon emissions. Several papers examine the drivers of local pollutant emissions (e.g. Shapiro and Walker 2018; Levinson 2009, 2015; Brunel 2017; Najjar and Cherniwchan 2021). These papers generally document large and negative technique effects suggesting that technology adoption has been a main driver of local pollutant emission reductions. A much smaller literature decomposes carbon emissions (Barrows and Ollivier 2018; Levinson 2021; Brunel and Levinson 2022), but these studies have focused on the US and India where climate policy has been comparatively lax. We provide evidence from a developed and export-oriented economy in which carbon emissions have been regulated since the early 2000s.

Lastly, we contribute to the literature evaluating the effect of environmental policies on the manufacturing sector. A growing literature studies the relationship between climate policies and energy demand as well as firm-performance in Germany (e.g. Flues and Lutz 2015, Lutz, 2016; Gerster and Lamp, 2020; Hintermann et al., 2020; Lehr et al., 2020; von Graevenitz and Rottner, 2022). This literature has focused on identifying causal effects of specific policies such as the European emissions trading scheme or the exemption from the German renewable energy surcharge. Exploiting quasi-natural experiments, this body of work mostly quantifies effects on emissions of large and energy intensive manufacturing

plants. Our analysis provides context for these individual policy evaluations. We are the first to apply the approaches by Levinson (2015) and Foster et al. (2008) to German emissions.¹

2 Data

We conduct our analysis using the official plant level micro-data from the federal statistical offices of the Bund and the Länder. All manufacturing plants in Germany with more than 20 employees must report in the surveys. We use data from 2005 to 2017. Our analysis requires information on each plant's emissions and total output, as well as aggregate emissions and output. Moreover, we need information on the output share and emission intensity of each subsector and plant.

The German Manufacturing Census does not contain any information on carbon emissions. We calculate plant level emissions by combining information on manufacturing plants' consumption of 14 different fuels and electricity with appropriate emission factors retrieved from the German Environmental Agency (Umweltbundesamt 2008, 2020a, b). Emission factors are national but time-varying. The emission factor for electricity reflects the German electricity mix as well as transmission losses.² Aggregate emissions are calculated by summing up plant level emissions. In the analysis, we abstract from analysing process emissions due to data limitations.³ Figure 1 shows the development of aggregate carbon emissions in the German manufacturing sector between 2003 and 2017. In 2017, carbon emissions were roughly 32 mio. tonnes higher than in 2003.

The German Manufacturing Census contains information about products at the 9-digit level. The 9-digit level is very fine-grained: In our base year 2005, we distinguish between 4,672 different 9-digit products. For comparison, there are only 1,356 products at the 6-digit level; 221 different sectors at the 4-digit level, and 91 sectors at the 3-digit level. Figure 2 shows an example of the breakdown of a 2-digit sector to the 9-digit product level for illustrative purposes. Aggregate output is calculated by summing gross output of each product produced by individual manufacturing plants.⁴ We deflate gross output using producer price indices (base year 2015) from the Federal Statistical Office (DeStatis 2018).⁵

¹ Petrick (2013); Kube and Petrick (2019) analyse CO₂ emissions at the firm level using the Logarithmic Mean Divisia Index. They do not take the effects of product mix into account.

² There are slight regional differences in emissions performance across German power plants. For example, coal fired power plants from the Rhineland emitted 113 t CO₂/TJ in 2016 whereas a coal fired power plant in middle Germany emitted 104 t CO₂/TJ in the same year due to differences in heat rates (Umweltbundesamt 2019a). Germany constitutes one electricity market and in general there is no way to determine which region has delivered electricity to individual plants.

³ According to the EEA (2015, 2016, 2017) process emissions made up about 10–16% of overall German emissions regulated under the EU Emissions Trading Scheme in the years 2013 to 2015. Within manufacturing, the sectors in which process emissions occur tend to be the same sectors that also have larger emissions from fuel combustion, i.e. pulp and paper, coke and petroleum, chemicals, other non-metallic mineral production and metal production.

⁴ Note that by using gross output as a measure for manufacturing activity, we cannot rule out the possibility that results are driven by the manufacturing sector outsourcing/starting to produce intermediate inputs that were produced/imported beforehand. Information on value added is only available at the firm level for a stratified sample of firms.

⁵ Where available, product level gross output is deflated using price indices at the 9-digit product level. In total, roughly 80% of gross output are deflated at the 9-digit level, 13% at the 6-digit level and the remaining 7% at the 4-digit level.

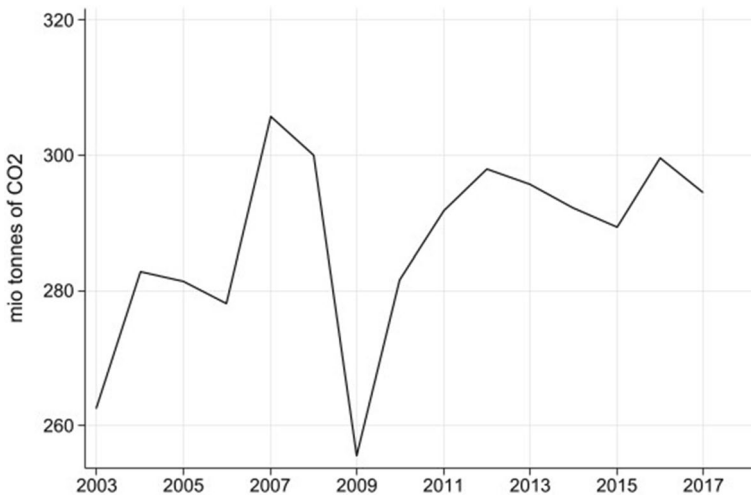


Fig. 1 The development of carbon emissions from fuel combustion in the German manufacturing sector. Notes: Source: DOI 10.21242/43531.2017.00.03.1.1.0. Own calculations

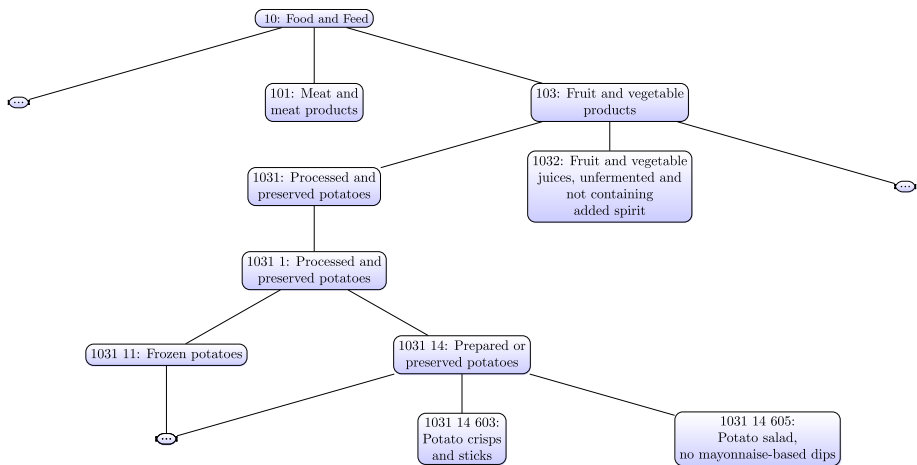


Fig. 2 Industries, sectors and products. Notes: Source: Goods catalogue of production statistics (DeStatis 2011)

Energy use and by extension CO₂ emissions are available at the plant level. We calculate emission intensities at the product level by allocating plant emissions to the different products based on output shares. The procedure is described in more detail in Additional file 1. Note that by using output shares to allocate plant level emissions onto the products, we implicitly assume that all products within a plant are produced with the same emission

intensity.⁶ We conduct the Levinson-style decomposition analysis at the 3-, 4-, 6- and 9-digit sector level to quantify aggregation bias.

3 Statistical decomposition methods

Decomposition tools are frequently used to disentangle the sources of emission changes. A wide variety of different approaches exist. We focus here on the decomposition into scale, composition and technique effects as in Levinson (2015), which is the "workhorse approach" in environmental economics. With our exceptionally granular data, we are able to analyse composition effects in more detail than past research and to assess the extent of aggregation bias in quantifying composition and technique effects using more aggregate data. We complement this product level decomposition of aggregate emissions with a plant level decomposition of emission intensity in the manufacturing sector inspired by Foster et al. (2008). The plant level decomposition does not allow us to analyse the role of product composition on emissions development in detail, but speaks to the effect of production allocation across plants and selection (entry and exit) among manufacturing plants in driving emission intensities.⁷ The combination of both decomposition approaches allows us to obtain a comprehensive picture of the drivers of emissions.

3.1 Product level decomposition of aggregate emissions

The statistical decomposition of aggregate emissions following Levinson (2015) can be carried out at different levels of sectoral disaggregation. It is grounded in a representation of total emissions, P_t , of, in this case, CO₂ in the German manufacturing sector at time t as the sum of emissions from s different subsectors in manufacturing. In each subsector, emissions are determined by the product of output produced, v_{st} , and the emission intensity of that subsector, z_{st} . Hence, total emissions from manufacturing depend on aggregate output V_t of the manufacturing sector as a whole, the share of each subsector from aggregate output θ_{st} and the emission factors of production in each subsector.

$$P_t = \sum_s p_{st} = \sum_s v_{st} z_{st} = V_t \sum_s \theta_{st} z_{st} \quad (1)$$

In vector notation, this is:

$$P_t = V_t \theta_t' \mathbf{z}_t \quad (2)$$

where θ_t and \mathbf{z}_t are $s \times 1$ vectors containing the market shares and emission intensities of each of the s different industries.

Total differentiation and division by emissions yields an expression for emission changes (with time subscripts dropped for notational convenience):

$$\frac{dP}{P} = \frac{dV}{V} + \frac{d\theta}{\theta} + \frac{dz}{z} \quad (3)$$

⁶ This most likely leads to some measurement error, as Barrows and Ollivier (2018) found substantial variation in emission intensities within multi-product firms across product lines. To assess robustness, we also conduct the product level analysis based on single-product plants.

⁷ We thank an anonymous referee for this suggestion.

The first term of the equation is the scale effect. The scale effect is given by the change in aggregate output and summarises how emissions would have evolved if only the production volume had changed. The second term, the composition effect, describes how emissions would have evolved if the sectoral composition of manufacturing had followed its historical path while keeping scale and emission intensities fixed. The third term is the technique effect and explains how emissions would have evolved if emission intensities had followed their historical paths while production scale and composition were fixed.⁸

The decomposition is straightforward on a conceptual level. The accounting identity in Eq. 3) is used to directly calculate the scale effect (keeping composition and technique constant) and either the technique or the composition effect (keeping scale and composition or scale and technique constant).

Scale, composition and technique effect add up to the actually observed emission changes as demonstrated in Eq. (3). Based on this identity, the remaining component is determined as the residual once scale and composition or scale and technique have been subtracted from the actual observed emissions. If, given scale and composition, emissions would have been higher than they actually were, the technique effect is negative. Conversely, if, given scale and composition, emissions would have been lower than they actually were, the technique effect is positive.

Note that estimating scale, technique and composition in this way attributes all interactions that might arise between the three effects to the effect estimated as the residual. Different estimates of the technique effect depending on whether it is estimated directly or indirectly as a residual are not an issue of robustness of the decomposition. Rather such differences arise when interaction effects are large. Levinson (2009, 2015) lists several potential types of interactions, e.g., larger industries having increasing returns to scale to pollution abatement or shrinking industries closing down the dirtiest plants first. It is not obvious which channel these interactions should be attributed to. In many studies, the choice of whether to calculate technique or composition directly is motivated by data availability. Our data allow us to calculate both composition and technique effect directly and as a residual, thereby allowing us to assess the importance of interaction effects.

For the sake of interpretation, the technique effect can also be depicted in a Laspeyres-like index. In this case, the predicted emissions with actual emission intensity developments but base year production scale and composition are divided by base year emissions. This index is equal to one when emission intensities remain unchanged as compared to the base year. Falling or rising emission intensities in contrast lead to the technique index taking on values smaller or larger than one. The index for the technique effect is given by the following equation:⁹

⁸ Our decomposition is based on the workhorse approach which relies on revenues. Recent work by Rodrigue et al. (2022) on SO₂ emissions in China has shown that this decomposition may be biased when markups change over the period under study. De Loecker and Eeckhout (2021) estimate markups for several countries including Germany to examine their development over time. In Germany markups remained approximately constant throughout our study period. While De Loecker and Eeckhout (2021) do not discuss markup heterogeneity within Germany, their finding of constant markups suggests that the bias is limited.

⁹ Similarly, the composition effect in index form can be written as:

$$C_L = \frac{\sum_s \theta_{st} z_{s0}}{\sum_s \theta_{s0} z_{s0}}$$

$$T_L = \frac{\sum_s z_{st} v_{s0}}{\sum_s z_{s0} v_{s0}} = \sum_s \frac{z_{st}}{z_{s0}} * \frac{z_{s0} v_{s0}}{\sum_s z_{s0} v_{s0}} \equiv \sum_s \frac{z_{st}}{z_{s0}} * \mu_{s0} \quad (4)$$

where 0 indicates the base year to which emission intensity changes are compared.¹⁰ Reformulating the estimated technique effect in this way clarifies some of the properties of the calculated effect. Specifically, the aggregate index consists in changes in individual subsectors s that are weighted by their relative importance in the base year 0. For our application to emission intensities, this means that the estimated technique effect is a weighted average of emission intensity changes in individual subsectors s where the weights are given by the subsectors' shares of total manufacturing emissions in the base year μ_{s0} .¹¹

In each subsector, our measure of the technique effect does not constitute a technique improvement within plant. The change in the emission intensity also depends on allocation of production across plants. Equation (7) shows this:

$$z_{st} = \frac{p_{st}}{v_{st}} = \frac{\sum_j p_{jst}}{v_{st}} = \frac{\sum_j z_{jst} * v_{jst}}{v_{st}} = \sum_j \frac{v_{jst}}{v_{st}} * z_{jst} \quad (5)$$

The first term in the last expression is the share of plant j in aggregate production of subsector s . The second term is the plant's emission intensity. Clearly, the emission intensity of different plants is weighted by their output share, which means that emission intensity improvements (i.e., the technique effect in the analysis) can be achieved both by emission intensity improvements within plants, and by a reallocation of production toward less emission intensive plants. To clearly disentangle the role of within plant changes versus across plant reallocation, we complement the sector level decomposition with a plant level decomposition of the technique effect.

3.2 The aggregation bias in statistical decompositions

The level of sectoral disaggregation has direct implications for the calculation of the composition and technique effect. Suppose, e.g., that no sector data are available at all, but only data on the aggregate manufacturing sector. In that scenario, it would not be possible to identify any composition effect. All changes in emissions would be attributed to either scale or technique effect. Specifically, changes in emission intensities caused by production composition changes would be attributed to the technique effect. More detailed sector level data makes it possible to separate a composition effect from the technique effect. If

¹⁰ In our application, 2005 constitutes the base year.

¹¹ Alternatively, Levinson (2015) proposes to use a Paasche-like measure where the weights are given by current shares:

$$T_P = \frac{\sum_s z_{st} v_{st}}{\sum_s z_{s0} v_{st}}$$

Differences between Laspeyres and Paasche indices capture one interaction attributed to the term estimated as a residual, namely whether or not the manufacturing sector shifts towards or away from sectors in which pollution intensities decline the most. The comparison does not capture all possible interactions between scale, composition and technique effect. We report comparisons between Laspeyres and Paasche technique effects in Additional file 1. Generally, we find that sectors for which the difference between Laspeyres and Paasche indices is big also display a big difference between estimating the composition or the technique effect as a residual. This suggests that a large share of interaction effects are between composition and technique rather than due to scale.

products within sectors differ in terms of their emission intensity, such data does not allow for distinction between within sector composition changes from technique-based reductions in emission intensities. These limitations of sector level data have been discussed, among others, by Shapiro and Walker (2018), Levinson (2009) or Ederington et al. (2004). Intuitively, the most accurate calculation of composition and technique effects would carry out the decomposition at the level where each product constitutes its own “sector”. In this case, the technique effect would identify pure emission intensity changes within product over time without capturing composition changes, while the composition effect would cover the universe of composition changes.

Using data at the product level introduces different challenges however. One set of challenges is related to (re-)allocation and selection within the manufacturing sector. Whereas only few sectors enter or exit manufacturing over the time period under study, we do have examples of products entering and exiting. As we have no baseline emission intensity for products that enter the data at a later stage, these products are excluded from the analysis as are the plants entering with them. This concerns 294 9-digit products over the 13 year period.¹²

Second, while our output data is available at the product level, emissions are allocated to products based on the product’s share of the plant’s total output. Implicitly, this assumption entails that a plant produces all of its products with the identical emission intensity. Emission intensity improvements due to a within plant shift in the product composition in the case of multi-product plants are not included in the composition effect, but attributed to the technique effect. We assess the robustness of our results by also conducting our analysis using single product plants only.¹³

3.3 Plant level decomposition of emission intensity

The decomposition at the product level following Levinson (2015) allows us to single out the role of production shifts for emissions even within manufacturing plants. It does not allow us to separate the drivers of changes in emission intensity of production such as plant entry, exit, reallocation of production shares and changes in within plant emission intensities. We therefore complement the product level decomposition with a plant level decomposition. The plant level decomposition builds on the productivity decomposition in Foster et al. (2008) which has been applied to emission intensities by Barrows and Ollivier (2018) for the case of India. This method was originally developed for narrowly defined sectors with homogeneous goods. It is therefore not particularly well-suited to take account of compositional changes in what is produced, but focuses instead on who is producing. We decompose changes in sector level emission intensity ΔZ_{st} into four components: within plant changes in emission intensity, between plant shifts in production shares, a cross effect, and the effect of net entries as shown in Eq. (8):

¹² To gauge whether the products that enter the sample at a later stage revert conclusions, we also conduct the decomposition analysis with varying base year. Instead of comparing each year to 2005, we compare production scale, composition and technique to the preceding year. Laspeyres and Paasche indices for the composition and technique effects are reported in Tables 11 and 12 in the Additional file 1. We thank an anonymous referee for this suggestion. Qualitatively, this does not change results, suggesting that the entering products do not strongly contribute to the observed developments.

¹³ Results for single product plants are shown in Figure 10 in the Additional file 1. Also with single-product plants only, we generally find that emission intensities of production increased.

$$\begin{aligned} \Delta Z_{s,t} = & \sum_{j \in C,s} \theta_{j,t-1} \Delta z_{j,t} + \sum_{j \in C,s} (z_{j,t-1} - \bar{z}_{s,t-1}) \Delta \theta_{j,t} + \sum_{j \in C,s} \Delta z_{j,t} \Delta \theta_{j,t} \\ & + \sum_{j \in N,s} \theta_{j,t} (z_{j,t} - \bar{z}_{s,t-1}) - \sum_{j \in X,s} \theta_{j,t-1} (z_{j,t-1} - \bar{z}_{s,t-1}) \end{aligned} \quad (6)$$

Plants in each sector s are divided into three groups: Continuing (C), entering (N) and exiting (X) plants. The first three segments in Eq. (8) refer to continuing plants. The first segment captures the within plant change in emission intensity. The second segment is the between plants effect composed of the change in output share of plant j times the relative emission intensity of that plant compared to the output-share weighted mean in industry s , $\bar{z}_{s,t-1}$. The third term is the cross effect. The last two terms in the second line of the equation describe the effect of net entry on emission intensity. They capture whether entering firms are less emission intensive than the sector average before their entry, and exiting firms more emission intensive than the sector average before their exit.

We decompose emission intensity according to Eq. (8) at the 4-digit level and calculate the contribution of within plant changes in emission intensity, (re-)allocation, and selection in each industry.¹⁴ We conduct the decomposition both year-on-year and in long differences (i.e., with t as 2017 and $t-1$ as 2005). For the aggregation across sectors we use the average revenue share of the sector in $t-1$ and t as Foster et al. (2008). Note that the within plant change in emission intensity mixes the effects of within product line changes, as well as the effects of a changing product mix at the plant level. Since we do not observe emissions at the plant-product level, it is impossible for us to clearly disentangle the roles of changing production composition, within product line technique effects and product entries and exits for within plant adjustments. For single product plants, however, we check whether plants tended to become more or less emission intensive after switching the products they produce by conducting the decomposition in Eq. (8) with s being the plant as the aggregate level instead of the sector as in Barrows and Ollivier (2018).

The decomposition methods by Levinson (2015) and Foster et al. (2008) not only consider different units of observation (products versus plants), they also use different weights in aggregating the results for the whole manufacturing sector. The Laspeyres index weighs sectors by their initial share of total emissions, whereas the plant level decomposition is aggregated based on output weights. This implies that for instance sectors such as the coke sector (NACE 19), which is very emission intensive, receive a higher weight in the product level decomposition than in the plant level decomposition. The two decomposition methods are also complementary in this sense.

4 Results: Decomposing carbon emissions in the German manufacturing sector

4.1 Product level decomposition

We first present our findings from the product level decomposition. Figure 3 shows the results from the decomposition analysis at the 9-digit product level for more than 4,600 products. The line marked with the triangles and labeled "Scale, composition and technique" depicts actual emissions as they developed over time, indexed to base year 2005.

¹⁴ The 4-digit level is the finest level at which we have a sector classification for the plant.

The line marked with dots depicts the scale effect. It shows how emissions would have developed had aggregate output followed its historical path, but keeping emission intensities and production composition constant since 2005. In this scenario, emissions would have increased by around 16% in 2017 as compared to 2005. Actual emissions have increased by 6% implying a clean-up of manufacturing of 9%. The line marked with squares shows the combined scale and composition effect (obtained by holding 2005 emission intensities constant), the line marked with diamonds the combined scale and technique effect (obtained by holding the 2005 production composition constant). The difference between the line marked with squares and the one marked with dots measures the directly estimated composition effect. The difference between the line marked with squares and the line marked with triangles shows the technique effect when measured as the residual. Equivalently, the difference between the line marked with diamonds and the line marked with dots measures the directly estimated technique effect, while the difference between the line marked with diamonds and the line marked with triangles shows the composition effect when measured as the residual.

Figure 3 shows that the technique effect is always smaller when estimated as a residual. A comparison of the Laspeyres and Paasche indices reported in Table 8 in the Additional file 1 indicates that industries with faster falling/more slowly growing carbon intensities grew at a faster rate. Qualitatively however, it makes little difference which of the approaches is chosen. Interaction effects between scale, composition and technique are mostly too small to reverse the sign of the effects observed, though reversals do occur in individual years. In 2008, the directly estimated technique effect is clearly positive while it is close to zero when also incorporating the interaction terms; in 2009 and 2010, the directly estimated composition effect is weakly positive, but negative when estimated as a residual. Particularly during the 2009 recession the interactions seem to make a difference: If there are any interactions of the scale effect with the other two effects, they arguably played out strongly in that year.

We find that up to the economic crisis, the production composition of the German manufacturing sector had only small effects on carbon emissions. From 2011 onwards, however, we observe a clear trend towards a cleaner production composition. This shift in the production composition is solely responsible for the clean up of manufacturing. Table 7 in the Additional file 1 reports the corresponding Laspeyres and Paasche indices for the composition effect. According to our calculations, by 2017, the production composition in German manufacturing was at least 10% less emission intensive as compared to 2005. This shift in the more recent years of our sample could indicate that either markets for green products are growing, or the increasingly stringent climate regulation enacted in recent years is associated with carbon leakage, i.e., the outsourcing of carbon intensive products to countries with less stringent climate policies. Section 4.4 takes a closer look at the composition of imports and exports.

With regard to the technique effect, we find a positive technique effect in every year except 2006 and 2011 where the technique effect is close to zero. Despite the introduction of several climate policies, our results indicate that compared to 2005, the emission intensity of production has mostly increased. The Laspeyres index for the technique effect (reported in Table 8 in the Additional file 1) reveals that emission intensities increased by up to 11% (in 2013) as compared to 2005. In 2009, the technique effect is quite large, suggesting that in economic downturns, manufacturing plants may not be able to adjust

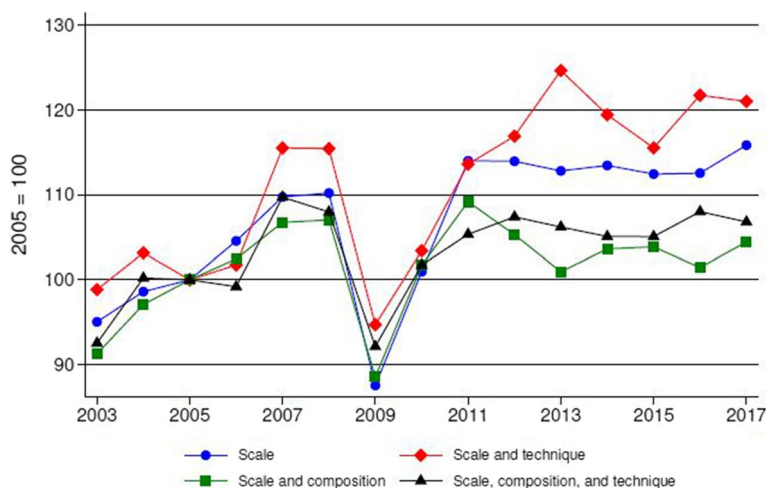


Fig. 3 Decomposing carbon emissions in the German manufacturing sector. Notes: Source: DOI 10.2124/2/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations

energy consumption at the same pace as production.¹⁵ The increase in emission intensity of production is entirely due to an increase in energy intensity of production as we show in Additional file 1. Fuel switching to less carbon intensive fuels and declining emission factors of electricity generation have worked in the opposite direction.

Our findings for the technique and the composition effect contrast with the findings of Brunel (2017) for local pollutants in the EU between 1995 and 2008. Different results could be due to the study period or due to the difference in coverage (e.g., Germany may not be representative of Europe). von Graevenitz et al. (2023) examine carbon emissions in Germany compared to the rest of the EU and find that Germany has become comparatively more carbon intensive from 2005 to 2019 than other EU countries. Alternatively, differing findings may be due to the different pollutants analysed. In the US, remarkable emission reductions in local pollutants were achieved through negative composition and technique effects (Levinson 2015), while carbon emissions displayed very little change (Brunel and Levinson 2022). Finally, different aggregation levels could also contribute to explaining different findings.

4.2 Aggregation bias

We assess the role of aggregation bias by comparing our main results with results from the decomposition analysis at the level of 3-, 4-, and 6-digit sectors. Table 1 displays the Laspeyres index for the composition and the technique effect. From left (9-digit products)

¹⁵ Note that these results are not driven by manufacturing plants' entries and exits: Figure 9 in the Additional file 1 shows that these patterns also hold in a balanced sample of manufacturing plants. In a similar vein, the plant level decomposition of emission intensity shows very small effects of net entry.

Table 1 Laspeyres indices: 9-digit products to 3-digit sectors

Year	Laspeyres index composition				Laspeyres index technique			
	9-digit	6-digit	4-digit	3-digit	9-digit	6-digit	4-digit	3-digit
2005	1	1	1	1	1	1	1	1
2008	0.972	0.974	0.972	0.966	1.048	1.028	1.023	1.026
2011	0.958	0.967	0.961	0.961	0.996	0.967	0.970	0.972
2014	0.914	0.936	0.937	0.936	1.053	1.029	1.007	1.008
2017	0.906	0.933	0.938	0.932	1.045	1.034	1.022	1.023

Source: Own calculations.

The table shows the Laspeyres indices for the composition and the technique effects calculated for the decomposition at the 9-digit product level, the 6-digit, 4-digit and 3-digit sector level

to right (3-digit sectors) the level of aggregation increases.¹⁶ Qualitatively the results are similar, but the magnitude of both composition and technique effects declines when the decomposition analysis is conducted at a more aggregate level. In 2017, the composition effect at the 3-digit level is only 71% (− 6.8 vs. − 9.4%) of the effect measured at the 9-digit level. In the same year, the technique effect at the 3-digit level is only 51% (2.3 vs. 4.5%) of the effect quantified at the 9-digit level. The within sector composition has clearly changed over time attenuating both the composition and technique effect as they have worked in opposite directions over the years studied.

The patterns displayed are not monotonic in the sense that the Laspeyres index at the 4- or 6-digit levels are sometimes larger and sometimes smaller than at the 3-digit level. In part this is due to products or sectors entering and exiting. The more disaggregated the decomposition, the more likely it is that a product or industry enters or exits over the 13 years studied. Entering goods will not be included as they have no baseline emission information. Similarly, an exiting good will drop out, whereas exiting sectors are rare. In other words, there is a trade-off between aggregation bias from misattributing compositional changes to technique effects, and selection bias from entries and exits. The general trend however shows that, in our case, more disaggregated data leads to both composition and technique effect being underestimated. Conducting the decomposition in year-on-year changes to reduce selection bias does not alter results qualitatively, suggesting that bias due to entry and exit at the product level is small in our case. Results are reported in Tables 11 and 12 in the Additional file 1.

4.3 The role of allocation and selection in manufacturing emissions

The technique effect measured in the previous section was a composite of the plant's emission intensity and its share of output of a given product. Competitive pressure could allow only the most productive plants to enter and stay in the market. If the most productive plants are also less emission intensive as discussed, e.g., in Forslid et al. (2018), we would expect the competitive pressure in an industry to be negatively related to the technique effect as

¹⁶ Sectors are assigned on the basis of the first digits of the 9-digit product-number. In this decomposition, therefore, we do not necessarily assign a given plant to one specific sector, even at broader aggregation levels. A plant can, e.g., be represented in different 3-digit sectors if it produces products in different 3-digit sectors. In the plant level decomposition, in contrast, plants are uniquely assigned to one 4-digit sector according to their main sector of activity.

entry and allocation changes the plant's market share. Our plant-based decomposition allows us to disentangle selection and allocation from changes in within plant emission intensity. We decompose emission intensity at the 4-digit level and calculate the contribution of within plant changes in emission intensity, allocation, and selection (entry and exit of plants) to the percentage change in emission intensity. Results in long differences (from 2005 to 2017) as well as averages from year-on-year changes for three distinct periods are reported in Table 2.

The first column shows the total percentage change in emission intensity over the whole manufacturing sector, whereas the remaining five columns show the contribution of each channel. The five contributors sum up to the actual emission intensity change (where net entries have to be subtracted, as in Eq. (8)).

Consistent with the positive technique effect in the product level decomposition, emission intensity within plant generally increased over the period. The year-on-year changes reveal that the within plant technique effect is positive in the years in which also the product technique effect from the Levinson decomposition increases. This suggests that within plant developments in technique (and not only reallocation between plants) is responsible for the increase in emission intensity we document.

The between plants effect is also positive indicating that allocation of production shifted towards more emission intensive plants. The cross effect is large and negative suggesting that emission intensive plants grew more, but also improved their emission performance relative to less emission intensive plants. Effects of net entry are very small ranging from -0.4 ($-0.7 - (-0.3)$) to 0.4 ($0.8 - 0.4$). Both entering and exiting plants display relatively low emission intensities. The net effect is an increase in emission intensity in manufacturing. The positive technique effect in the product decomposition seems to stem both from an increase in within plant emission intensities and a reallocation towards more emission intensive plants, countered by a relative improvement in emission performance of these emission intensive plants. Barrows and Ollivier (2018) report similar findings for India concerning the importance of selection and reallocation: Entries and exits have very little impact on emission intensity, whereas reallocation (and in particular the cross effect) contributes substantially to the clean-up they observe.

What is happening within plant that leads to the plant level increase in emission intensities? Are plants shifting output toward more emission intensive products, adjusting their product portfolio, or do they increase the emission intensity within product line? Since we lack emission data at the plant-product level, we cannot disentangle these forces, except in the sample of single product plants. Table 3 reports the results from running the decomposition at the plant-product level for single product plants, in long differences between 2005 and 2017 and as averages for year-to-year changes over the time period.^{17,18}

Single product plants, in contrast to overall trends, generally have improved their emission intensity.¹⁹ This is both due to changes within product line and due to product

¹⁷ In principle, this effect decomposes the “within plant” effect from Table 2. The samples from the analyses however differ, as Table 3 specifically focuses on single product plants. Also, difference in weighting lead to emission intensity changes not necessarily summing to the within plant effect from Table 2.

¹⁸ For total change in emission intensity the numbers for individual subperiods (aggregated by year) add up to the long differences effect. For the other columns, this does not have to be the case. For instance, in long differences a plant may exit and therefore fall in the “exits” category, but it will in individual subperiods either not be present at all, or belong to another category as a continuing plant.

¹⁹ The fact that single product plants show a different overall trend in emission intensity than other plants is noteworthy. The sample however is very specific, as single product plants in the decomposition have to be single product plants at both observation points. In the long differences design, this limits the sample to roughly 8,500 plants (out of roughly 40,000). In the year-on-year changes, for each decomposition, there are roughly 15,000–18,000 plants that are single product plants in consecutive years.

Table 2 Allocation and selection

Time period	Total change	Within plant	Between plants	Cross effect	Entry	Exit
2005–2017	4.2	19.5	10.5	-25.4	-0.7	-0.3
2005–2009	1.3	3.6	5.4	-7.6	0.4	0.4
2010–2013	-0.0	2.9	1.0	-3.9	-0.3	-0.1
2014–2017	-0.3	0.5	2.0	-3.2	0.8	0.4

Source: Own calculations.

The table shows the results of the plant level decomposition of emission intensities calculated at the 4-digit sector level. Sectors are aggregated using output weights. The first row shows results in long differences between 2005 and 2017. The three remaining rows report averages of year-on-year changes for distinct periods

Table 3 Product entry effects within single product plants

Plants	Long differences	Total change	Product switch	Technique
Single product	Yes	- 11.99	- 1.48	- 10.52
Single product	No	- 8.47	- 0.67	- 7.80

Source: Own calculations.

The table shows the results of a product level decomposition of emission intensities calculated at the plant level. Plants are aggregated using output weights. The first row shows results in long differences between 2005 and 2017. The second row reports averages of year-on-year changes between 2005 and 2017

switches. The importance of product switches for the observed emission intensity improvements is relatively small. This is grounded in the fact that only a relatively small share of single product plants switched their products between 2005 and 2017 (overall roughly 6%, from year to year less than 1%). Still, on average, plants seem to have switched toward less emission intensive products (i.e., they became less emission intensive after a product switch). This switching behaviour might be one driving force for the clean composition effect identified in the product level decomposition.

4.4 Carbon leakage and a change in the product composition

The clear trend towards a less emission intensive production composition that we find at the 9-digit product level could indicate carbon leakage. If especially energy intensive sectors outsource the production of the most emission intensive products, this would lead to a less carbon intensive domestic production composition. Suggestive evidence for the occurrence of carbon leakage and for the loss of competitiveness of German energy intensive sectors could be found if we observed a simultaneous shift in German exports toward less emission intensive sectors and in German imports toward more emission intensive sectors. We decompose German trade flows following Eq. (3), akin to the approach taken in Levinson (2009). The decomposition is conducted at the 3-digit sector level using imports and

Table 4 Laspeyres and Paasche indices for the composition effect of German trade flows

Year	Laspeyres Exports	Paasche Exports	Laspeyres Imports	Paasche Imports
2005	1	1	1	1
2006	1.002387	1.001079	1.008533	1.003687
2007	0.9569227	0.9535437	1.009588	1.003167
2008	0.950685	0.9394742	0.9987149	0.9887199
2009	0.9790129	0.9720478	0.8985757	0.8895001
2010	0.9624456	0.9484019	0.9516796	0.9256257
2011	0.9259918	0.9122524	0.9341809	0.910885
2012	0.9189055	0.9039791	0.9045228	0.8831315
2013	0.9114583	0.8901056	0.901652	0.8795794
2014	0.907735	0.8805468	0.9000167	0.8723223
2015	0.8880442	0.8578597	0.8838269	0.8516514
2016	0.8824099	0.8520127	0.8584881	0.819602
2017	0.8790151	0.8361229	0.8638813	0.8129885

Source: Own calculations.

The table shows the Laspeyres and Paasche indices for the composition effect calculated for the decomposition of German exports (left) and German imports (right). Comparing the two shows, that the Paasche index is consistently smaller than the Laspeyres index indicating that trade flows in industries with faster falling/more slowly growing carbon intensities grew at a faster rate

exports from Eurostat (2023). Base year, i.e., 2005 emission intensities at the 3-digit level are computed from the German Manufacturing Census.²⁰

Table 4 shows Laspeyres and Paasche indices of the composition effect for German manufacturing imports and exports, respectively. Clearly, the composition shift toward less emission intensive sectors is not limited to overall German production, but also extends to both German imports and German exports. Imports have even shifted faster toward cleaner sectors than domestic production. This suggests that carbon leakage and stringent German climate policies may not be at the roots of the German production shift toward less emission intensive goods.

²⁰ In the decomposition of exports, we implicitly assume that exports are produced with the same emission intensity as overall production. While this is not necessarily true (see, e.g., Forslid et al. 2018 for evidence that exporters tend to be less emission intensive), note that the decomposition exploits variation relative to the base year. There will only be bias if the “export premium” in terms of emission intensity differs systematically across 3-digit sectors. In the decomposition of imports, for the lack of international emissions data at the 3-digit sector level, we also rely on German emission intensities, not the emission intensities of production in the origin country. We trust that Germany serves as a reasonable approximation to the relative emission intensity of different sectors, even if emission intensities from different origin countries might differ. Alternatively, as in Levinson (2009), the exercise can be viewed as analysing the emissions displaced, i.e., the emissions that would have occurred in Germany absent imports.

4.5 Sectoral heterogeneity in the development of emissions and emission intensities

We aggregate sector and product specific developments using weights for their emission share in the base year 2005 (as shown in Eq. (5)). This means that the product and sector specific decomposition results are heavily driven by developments in the very energy and emission intensive sectors metal production, chemicals, coke and petroleum, other non-metallic mineral products and pulp and paper.^{21,22} In this section, we show disaggregated results by 2-digit sector. This reveals substantial heterogeneity in emission drivers across sectors. It also shows that aggregation and selection bias matter to a different extent in different sectors.

Figure 4 contrasts the Laspeyres indices for the composition and the technique effect at the 2-digit sector level for the year 2017 relative to 2005. Both sign and magnitude of technique and composition effects vary substantially.²³ Table 5 provides a list of brief sector descriptions with the sector codes.

Despite the positive technique effect in 2017 for the manufacturing sector overall, in the same year, negative technique effects prevail when it comes to the 2-digit sectors (i.e., most sectors lie below the horizontal line in the figure). Several sectors experienced continuous improvements in terms of their emission intensity (among others, NACE 15: manufacture of leather and related products, NACE 18: printing and reproduction of recorded media, and NACE 26: manufacture of computer, electronic and optical products). The more energy intensive sectors (highlighted by the black boxes in the figure), however, are the ones that really matter for manufacturing's emissions, and they tend to display positive, i.e., emission increasing, technique effects.²⁴

Why have especially those sectors that matter in terms of manufacturing's emissions not managed to improve their emission intensity of production? A potential reason for energy intensive sectors generally experiencing more of an increase in emission intensities could lie in those sectors benefiting to a higher degree from exemption and compensation schemes that were introduced alongside climate policies to prevent a loss in competitiveness and leakage effects. In the observation period, large and intensive electricity users could, e.g., get exempt from paying the Renewable Energy Surcharge which accounted for roughly a third of electricity prices. Manufacturing plants above a certain electricity procurement threshold could also benefit from paying reduced electricity network tariffs, and since 2013 a subset receive electricity cost compensation due to higher electricity prices owing to the EU ETS. Also, through the leakage list of the EU ETS, energy intensive and trade exposed sectors are eligible for a higher share of free allowances or electricity price

²¹ The development of energy consumption in German manufacturing, split across 2-digit sectors, is shown in Figure 7 in the Additional file 1.

²² A similar argument applies to the plant level decomposition which is aggregated based on output shares. Heterogeneity in terms of output shares is of a similar magnitude, but only chemicals belong to the top five sectors in both categories. The other four top five sectors in terms of output shares are food, machinery, motor vehicles, and metal products. The food sector holds a 6th place in terms of energy intensity.

²³ The same can be seen from Tables 9 and 10 containing the Laspeyres indices for technique and composition effects in the Additional file 1.

²⁴ The outliers in Figure 4 (e.g. NACE 33 (Repairs) and NACE 26 (Computers and electronics) and NACE (Tobacco)) are small in terms of emissions. They do not contribute substantially to the main results. The development of emission intensities in computing is partially driven by technological development and resulting price decreases affecting deflated output. Repairs are generally an additional product with limited importance for manufacturing plants producing machinery. In consequence activity displays substantial variation over time.

Table 5 Overview over two-digit sectors in manufacturing

Sector Code	Sector name
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture
17	Manufacture of pulp, paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Metal production and processing
25	Manufacture of fabricated metal products
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Machine manufacturing
29	Manufacture of motor vehicles
30	Other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment

compensation in the study period.²⁵ Aside from directly facing different prices, the energy intensive sectors tend to use a different energy mix. Specifically, they rely a lot more on onsite electricity generation, and as such have been less exposed to the regulation-induced electricity price increases over our observation period. Consequently, they might have been subject to a lower shadow price on emissions and therefore have faced lower incentives to decrease their emission intensity.

Composition effects also vary across sectors with sectors like NACE 13: textiles, or NACE 20: chemicals shifting towards less carbon intensive goods. Sectors like NACE 16: manufacture of wood and wood products, and NACE 26: manufacture of computer, electronic and optical products shift toward more emission intensive goods. In some sectors, the production composition remains virtually unchanged over time with regards to the emission intensity (e.g., NACE 22: manufacture of rubber and plastic products).

Aggregation bias is also present in the sector-specific decompositions. Moving from the 3-digit decomposition to the 9-digit decomposition, it is clear that dispersion increases in the scatter plot. This is consistent with underestimation due to aggregation

²⁵ An overview of existing exemptions in Germany for energy and electricity taxes and levies with the relevant thresholds can be found in a publication by the Umweltbundesamt (2019b).

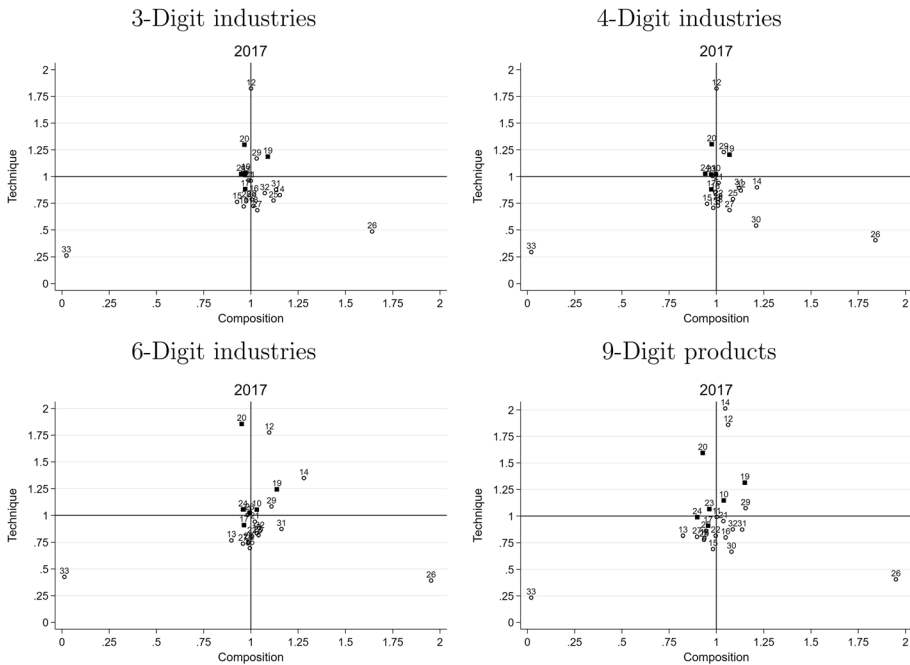


Fig. 4 Laspeyres indices for composition and technique effect in 2017 across sectors. Source: DOI 10.21242/43531.2017.00.03.1.1.0. Own calculations. Notes: The figures display scatter plots of Laspeyres indices for technique and composition aggregated at the 2-digit sector level. The six most energy intensive sectors are marked by black boxes, whereas the remaining sectors are marked with circles. Values above one indicate that the sector uses more emissions intensive techniques in 2017 as compared to 2005 (Y-axis) and/or produces more emissions intensive products in 2017 as compared to 2005 (X-axis)

bias. We also see that the pattern is not entirely consistent. Some sectors shift around considerably depending at the aggregation level. For example, sector 14: Clothing goes from having a moderate positive composition effect and a small but negative technique effect in the 3-digit decomposition to having a small positive composition effect and a large positive technique effect in the 9-digit decomposition. There are two reasons for these large shifts: First, composition might have changed substantially within the clothing industry, with a shift toward less emission intensive products within 3-digit industries. Second, there might be many product entries and exits such that the decompositions for the various aggregations differ in terms of their plant-coverage. Despite these shifts, a general pattern towards more dispersion at higher levels of disaggregation is visible.

5 Conclusion

We have yet to make substantial progress on the reduction of CO₂ emissions. Despite the introduction of several climate policies in Germany in the period between 2005 and 2017 carbon emissions continued to increase. To understand drivers of this emissions

development, we apply a workhorse decomposition method from the environmental economics literature to extraordinarily fine-grained data on 9-digit products.

We show that the increase in carbon emissions from the manufacturing sector can to a large extent be attributed to an increase in production scale. We observe a clean-up of German manufacturing in the order of 9% reduction of emissions compared to what they would have been had composition and technique remained unchanged since 2005. This clean-up is due to a change in product composition. From 2011 onwards, the German manufacturing sector has shifted towards greener products. In contrast, emission intensities of production have mostly increased as compared to 2005. We show that data aggregation matters in decomposition analyses. Both the composition and the technique effect are substantially underestimated if conducting the analysis at the more standard 3-digit sector level, rather than using data on 9-digit products: The clean-up resulting from changing product composition is smaller (71% of the effect calculated at the 9-digit level) and the increase in emission intensity of production technique is also attenuated (51% of the effect calculated at the 9-digit level), though the conclusions still hold. The changing composition of production raises concern whether these patterns are due to outsourcing of more carbon intensive products and could be indicative of carbon leakage. Our preliminary analyses decomposing imports and exports do not support this conclusion, but more research is required to rule out such concerns.

Our measure of the technique effect depends on within plant emission intensity as well as production allocation across plants. We complement the product level decomposition with a plant level decomposition to better understand the roles of selection and allocation in driving the increase in emission intensities. This second decomposition shows that emission intensity within plants generally increased over the period. The between plants effect is also positive indicating that allocation of production shifted towards more emission intensive plants. A large and negative cross effect indicates, that plants that were initially highly emission intensive improved their emission performance more than less emission intensive plants. Effects of net entry on aggregate emission intensity are negligible. The net effect remains an increase in emission intensity in the manufacturing sector over the period studied.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10640-024-00894-7>.

Funding Open Access funding enabled and organized by Projekt DEAL.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Barrows G, Ollivier H (2018) Cleaner firms or cleaner products? How product mix shapes emission intensity from manufacturing. *J Environ Econ Manag* 88:134–158
- Brunel C (2017) Pollution offshoring and emission reductions in EU and US manufacturing. *Environ Resour Econ* 68:621–641
- Brunel C, Levinson A (2022) Globalization and greenhouse gas emissions: is the United States a pollution haven?, Edward Elgar Publishing
- De Loecker J, Eeckhout J (2021) Global Market Power. Working Paper
- DeStatis (2011) Güterverzeichnis für Produktionsstatistiken (GP 2009). Further information: <https://www.destatis.de/DE/Methoden/Klassifikationen/Gueter-Wirtschaftsklassifikationen/klassifikation-gp-19.html>.
- DeStatis (2018) Erzeugerpreisindex gewerblicher Produkte. Further information: <https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Erzeugerpreisindex-gewerbliche-Produkte-inhalt.html>
- Ederington J, Levinson A, Minier J (2004) Trade liberalization and pollution havens. *B.E. J Econ Anal Policy* 4(2)
- EEA (2015). Application of the EU Emissions Trading Directive - Analysis of national responses under Article 21 of the EU ETS Directive in 2014. *EEA Technical Report No. 3*
- EEA (2016) Application of the EU Emissions Trading Directive—analysis of national responses under Article 21 of the EU ETS Directive in 2015. *EEA Report No. 6*
- EEA (2017) Application of the EU Emissions Trading Directive—analysis of national responses under Article 21 of the EU ETS Directive in 2016. *EEA Report No. 4*
- Eurostat (2023). EU trade 1988–2022 by CPA 2008 (DS-057009). Available at <https://ec.europa.eu/eurostat/databrowser/> (accessed on 25 May 2023)
- Flues F, Lutz BJ (2015) The effect of electricity taxation on the German manufacturing sector: a regression discontinuity approach. *ZEW discussion papers No. 15-013*
- Forslid R, Okubo T, Ulltveit-Moe KH (2018) Why are firms that export cleaner? International trade, abatement, and environmental emissions. *J Environ Econ Manag* 91:166–183
- Foster L, Haltiwanger J, Syverson C (2008) Reallocation, firm turnover, and efficiency: selection on productivity or profitability? *Am Econ Rev* 98(1):394–425
- Gerster A, Lamp S (2020) Energy tax exemptions and industrial production. Working Paper
- Hintermann B, Zarkovic M, di Maria C, Wagner U (2020) The effect of climate policy on productivity and cost pass-through in the German manufacturing sector. *CRC TR224 Discussion Paper No. 249*
- IPCC (2014) Climate change 2014: mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change
- Kube R, Petrick S (2019) Cleaner production or structural change? A breakdown of CO₂ emissions reductions in the German manufacturing sector using firm-level data. Unpublished working paper
- Lehr J, Gerster A, Pieper S, Wagner U (2020) The impact of carbon trading on industry: evidence from German manufacturing firms. mimeo
- Levinson A (2009) Technology, international trade, and pollution from US manufacturing. *Am Econ Rev* 99(5):2177–2192
- Levinson A (2015) A direct estimate of the technique effect: changes in the pollution intensity of US manufacturing, 1900–2008. *J Assoc Environ Resour Econ* 2(1):43–56
- Levinson A (2021). Energy intensity: Deindustrialization, composition, prices, and policies in U.S. states. *Resour Energy Econ* 65
- Lutz BJ (2016) Emissions trading and productivity: firm-level evidence from German manufacturing. *ZEW Discussion Paper*, 16-067
- Lyubich E, Shapiro JS, Walker R (2018) Regulating mismeasured pollution: implications of firm heterogeneity for environmental policy. *AEA Papers and Proceedings* 108:136–142
- Najjar N, Cherniwchan J (2021) Environmental regulations and the clean-up of manufacturing: plant-level evidence. *Rev Econ Stat* 103(3):476–491
- Petrick S (2013) Carbon efficiency, technology, and the role of innovation patterns: evidence from German plant-level microdata. *Kiel Working Papers* 1833
- Rodrigue J, Sheng D, Tan Y (2022) The curious case of the missing Chinese emissions. *J Assoc Environ Resour Econ* 9(4):755–805
- Shapiro JS, Walker R (2018) Why Is pollution from US manufacturing declining? The roles of environmental regulation, productivity, and trade. *Am Econ Rev* 108(12):3814–3854
- Umweltbundesamt (2008) Bestimmung spezifischer Treibhausgas-Emissionsfaktoren für Fernwärme. *Climate Change*. 08/08

- Umweltbundesamt (2019a) Aktualisierung der Emissionsfaktoren für Großfeuerungsanlagen. *Texte*, 140/2019, further information (only available in German): <https://www.umweltbundesamt.de/publikationen/aktualisierung-emissionsfaktoren-grossfeuerungsanlagen>
- Umweltbundesamt (2019b) Reform und Harmonisierung der unternehmensbezogenen Ausnahmeregelungen im Energiebereich. *Texte*, 23/2019, further information (only available in German): <https://www.umweltbundesamt.de/publikationen/reform-harmonisierung-der-unternehmensbezogenen>
- Umweltbundesamt (2020a) Carbon Dioxide Emissions for the German Atmospheric Emission Reporting 1900–2018
- Umweltbundesamt (2020b) Entwicklung der spezifischen Kohlendioxid-Emissionen des deutschen Strommix in den Jahren 1990–2019. *Climate Change*, 13/2020, further information (only available in German): <https://www.umweltbundesamt.de/publikationen/entwicklung-der-spezifischen-kohlendioxid-2>
- von Graevenitz K, Rottner E (2022) Do manufacturing plants respond to exogenous changes in electricity prices? Evidence from administrative micro-data. *ZEW Discussion Paper*, 22-038
- von Graevenitz K, Rottner E (2023) Energy Use Patterns in German Manufacturing from 2003 to 2017. *Jahrbücher für Nationalökonomie und Statistik* 243(3–4):319–354
- von Graevenitz K, Rottner E, Richter P (2023) Is Germany becoming the European Pollution Haven? *ZEW Discussion Paper*, 23–069

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.