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DISCUSSION PAPER

// ELISA ROTTNER AND KATHRINE VON GRAEVENITZ

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

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

Elisa Rottner*and Kathrine von Graevenitz†

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Abstract

Drastic emission reductions are necessary to combat climate change. However, despite several climate policies, carbon emissions from German manufacturing have actually increased between 2005 and 2017. In this paper, we provide evidence of how the policy mix overall has affected the German manufacturing sector in its entirety. Using detailed administrative micro-data at the product-level, we decompose changes in carbon emissions between 2005 and 2017 into scale, composition (changes in the mix of goods produced) and technology (emission factors of production) effects. We find that much of the increase in carbon emissions is due to an increase in manufacturing's production scale. Relative to the strong output growth, our analysis reveals a clean-up of manufacturing of 9 %. This clean-up is exclusively due to a shift towards a cleaner product composition from 2011 onwards, while production technique has mostly become dirtier. The results display substantial sectoral heterogeneity and are largely driven by the most energy and emission intensive sectors.

Keywords: Carbon emissions, Climate Policy, Statistical Decomposition, Manufacturing

JEL-Classification: D22, L60, Q41, Q48

*ZEW – Leibniz Centre for European Economic Research and University of Basel, P.O. Box 10 34 43, 68034 Mannheim, Germany, Email: rottner@zew.de.

†ZEW – Leibniz Centre for European Economic Research and University of Mannheim, P.O. Box 10 34 43, 68034 Mannheim, Germany, Email: vongraevenitz@zew.de.

1 Introduction

Drastic reductions of greenhouse gas emissions are necessary to limit global warming to below two degrees celsius. This concerns also the industrial sector, which in 2010, accounted for more than 30 % of greenhouse gas emissions globally, exceeding the respective shares of transportation and buildings (IPCC, 2014). However, climate policies to reduce emissions from industry are still not in place in many countries. A rich and growing literature studies the challenges associated with incomplete climate regulation across and within countries (cf. Fowlie, 2009, Caron *et al.*, 2015). Similarly, a strong literature on the causal effects of individual climate policies has emerged over recent years (cf. Germeshausen, 2020, Martin *et al.*, 2014, Martin *et al.*, 2016). In this paper we pose a different question, and examine the overall impact of policies in place in a relatively stringently regulated developed economy. Even in countries where such policies are implemented and are comparatively strict, a reduction in emissions has not necessarily materialized: In Germany, carbon emissions from manufacturing have increased in recent years and were about 32 million tonnes higher in 2017 than in 2003. Being a highly developed economy with comparatively stringent climate policies per se does not seem to guarantee a decrease in industrial carbon emissions, though emissions may be lower than they would have been in the absence of regulation. Nevertheless, the lack of progress in absolute terms is worrying, especially if Germany is to serve as a blueprint for decarbonization without deindustrialisation in other countries. The manufacturing sector in Germany remains economically important: it employed 20 % of the German workforce, accounted for 25 % of GDP, and emitted 23 % of the country's carbon dioxide emissions in 2018.

What drives this development in the German manufacturing sector? Answering this question is crucial to determine appropriate countermeasures. The increase in carbon emissions is accompanied by an increase in revenues of the average German manufacturing plant of 6.5 million Euro. This corresponds to an annual decline in emissions intensity of production of around 0.6 % on average. In other words, either German manufacturing is producing greener goods or the sector is producing the goods in a cleaner way using different production techniques. The way in which the reduction in emission intensities has been achieved matters. If changing product composition is due to outsourcing of dirtier products, the reduction in German carbon intensities has no positive effect on reducing the risk of climate change. Emission reductions due to technological improvements reducing energy intensity of production hold more promise as these might be exported to other countries and facilitate emission reductions there as well. If on the other hand, reduced emissions intensity of production has been achieved through fuel switching to less emissions intensive fuels, the potential for further reductions along this channel or for other countries to copy the strategy may be limited. We use detailed administrative micro-data and couple regression analysis with statistical decomposition methods to provide a comprehensive picture of the development of carbon emissions and carbon intensities in German manufacturing. Specifically, we disentangle the roles of production scale, production composition and production techniques for the development of carbon emissions as well as the roles of changing emission factors, fuel mixes and energy intensities for the development of carbon intensities.

Although total emissions increased, our decomposition anlaysis reveals a moderate clean up, which is relative to the strong growth in output. In 2017, emissions were 9 % lower than they would have been had product composition and production technique remained as in our base year 2005. This clean-up is exclusively due to a shift towards a cleaner product composition from 2011 onwards. In contrast, we find that production technique has mostly become dirtier, i.e., emission factors of production have increased. This is true even though emission factors of energy carriers have generally declined and fuel mixes have tended to become less carbon intensive. Hence, increasing emission intensities are a result of rising energy intensities which stands in stark contrast to the emphasis on and promotion of energy efficiency by policy makers (BMWi, 2014). These results are largely driven by the three very energy and emission intensive sectors of chemicals, coke, and other non-metallic mineral products, while fifteen less emission intensive sectors display clearly opposing patterns.

The paper contributes to the literature using decomposition tools to study emissions developments (e.g. Shapiro and Walker, 2018; Brunel, 2017; Levinson, 2009, 2015, 2021; Brunel and Levinson, 2021). One of the big issues with past research is that the decomposition is typically carried out at the sector level often comprising just a few hundred industries. As a result, within sector compositional changes may be classified as technique effects leading to overestimation of the technique effect and a corresponding underestimation of the composition effect, which we show empirically. This is problematic given the interest in identifying potential offshoring of emission intensive production. We conduct the decomposition at an exceptionally granular level. By distinguishing between more than 4,600 products our analysis exceeds even the granularity of the study by Shapiro and Walker (2018) who distinguish between roughly 1,400 products. We find large and negative composition effects in contrast to previous studies for the US and Europe focusing on emissions of local pollutants.

Our data also allows us to examine interactions between technique, scale and composition in determining emissions performance. Specifically, in previous analyses limited data on emission intensities have often led researchers to estimate the technique effect as a residual implicitly attributing all potential interactions to the technique effect. We are able to calculate both the technique and the composition effect directly. This allows us to compare the directly calculated effect with the effect determined as a residual to examine whether interaction effects are large enough to change conclusions about the sign of the effect. We find that the technique effect is always smaller when estimated as a residual. In other words, interaction effects reduce emission intensities. Further analyses suggest that industries with faster falling or more slowly increasing emissions intensities tend to grow at a faster rate in the period under study.

Evidence on emissions decomposition for Germany is scarce.[1] Our study is the first decomposition using the approach in Levinson (2015) for Germany. Our paper complements the literature on the relationship between climate policies and energy demand as well as firm-performance in Germany (e.g. Flues and Lutz, 2015; Gerster and Lamp, 2020; Hintermann *et al.*, 2020; Lehr *et al.*, 2020). While this literature has focused on identifying causal links of specific policies on specific subsets of firms by exploiting quasi-natural experiments, these papers could be missing the big picture with their strong focus on individual policies. We, in contrast, provide evidence on the overall effect of the policy mix on the manufacturing sector in its entirety. Compared to past research based on the German manufacturing census, a further contribution of this paper is a novel method to correct fuel consumption in the data for the occurrence of conversion losses. Conversion losses occur in the process of fuel combustion. Energy consumption numbers in

[1] Petrick (2013); Kube and Petrick (2019) are the only previous analyses based on detailed micro data. They conduct their analyses at the firm-level using the Logarithmic Mean Divisia Index and do no take the effects of product mix changes within firms into account.

the German manufacturing census are stated "gross", i.e. before conversion losses. The magnitude of these losses are larger for electricity as compared to heat generation. As onsite generation has become increasingly important in the last 15 years, failure to adjust for conversion losses would make the manufacturing sector appear more energy intensive than it actually is. Our result of an increasing energy intensity of production is even more notable considering that we take conversion losses properly into account.

The remainder of this paper is structured as follows: Section 2 presents the data used in the analysis and discusses first evidence on the development of carbon emissions and carbon intensities in the German manufacturing sector. Section 3 reports the statistical decomposition of carbon emissions, while in Section 4, we shed light on the development of carbon intensities. Section 5 deals with sectoral heterogeneity. Finally, Section 6 concludes.

2 Data and first evidence

2.1 Data

We conduct our analysis using the official plant-level micro-data from the federal statistical offices of the Bund and the Länder. For all manufacturing plants in Germany with more than 20 employees, participation in the survey panels we use in this analysis is mandatory. We have data available from 2003 to 2017. However, we conduct our decomposition only with data from 2005 onwards. We do so because reporting requirements for energy statistics were changed in 2003, which could lead to reporting errors in the first years of the new survey.[2]

Our analysis requires information on manufacturing's aggregate emissions, total output, each manufacturing subsector's output share, each subsector's emission intensity and each subsectors's energy consumption. The German manufacturing census does not contain any information on carbon emissions. Therefore, 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

[2]Consultations with staff from the Statistical Offices lead to the conclusion that energy consumption data are significantly more reliable from 2005 onwards than in the preceding years.

but time-varying.[3] The emission factor for electricity reflects the German electricity mix as well as transmission losses. Aggregate emissions are calculated by summing up the plant-level emissions. In the analysis, we abstract from analysing process emissions due to data limitations.

An additional issue arises with the information on energy use at the plant level. Note that fuel consumption in our data is stated in terms of the fuel's complete energy content, while the usable energy content for a plant is lower due to conversion losses in the combustion process. To obtain a measure of fuel consumption that is comparable with electricity procurement (for which no conversion losses occur), we apply fuel-specific efficiency factors to downwardly correct fuel consumption numbers for the presence of conversion losses and analyse changes in energy intensity and fuel mix based on these corrected numbers.[4]

Aggregate output is calculated by summing up gross output of the products produced by each manufacturing plant.[5] We deflate gross output numbers using producer price indices (base year 2015) from Destatis (DeStatis, 2018).[6] Since the German manufacturing census contains information about the products manufacturing plants produce at the 9-digit product-level, we can calculate output shares from aggregate output at the 9-digit product-level. Figure 10 in the appendix shows an example of the breakdown

[3]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). However, Germany constitutes one electricity market and in general there is no way to determine which region has delivered electricity to individual plants.

[4]Failure to make this adjustment would overestimate energy intensity due to the fact that onsite industrial electricity generation has increased in the German manufacturing sector (von Graevenitz and Rottner, 2020). This increase has replaced a substantial share of electricity procurement. For more details on how we correct fuel numbers for the presence of conversion losses, see the description in Section 7 in the appendix.

[5]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 not available for the universe of manufacturing plants and only at the firm level.

[6]Where available, product-level gross output is deflated using price indices on the 9-digit product level. When no such fine-grained price indices are available, we use more aggregate deflators. In total, roughly 80% of gross output are deflated on the 9-digit level, 13% on the 6-digit level and the remaining 7% on the 4-digit level.

of a 2-digit sector to the 9-digit product-level for illustrative purposes. This data granularity allows us to fix production composition (and emission intensities) in our base year 2005 at the level of 4,672 different products. To the best of our knowledge, this exceeds the granularity of the existing decomposition studies and thereby improves the accuracy of the estimated composition and technique effects. Since for each manufacturing plant, emissions are defined only at the plant-level while output data are available at the product-level, calculating emission intensities at the product-level requires us to allocate plant-emissions to the different products. We do so based on revenue shares of the individual products.[7] For comparison with past work we also conduct the decomposition analysis on the 3-digit sector level, which also has the advantage that plant-level emissions need not be allocated onto different products.

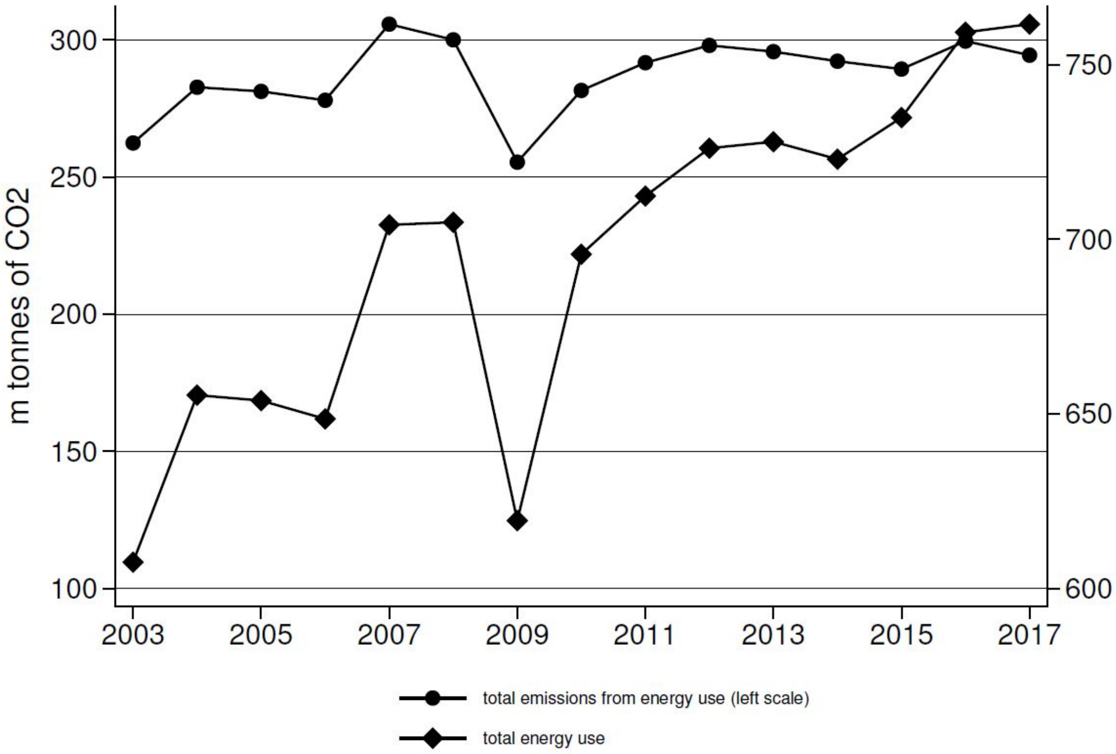
2.2 First evidence: Carbon emissions and carbon intensities in the German manufacturing sector

Figure 1 shows the development of aggregate energy consumption and carbon emissions in the German manufacturing sector between 2003 and 2017. Both measures increased between 2003 and 2017. In 2017, energy consumption was around 154 TWh higher than in 2003 and carbon emissions rose by roughly 32 mio. tonnes.

These increases in energy consumption and carbon emissions go alongside with an increase in output: As shown in Figure 2, manufacturing plants' average sales increased by around 6.5 mio. Euro between 2003 and 2017.

At the same time, manufacturing plants' average carbon intensity has decreased, as shown in Figure 3. Running plant-level regressions of log carbon intensity on a linear time trend and plant fixed-effects reveals that on average, manufacturing plants' carbon intensity decreased each year by a statistically significant 0.6%. Regression results are reported in Table 1. Columns 3 and 5 of the table show that within plant, both energy

[7] The relevant procedure is described in Section 7 in the appendix. Note that by using revenue shares to allocate plant-level emissions onto the products, we implicitly assume that all products within a firm are produced with the same emission intensity. 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. For robustness, therefore, we also conduct the product-level analysis based on single-product plants only.



Source: DOI 10.21242/43531.2017.00.03.1.1.0. Own calculations.

Figure 1: The development of energy consumption and carbon emissions in the German manufacturing sector

and electricity intensity on average increased significantly each year. The decline in carbon intensity is due to declining emission factors for electricity and fuel switching to less carbon intensive fuels (von Graevenitz and Rottner, 2020).

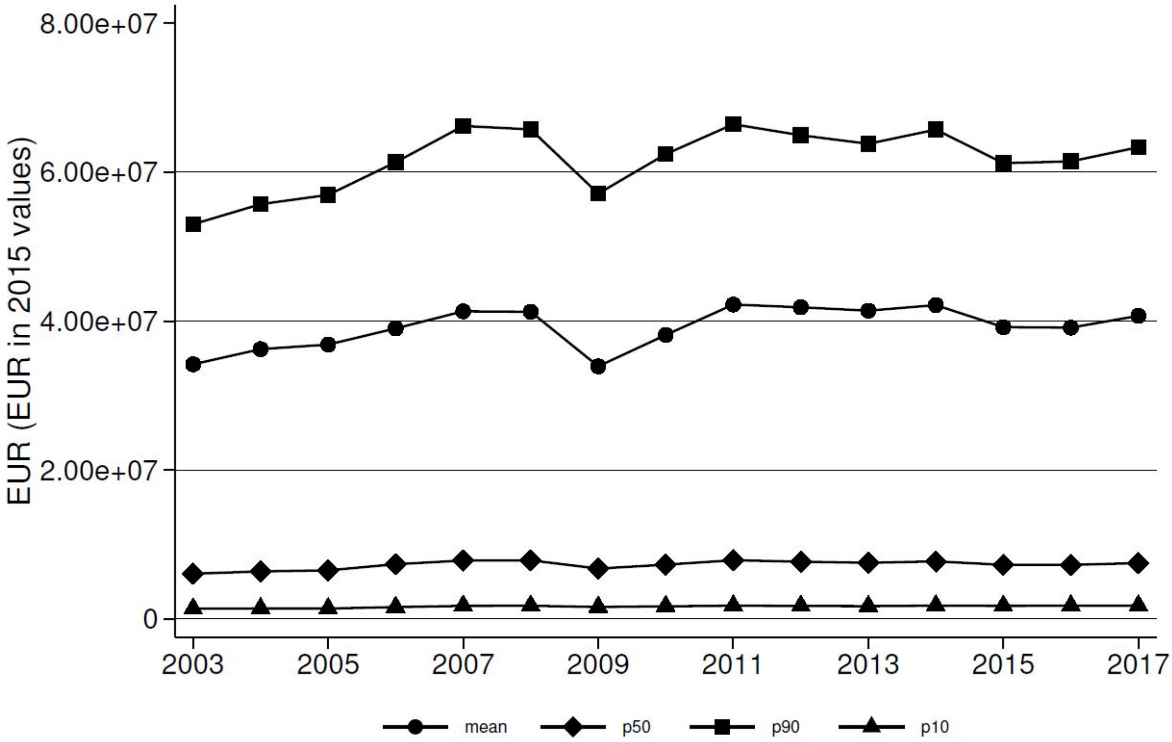
Table 1: The development of carbon, energy and electricity intensity

	Carbon intensity (1)	**Carbon intensity** (2)	**Energy intensity** (3)	**Energy intensity** (4)	**Electricity intensity** (5)	**Electricity intensity** (6)
year	-0.006***	-0.015***	0.002***	-0.008***	0.003***	-0.004***
	(0.0003)	(0.0005)	(0.0003)	(0.0005)	(0.0003)	(0.0005)
Plant FE	YES	NO	YES	NO	YES	NO
N	569,643	569,643	569,643	569,643	569,643	569,643
N_{groups}	62,120	-	62,120	-	62,120	-
R^2	0.003	0.003	0.001	0.001	0.000	0.000

Notes: The regressions include observations from 2003–2017. The dependent variable is the logarithm of carbon intensity (columns (1) and (2)), energy intensity (columns (3) and (4)) or electricity intensity (columns (5) and (6)). Standard errors are clustered at the plant level. p-values are in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

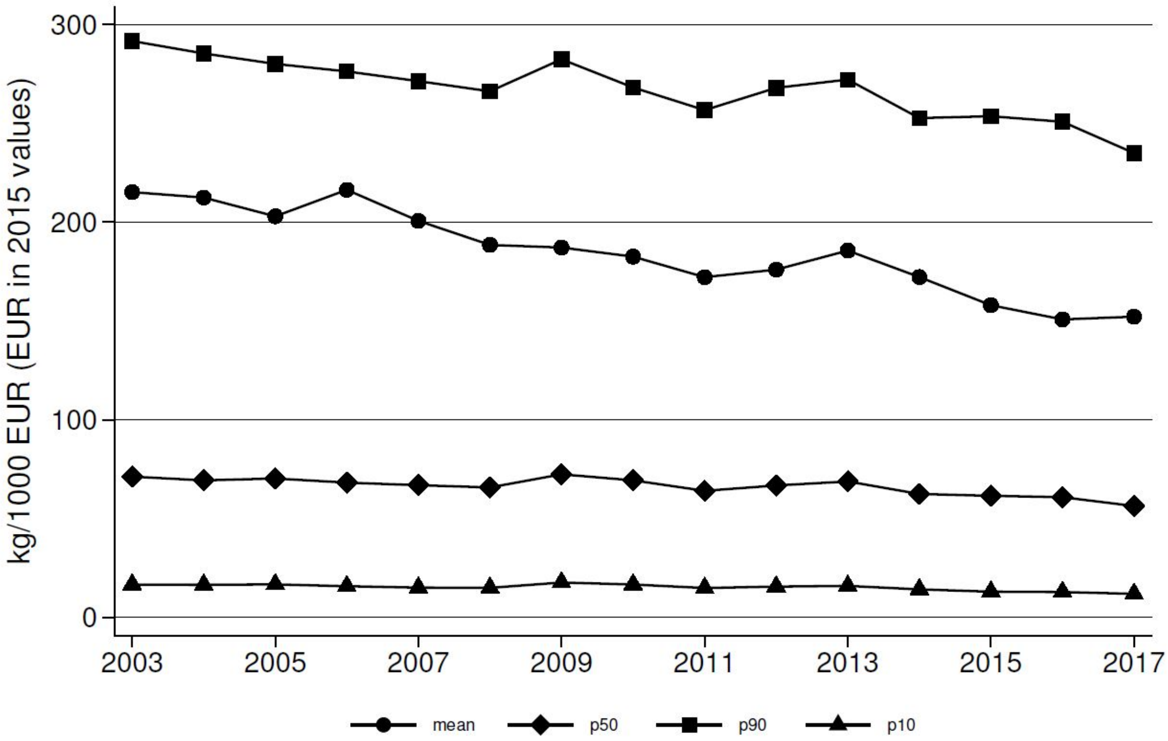
This descriptive evidence suggests that growing output had an emission-increasing effect in the German manufacturing sector. While this result follows straightforwardly from Figure 2, the decrease in the emission intensities shown in Figure 3 and Table 1 could be rooted in different factors. First, decreasing emission intensities could result from increasing production scales if there are increasing returns to scale. Second, emission intensities would also decrease if manufacturing plants switched from producing relatively carbon intensive goods towards goods that are less carbon intensive. Lastly, also a technology improvement, i.e. a decrease in the amount of emissions required to produce one unit of a given product, would lead to the patterns shown above.

The contribution of each of these channels is of crucial interest to policy-makers. From a global perspective, a cleanup in one country resulting from a change in the production composition might not lead to a reduction of global emissions, if the production of polluting goods is simply shifted abroad. In this sense, emission reductions resulting from declining emission intensities of production are only effective in reducing the threat of climate change when they are not due to outsourcing of CO2-intensive intermediate products. Moreover, different channels for emission reduction have varying potential: For instance, while fuel switching can contribute to decreasing emission intensities, at some



Source: DOI: 10.21242/42111.2017.00.01.1.1.0. Information on price deflators are taken from DeStatis (2018).

Figure 2: The development of sales of German manufacturing plants



Source: DOI 10.21242/43531.2017.00.03.1.1.0 and 10.21242/42111.2017.00.01.1.1.0. Own calculations. Information on price deflators are taken from DeStatis (2018).

Figure 3: The development of emission intensity of German manufacturing plants

point this potential might be exhausted (e.g. once all manufacturing plants switched from burning coal to using renewable energy sources and gas). However, industry is not the only sector that needs to decarbonize and the limited supply of renewable energy sources and related fuels such as green hydrogen is going to be needed in other sectors as well. For this reason, technological change improving energy efficiency of production will be necessary to achieve the long term goals of decarbonization. Improving energy efficiency is a declared policy goal both nationally and at the EU level with specific targets to be achieved by 2030, 2045 and 2050.

To disentangle the channels through which both carbon emissions and carbon intensities have changed in the German manufacturing sector, and to explain the patterns shown in this section, we conduct a statistical decomposition analysis. The decomposition of carbon emissions is discussed in the next section.

3 Decomposing carbon emissions in the German manufacturing sector

3.1 Statistical decomposition method

Decomposition tools are frequently used to disentangle the sources of emission changes. Levinson (2009, 2015, 2021) and Shapiro and Walker (2018) decompose the emission development of local pollutants in the US into scale, composition and technique components. Brunel (2017) investigates local pollutants in Europe, Najjar and Cherniwchan (2021) local pollutants in Canada.[8]

The statistical decomposition can be carried out at different levels of sectoral disaggregation. It is grounded on a representation of total emissions P_t of, in this case, CO_2 in the German manufacturing sector at a given point in time, 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 can be written as a function of aggregate output V_t of

[8] The analyses of Petrick (2013); Kube and Petrick (2019) decompose carbon emissions for Germany using a different approach based on the logarithmic mean divisia index.

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.

$$P_t = \sum_s p_{st} = \sum_s v_{st} z_{st} = V_t \sum_s \theta_{st} z_{st} \tag{1}$$

In vector notation, this is:

$$P_t = V_t \theta'_{\mathbf{t}} \mathbf{z_t} \tag{2}$$

where $\theta_{\mathbf{t}}$ and $\mathbf{z_t}$ are $S \times 1$ vectors containing the market shares and emission intensities of each of the S different industries.

This equation can be totally differentiated and divided by emissions to learn about emission changes, which yields (with time subscripts dropped for notational convenience):

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

The first term of the equation is the so-called scale effect. The scale effect is given by the change in aggregate output and thereby summarises how emissions would change if the production volume changed while holding both production composition and production technique constant. The second term constitutes the so-called composition effect which captures changes in emissions from changes in the sectoral composition of manufacturing for constant scale and emission intensities of sectors. Finally, the third term is the so-called technique effect that explains how emissions would change if emission intensities changed while production scale and composition were fixed.[9]

While this decomposition is straightforward on a conceptual level, several issues arise when taking the decomposition to the data: most importantly, this concerns the actual calculation of composition and technique effects and the level of sectoral disaggregation. For calculating composition and technique effects, researchers have resorted to two different approaches in which the identity shown in equation 3 is used to either calculate

[9]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. They propose an alternative method based on estimating production functions, markups and marginal costs following De Loecker *et al.* (2016). While their approach has many appealing features it also requires strong assumptions for the structural estimation of the relevant parameters.

technique or composition effect as a residual. One approach predicts total emissions holding emission intensities constant, but using actual composition and output values:

$$\hat{P}_t = V_t \sum_s \theta_{st} \bar{z}_s \tag{4}$$

The difference between these predicted emissions and the calculated scale effect yields the composition effect. Scale, composition and technique effect add up to the actually observed emission changes as demonstrated in equation 3. Based on this identity, the technique effect is determined as the residual once scale and composition have been subtracted from the actual observed emissions. If emissions would have been higher (lower) given scale and composition than they actually were, the technique effect is negative (positive). Note that this approach attributes all interactions that might arise between scale, composition and technique effect to the technique effect estimated as the residual.

Conversely, the technique effect could be calculated by predicting emissions under a constant production composition and taking the difference between these predicted emissions and the scale effect:

$$\hat{P}_t = V_t \sum_s \bar{\theta}_s z_{st} \tag{5}$$

For the sake of interpretation, the predicted technique effect can be divided by the calculated scale effect (– i.e. the development of aggregate output rescaled to the base year). This transformation yields a Laspeyre-like index which is equal to one in case emission intensities remain unchanged as compared to the base year. Falling or rising emission intensities in contrast lead to the index taking on values smaller or larger than one, respectively. The index is given by the following equation:[10]

$$T_L = \frac{\sum_s z_{st} v_{s0}}{\sum z_{s0} v_{s0}} = \sum_s \frac{z_{st}}{z_{s0}} * \frac{z_{s0} v_{s0}}{\sum_s z_{s0} v_{s0}} \equiv \sum_s \frac{z_{st}}{z_{s0}} * \mu_{s0} \tag{7}$$

[10]Similarly, the composition effect described above can be written as a Laspeyre-like index:

$$C_L = \frac{\sum_s \theta_{st} z_{s0}}{\sum_s \theta_{s0} z_{s0}} \tag{6}$$

where 0 indicates the base year to which emission intensity changes are compared.[11] Reformulating the estimated technique effect in this way makes some of the properties of the calculated effect better visible. Specifically, as in the well-known Laspeyre price index, 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 from total manufacturing emissions in the base year μ_{s0}.

After calculating the technique effect in this way, the composition effect can be estimated as a residual, meaning that all possible interactions between scale, composition and technique are attributed to the composition effect. As noted by Levinson (2009, 2015), differences between the results from these approaches can occur if any interactions between the different effects exist. He 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. While it is not obvious which channel these interactions should be attributed to, implicitly, the approach chosen determines to which channel the interactions are ascribed. In many studies, the choice of whether to calculate technique or composition directly is motivated by data availability. Our data however allow us to calculate composition and technique effect according to both approaches and thereby put bounds on the effects, depending on the share of interactions one is willing to attribute to each of these terms.[12]

[11] Note that in our analysis, we choose 2005 as a base year at which emission intensities or production composition are held constant even though in principle, we would have data available already from 2003 onwards. This is motivated by a change in the reporting structure in 2003 which might lead to reporting errors in the first years of the new survey. Results with 2003 as a base year are available from the authors upon request.

[12] This issue is related, but not identical to Levinson (2015)'s discussion of the index measurement. As noted above, our measure of the technique effect is a Laspeyre-style index, where the changes in emission intensities in each sector are weighted by the share of the sector's emissions from aggregate emissions in the base year (μ_{s0}). Alternatively, Levinson (2015) proposes to use a Paasche-like measure where the weights are given by current shares:

$$T_P = \frac{\sum_s z_{st} v_{st}}{\sum_s z_{s0} v_{st}} \tag{8}$$

Differences between Laspeyre- and Paasche-index therefore capture one interaction attributed to the term estimated as a residual, namely whether or not the manufacturing sector shifts towards or away

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. Broad sector-level data makes it possible to separate a composition effect from the technique effect. However, if products within the sectors differ in terms of their emission intensity, the 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 effect would carry out the decomposition at the level where each good 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. Whereas most decomposition studies so far use data on the industry-level, our data allow us to go down to the 9-digit product level, thereby enabling us to take a big step in clearly separating the effects.[13]

However, our ability to carry out a decomposition at such a fine-grained product level also raises a conceptual question about what we understand to be a technique. Specifically, by going down to the 9-digit product level, we rule out switching 9-digit products within narrowly defined industries as a technique-adjustment. Ultimately, the

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 Laspeyre- and Paasche-technique effects in the appendix. Generally, we find that sectors for which the difference between Laspeyre- and Paasche-index 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.

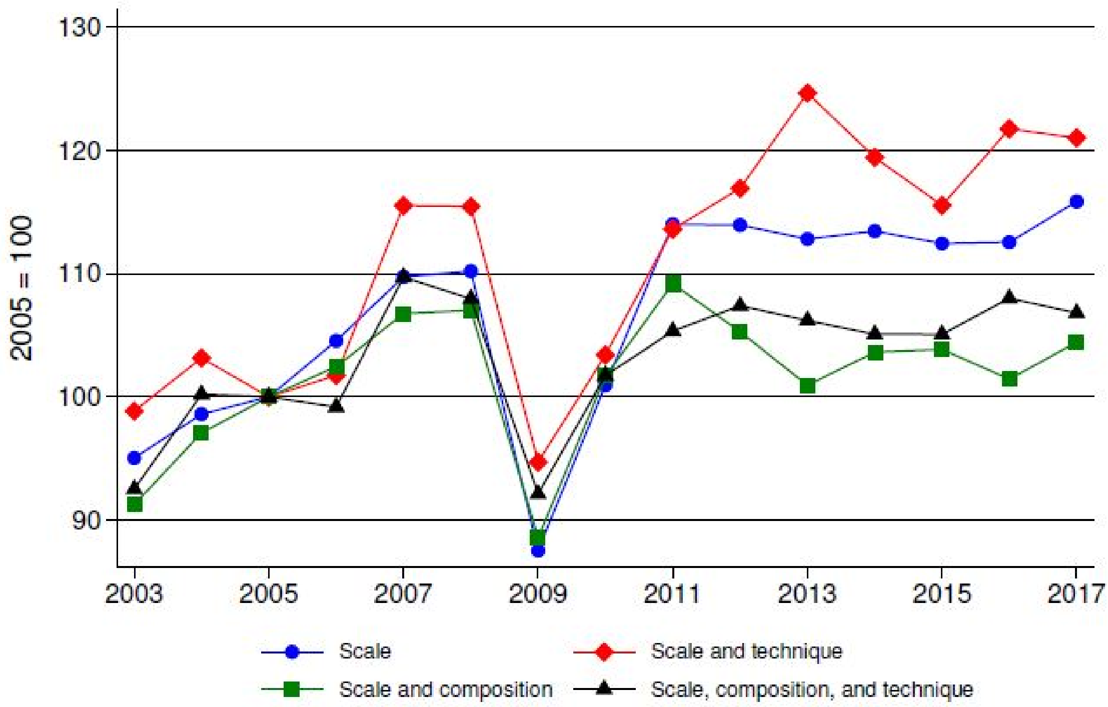
[13]Using data at the product level introduces a set of different challenges however. For instance, whereas only few sectors enter or exit manufacturing over the time period under study, we do have examples of products entering and exiting. As we have no baseline emission intensity for products that enter the data at a later stage, these products are excluded from the analysis. This concerns 294 products over the 13 year period.

issue relates to the question of whether a product is defined by its physical characteristics, or by its functional use. In our analysis, e.g., we treat butter and margarine, and even butter with differing fat content, as separate products for which we calculate separate technique effects. One might in contrast argue that those serve the same purpose (i.e. fat used as a spread or for baking) so that switching between them would also constitute a technique-adjustment. While using narrowly defined products at the 9-digit level serves well to capture technique adjustments of products as defined by the former definition, our estimated technique effect will not capture emission intensity changes of products as defined by the latter one. Adjusting the product portfolio has been identified as an important margin for adjustment in the face of rising electricity prices by Abeberese (2017). In our analysis such adjustments are reflected in the composition effect. We do not attempt to provide an answer as to which approach is more correct on a conceptual level, but being clear on the implications of our approach is important for interpretation.

3.2 Results: Decomposing carbon emissions in the German manufacturing sector

Figure 4 shows the results from the decomposition analysis on the 9-digit product-level for more than 4,600 products. For comparison, Figure 11 in the appendix shows the same analysis on the 3-digit sector-level which distinguishes between approximately 100 different sectors. Qualitatively, the results are similar; however, it is notable that both composition and technique effects take on larger magnitudes if the decomposition analysis is conducted at the 9-digit product-level. This suggests that there have been some within-sector composition shifts which cannot be accurately captured at the 3-digit sector-level.

Actual realized emissions are depicted in the line marked with the triangles and labeled "Scale, composition and technique". The line with the dots depicts the scale effect, i.e. it shows how emissions would have developed had only aggregate output followed its historical path while emission intensities and production composition had stayed constant since 2005. The line shows that in this scenario, by 2017, emissions would have increased by around 16% as compared to 2005. This finding is consistent with Figure 2, showing that manufacturing plants' average sales have been increasing over this time period. At the same time, actual emissions have increased by 6% implying a clean-up of manufacturing of 9%. The line marked with the squares shows the combined scale and



Source: DOI 10.21242/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations.

Figure 4: Decomposing carbon emissions in the German manufacturing sector

composition effect (obtained by holding 2005 emission intensities constant), the line with the diamonds the combined scale and technique effect (obtained by holding the 2005 production composition constant). Hence, the difference between the line with the squares and the one with the dots constitutes the directly estimated composition effect, while the difference between the line with the squares and the line depicting the actual emissions development (triangles) shows the technique effect when measured as the residual. Equivalently, the difference between the line marked by diamonds and the line with the dots constitutes the directly estimated technique effect, while the difference between the line with the diamonds and the one with the triangles shows the composition effect when measured as the residual. Figure 4 shows that the technique effect is always smaller when estimated as a residual, which, together with the comparison of Laspeyre- and Paasche index, indicates that industries with faster falling/more slowly growing carbon intensities grew at a faster rate.[14]

Qualitatively however, it makes little difference which of the approaches is chosen, indicating that interaction effects between scale, composition and technique are mostly too small to reverse the sign of the effects observed. That being said, 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 interaction terms 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. Moreover, comparing the sizes of the effects estimated with the different approaches, e.g. in 2013, reveals that interaction effects may sometimes reverse conclusions.

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, for which we find evidence both in the direct estimation as well as the indirect calculation of the effect at the 9-digit product- and the 3-digit sector-level, is solely responsible for the clean up of manufacturing. Table 4 in the appendix reports the corresponding Laspeyre- and Paasche-indices for this composition

[14]The corresponding Laspeyre- and Paasche-indices for the technique effect are reported in Table 5 in the appendix.

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 indeed associated with carbon leakage, i.e. the migration of the production of carbon-intensive products to countries exempt from stringent climate policies. Section 5 takes a closer look at the relation between imports and composition effect at the sector-level.

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, emission factors of production have mostly increased. This conclusion holds both for the direct and indirect estimates of the technique effect, both at the 9-digit product-level and at the 3-digit sector-level. The Laspeyre-type index for the technique effect (reported in Table 5 in the appendix) reveals that emission intensities increased by up to 11% (in 2013) as compared to 2005. Also in 2009, the technique effect is quite large, suggesting that in economic downturns, manufacturing plants may not be able to downwardly adjust energy consumption at the same pace as production.[15]

It is striking that the technique effect takes on clearly larger positive values and the composition effect larger negative values in the decomposition on the 9-digit product-level as compared to the decomposition on the 3-digit sector-level. This suggests that also within 3-digit sectors, there has been a shift towards the production of less carbon-intense products which is erroneously captured by the technique effect when the decomposition is conducted at the more aggregate level.

It also stands out that our results for both the technique and the composition effect directly oppose the ones obtained by Brunel (2017) for local pollutants in the EU between 1995 and 2008. This divergence could be rooted in the different study period, in the difference in coverage (e.g., because Germany behaves differently than other countries such that other EU members have compositional and technique changes in the opposite direction making up for the trends in Germany), or in the different pollutants analysed. Evidence from the US supports the latter explanation by showing that it is possible to

[15]Note that these results are not driven by manufacturing plants' entries and exits: Figures 12 and 15 in the appendix show that these patterns also hold in a balanced sample of manufacturing plants.

achieve strong emission reductions in local pollutants through both composition and technique effect (Levinson, 2015), while in the same time period displaying different patterns, and more specifically small positive composition effects, when it comes to decomposing carbon emissions (Brunel and Levinson, 2021).

The next section takes a closer look at the channels through which emission intensities increased as compared to 2005.

4 Explaining the development of carbon intensities in the German manufacturing sector

Carbon intensities in each sector depend on different factors: They are calculated by dividing sectoral emissions by sectoral gross output. Emissions in turn depend on the quantity of each fuel f consumed (q_{fst}) and the emission factor that applies to the different fuels (EF_{ft}). Therefore, as the following equation shows, carbon intensities are a function of energy intensity, fuel mixes (i.e., the share Θ_{fst} that each fuel has from total energy input e_{st}) and emission factors. The development of each of these factors could result in an increasing emission intensity.

$$z_{st} = \frac{p_{st}}{v_{st}} = \frac{\sum_f q_{fst} EF_{ft}}{v_{st}} = \frac{e_{st} \sum_f \Theta_{fst} EF_{ft}}{v_{st}} = \frac{e_{st}}{v_{st}} \sum_f \Theta_{fst} EF_{ft} \tag{9}$$

We investigate the sources of the rising emission factors of production by decomposing carbon intensities in a similar vein as total emissions in the last section: We compare the actual technique effect shown in the previous section with what the technique effect would have been, had either both fuel mixes and emission factors stayed constant at their 2005-levels or had only emission factors remained the same as in 2005. This allows us to back out the contribution of energy intensity changes, fuel mix changes and emission factor changes to the development of emission intensities.[16]

Figure 5 shows the results of this decomposition. Again, the line with the dots depicts the scale effect and the line with the diamonds the combined scale and technique effect, as reported in the last section. The remaining two lines show how emission intensities

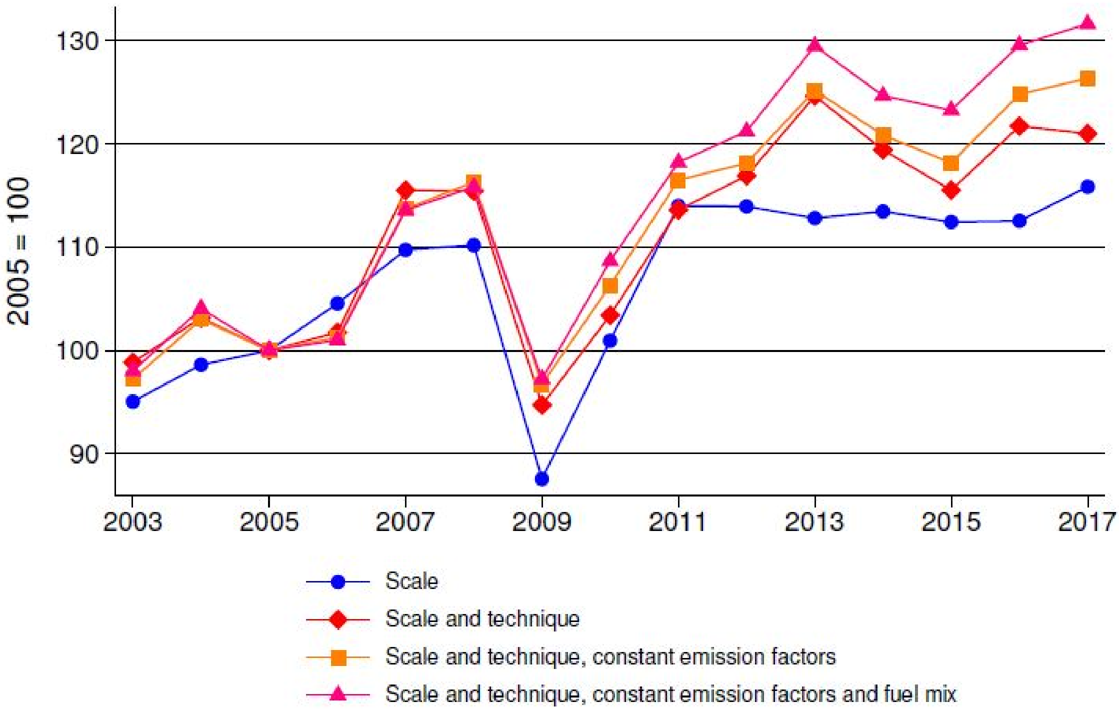
[16]To hold fuel mix constant, we divide each product's 2005-emissions by the 2005-energy input for that product to obtain an average emission factor applicable in 2005 which is then used to calculate emissions in the following years.

would have developed had either only emission factors or both emission factors and fuel mixes remained constant since 2005. As can be seen, the technique effect would have been more pronouncedly positive had the emission factors stayed the same as in 2005. This reflects the fact that the emission factor of electricity has declined for most of the observation period, while the other emission factors did not change much.[17] Hence, the greening of the German electricity mix with its increasing reliance on renewable energy sources contributed to decreasing emission intensities.

The figure also shows that fuel mixes in the German manufacturing sector became less carbon-intensive over the years, as compared to the base year 2005. This can be attributed to the increasing usage of natural gas in industry, while the relative importance of more carbon-intensive fuels like coal and oil is declining, as also documented by von Graevenitz and Rottner (2020). Thus, the technique effect would have been even more pronouncedly positive had fuel mixes stayed the same as in 2005. Therefore, the rising emission factors of production in the German manufacturing sector between 2005 and 2017 appear to be rooted in increasing energy intensities. The results mostly hold on the 3-digit sector level as well; however, at the sector level, the increases in energy intensity are much smaller suggesting that within sector changes in composition play a role.

The result of an increasing energy intensity in German manufacturing stands in stark contrast to both the emphasis that policy-makers put on promoting energy efficiency, and to the development in other countries. For the US, e.g., Levinson (2021) documents a declining trend in the energy intensity of manufacturing, albeit along a more extended time period between 1982 and 2007. He offers two potential explanations, namely policies and energy prices. Unlike Levinson we cannot make use of cross-sectional variation in energy prices and policies across states to test the extent to which these factors correlate with the rising energy intensity of production we observe. This increase in energy intensity in Germany is however consistent with the fact that the share of energy cost in total cost in German manufacturing has increased by 37 % on average between 2003 and 2014 (von Graevenitz and Rottner, 2020). Our analysis suggests that this rise in the energy cost

[17]While the nuclear phase-out in Germany anounced in 2011 did lead to a small increase in the coal share in the German electricity mix, this effect was counteracted by the rise in renewable energy sources, so that emission factors of electricity continued to decrease over the whole time period.



Source: DOI 10.21242/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations

Figure 5: Decomposing emission factors of production in the German manufacturing sector

share might not exclusively be due to a more stringent climate policy regime introduced over this period, but also simply be caused by an increase in energy intensity.

There are several potential channels through which energy intensities (and emission intensities) of production could increase: First, within-plant energy intensies might have increased. Second, the composition of plants producing a given product might have changed, e.g. because the plants producing the product in a relatively less energy intensive way close down or plants producing the good in a relatively energy intensive way open up. We already showed in Table 1 that within-plant energy intensities have indeed increased over time.[18] The impression that the results are driven by within-plant changes rather than plant entries and exits is also supported by the fact that the decomposition of emission intensities using a balanced sample of manufacturing plants (and hence shutting off the entry/exit channel) are qualitatively identical to those using the complete sample of manufacturing plants, as shown in Figure 15 in the appendix.

5 Sectoral heterogeneity in the development of emissions and emission intensities

All previous results were shown for the manufacturing sector as a whole and important sectoral heterogeneity was ignored. Equation 7 shows that the aggregate technique effect is a weighted average of the emission intensity changes of each product, where the weights are given by the share that each product had from total emissions in the base year 2005. Of course, a similar argument holds for the composition effect. This means that different products (and sectors) do not enter the calculation of the aggregate effects with equal importance. Figure 6 depicts the development of energy consumption in the German manufacturing sector, split according to 2-digit sectors. As can be seen, the top five energy-consumers among 2-digit sectors in German manufacturing – i.e. metal production, chemicals, coke and petroleum, other non-metallic mineral products and pulp and paper – together are responsible for more than 70% of manufacturing's energy use, while the remaining 19 2-digit sectors together account for less than 30%. Given

[18]Note that this is not due to the increase in electricity self-generation that we observe. Accounting for transmission losses, onsite generation generally is still less emission intensive than electricity procurement from the grid.

that energy consumption is the only source of emissions in our analysis, the aggregate technique effects shown in the last sections strongly depend on the development of energy intensities in those heavily energy consuming sectors.[19]

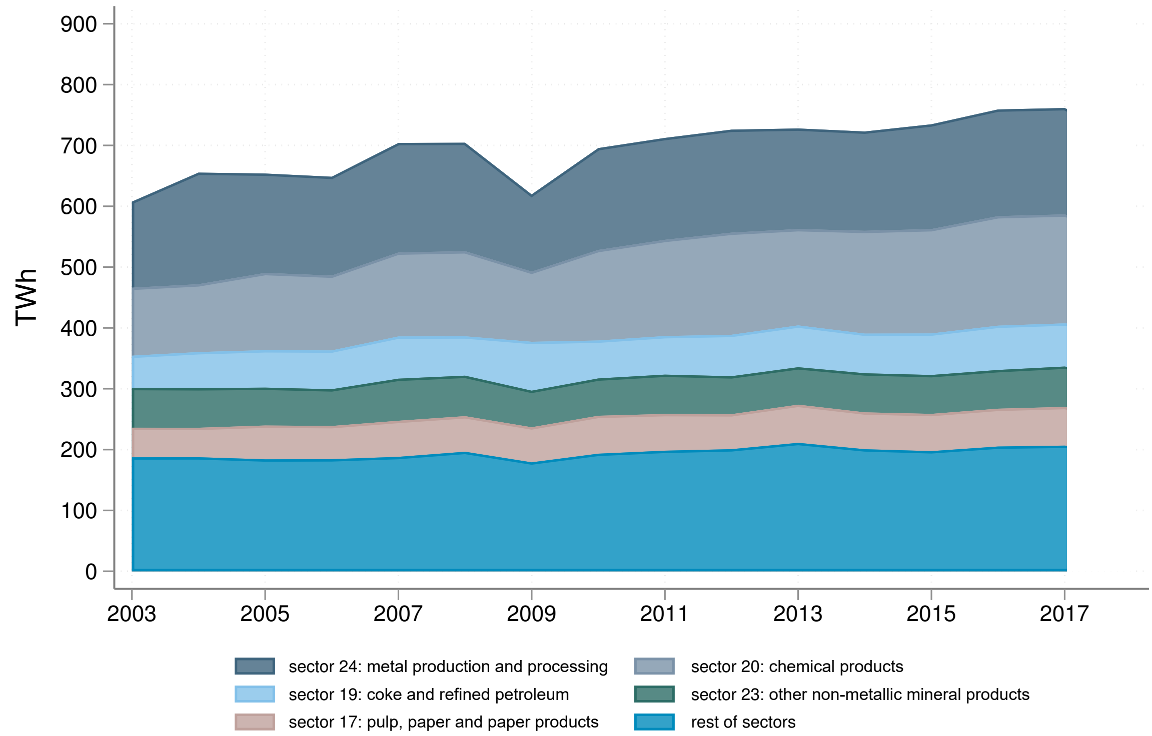
We show the vast heterogeneity of sectors by decomposing carbon emissions separately for each 2-digit sector. Figure 7 contrasts the results for the chemicals sector (NACE 20) and the electronics and computer sector (NACE 26), the former being a strongly energy-consuming sector and the latter being one of the least energy intensive sectors in German manufacturing. A comparison of the figures shows that patterns for the two sectors are completely opposed: In the chemicals sector, the production composition became significantly less carbon-intense over time, but a large increase in emission intensities (technique effect) can be observed. In the electronics and computer sector, the technique effect is negative throughout and the composition effect clearly positive.

Sectoral differences in both composition and technique effect for all sectors are visible in Figure 8 which contrasts the Laspeyre indices for the composition and the technique effect, respectively, for all two digit sectors. It is evident that sectoral heterogeneity in both sign and magnitude of technique and composition effects is large.[20] Note that a list of brief sector descriptions going alongside with the sector codes is available in Table 2

When it comes to the technique effect, the figure shows that 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).

[19] We are aware that there are also process emissions associated with manufacturing. However, as we have no data on these, we were not able to include them in the analysis. 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. This share might be larger in the industry sector. 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.

[20] The same can be seen from Tables 6 and 7 containing the Laspeyre-indices for technique and composition effects in the appendix.



Source: DOI 10.21242/43531.2017.00.03.1.1.0. Own calculations

Figure 6: Development of energy use split along 2-digit-sectors in German manufacturing

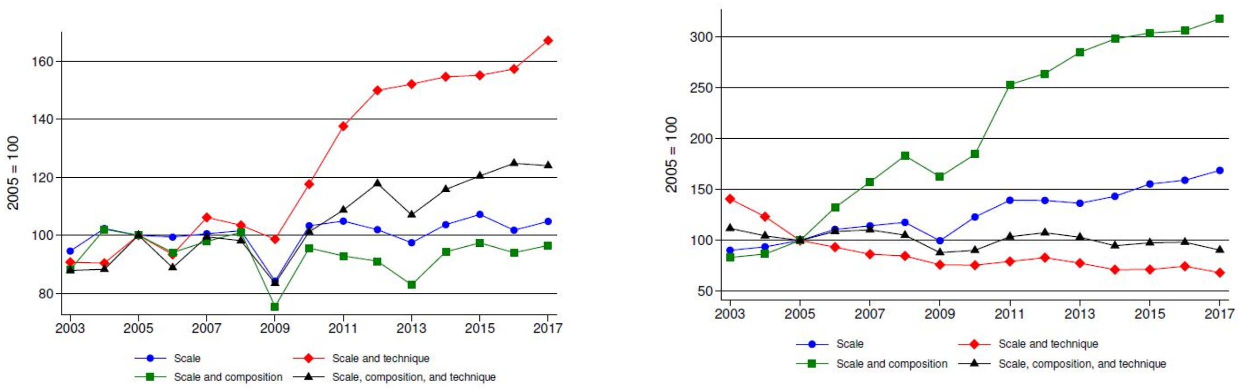


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Figure 7: Decomposition of carbon emissions for the chemical sector (left) and the computer and electronics sector (right)

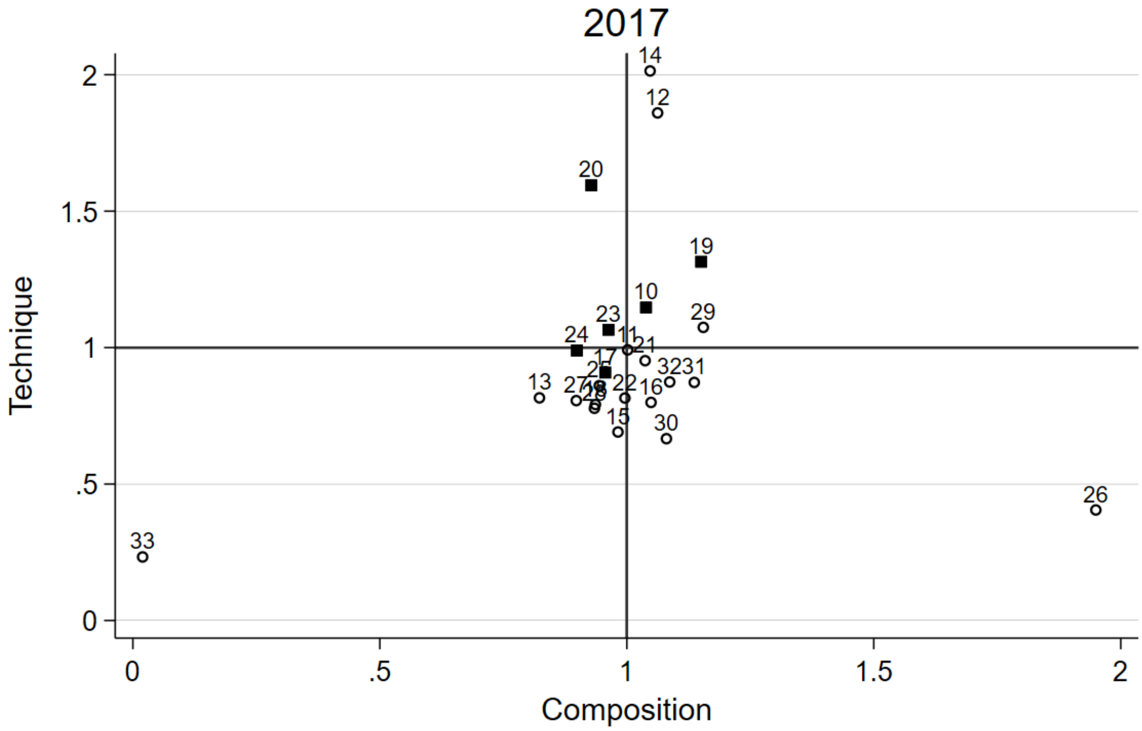

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Figure 8: Laspeyre indices for composition and technique effect in 2017 in different sectors

Notes: The figure displays a scatter plot of Laspeyre indices for technique and composition 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).

Table 2: 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

In parts, the differing effects might be grounded in climate policy exemptions that apply to different extents to manufacturing plants in the different sectors. Specifically, we find that the more energy-intensive sectors (highlighted by the black rectangles in the figure), in which more plants are likely subject to exemptions or other compensating measures with regard to existing climate policies, tend to display positive, i.e. emission increasing, technique effects. Exemptions from climate policies predominantely target energy-intensive plants and firms. This is meant to prevent a potential loss of competitiveness of German industry and related leakage effects. Exemptions from the Renewable Energy Levy, e.g., are granted for users exceeding certain thresholds of electricity procurement and of the ratio of electricity costs to gross value added. Similarly, manufacturing plants can benefit from paying reduced electricity network tariffs if they are large electricity users. Also, through the leakage list of the EU ETS, energy intensive and trade exposed sectors obtain a higher share of free allowances.[21]

Another source of variation in the technique effect between sectors could lie in differing competitive pressures. High degrees of competition allow only the most productive plants

[21] 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).

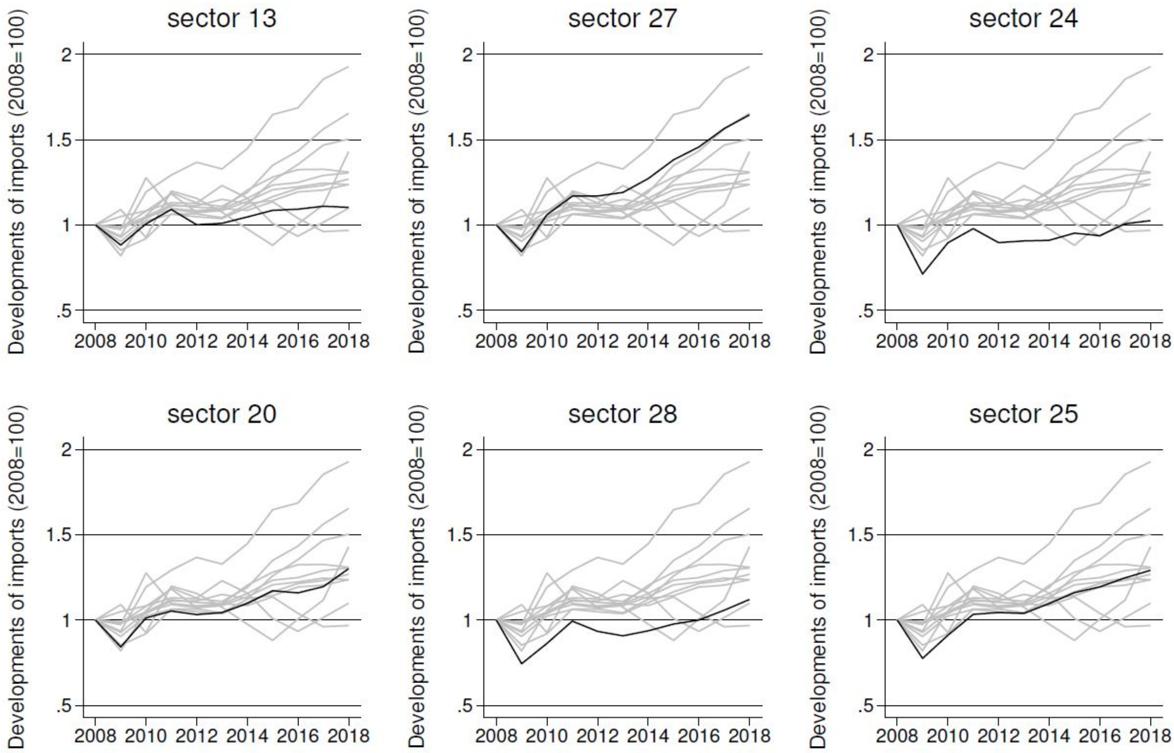
to enter and stay in the market. If the most productive plants are also the least emission intensive ones, as discussed e.g. in Forslid *et al.* (2018), we would expect the competitive pressure in an industry to be negatively related to the technique effect observed in that sector. We leave the empirical investigation of these issues for future work.

Heterogeneity is also large with regard to the composition effect. Some sectors (e.g., NACE 13: textiles, NACE 20: chemicals, or NACE 27: manufacture of electrical equipment) increasingly shift towards producing less carbon intensive goods, while for other sectors, the opposite is true (e.g., NACE 16: manufacture of wood and wood products, and NACE 26: manufacture of computer, electronic and optical products). 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).

The negative, i.e. emission decreasing, composition effects could be explained by the occurrence of 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. Figure 8 shows that indeed, some, but not all, of the most energy intensive sectors display neagtive composition effects (i.e. NACE 20: chemicals, NACE 24: metal production, NACE 23: other non-metallic mineral products, and NACE 17: pulp and paper). Supporting evidence for the occurrence of carbon leakage could be found if these sectors that display shifts towards a less carbon intensive production composition (those to the left of the vertical line in Figure 8) at the same time also increase their imports. For a first assessment of this concern, we combine the calculated composition effects at the 2-digit sector-level with import and export revenues from the Foreign Trade Statistics of the Federal Statistical Office (DeStatis, 2021). Trade statistics are available from 2008 onwards. Figure 9 compares the development of import revenues of those sectors experiencing the largest negative composition effects[22] (black line) with the developments of imports of the sectors in which the production composition shifts towards more carbon intensive goods (grey lines). No clear difference in trends is visible. While this does not preclude the presence of carbon leakage – carbon leakage could still be present if not the value, but rather the emission intensity of imports increased by

[22]While sector 33 (Repair and installation of machinery and equipment) is among the sectors with the largest negative compositional changes, we do not display results on this sector, as it is a very small sector for which no trade statistics are available.

more in the sectors with the negative composition effects as compared to those with positive composition effects –, at least this descriptive evidence does not provide compelling support for the carbon leakage hypothesis. This finding is also in line with the one by Naegele and Zaklan (2019) who do not find evidence for the EU ETS causing carbon leakage between 2005 and 2011.



Source: DOI 10.21242/43531.2017.00.03.1.1.0 and External Trade Statistics from the Federal Statistical Office (Code: 51000). Own calculations

Figure 9: Development of imports for sectors with a clean (black line) and sectors with a dirty composition shift (grey lines)

6 Conclusion

The introduction of several climate policies in Germany in the period between 2005 and 2017 combined with generous exemptions for the most energy-intensive and/or trade-exposed sectors has spurred debate about both their effectiveness and their potential to induce carbon leakage. In this paper, we provide descriptive evidence of how production scale, production composition, and production technique in the German manufacturing sector have evolved in this context of increased climate regulation.

Using rich administrative data, we show that carbon emissions in the German manufacturing sector have increased between 2005 and 2017, which can to a large part be attributed to an increase in production scale. However, 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, we find that the German manufacturing sector has shifted towards greener products. In contrast, emission intensities of production have mostly increased as compared to 2005. This is true although the increasing share of renewables in the German electricity mix and fuel switching in the manufacturing sector have contributed to decreasing emission intensities. Our findings suggest that these tendencies have been countered by increasing energy intensity. In our ancillary regressions we also find that within-plant energy intensity has increased in the period under study.

We carry out the decomposition at the 9-digit product level, which allows us to better differentiate between changes in product composition and production technique. In comparing our results with a decomposition at the more standard 3-digit sector level, we see that the cruder decomposition dampens the observed patterns: The clean-up resulting from changing product composition is smaller and the increase in emission intensity of production technique is also attenuated, though the conclusions above still hold.

Our findings are driven by developments in the most energy intensive sectors in German manufacturing. Among the less energy intensive sectors we find a more mixed pattern, with most of them improving their emission intensity of production. Due to concerns about competitiveness impacts of climate policy and related high energy cost, several policy exemptions for energy intensive industries apply in Germany. The extent to which these exemptions are related to the increase in energy intensity of production is a subject for future research directed at establishing causal effects. First steps in this direction have been made, e.g. in Gerster and Lamp (2020), who find that the exemption from the renewable energy surcharge causes a relative increase in electricity use among exempted plants.

The changing composition of production raises concern whether these patterns are due to outsourcing of more carbon intensive products and in that sense a symptom of leakage. Our preliminary analyses do not support this conclusion, but more research is required to rule out such concerns. The increase in energy intensity is concerning. While in principle fuel switching is an effective way of reducing emissions it is unlikely, that decarbonizing the economy will be possible within the coming 30 years without substantially improving energy efficiency of production. Renewable energy sources will be needed in multiple sectors and for production of e.g. green hydrogen to replace fossil fuels in industrial heat processes or transportation. Understanding why energy efficiency has improved so little in the past 15 years remains an important task for future research.

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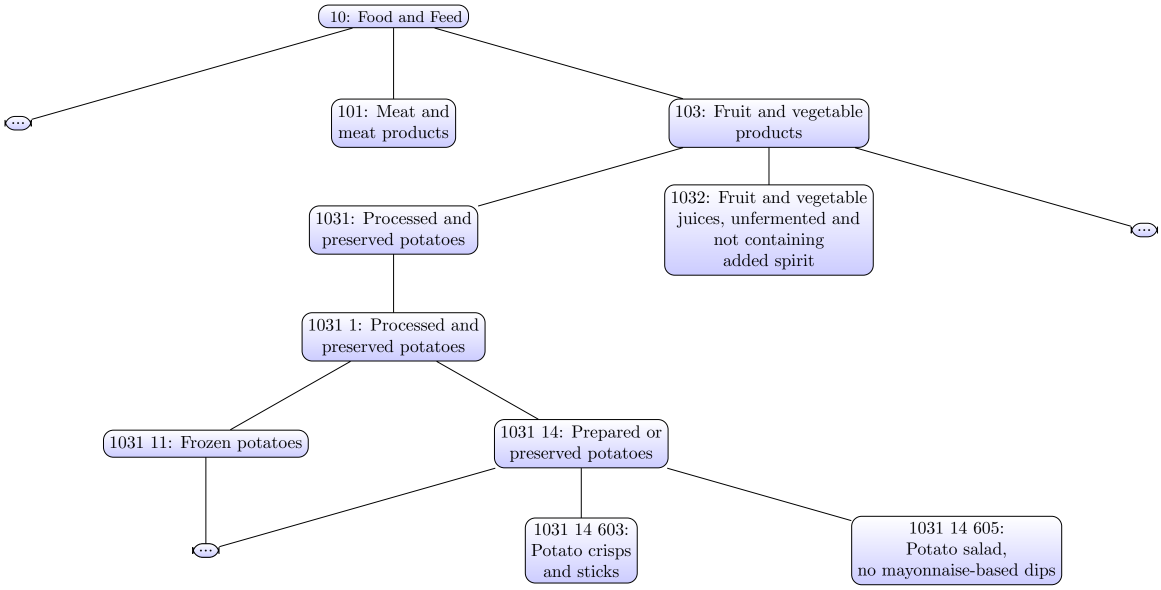
7 Appendix

Breakdown of 2-digit sectors to the 9-digit product level

For each 9-digit product and each year, we calculate emission intensities by dividing the sum of the emissions attributable to that product through the sum of deflated gross output of that product. Note that emissions are defined at the plant-level, while gross output can be precisely assigned to each product. Hence, only for plants producing a single product, the emissions of the plant are equivalent to the emissions of the product. Each year, around 41-45% of German manufacturing plants are single-product plants. For the remaining plants, we follow the procedure by Shapiro and Walker (2018) and allocate the plants' emissions onto the products according to output shares of the products from the plants' total gross output. Hence, implicitly we assume that a manufacturing plant produces all of its products with the same emission intensity. To alleviate concerns about this procedure, we conduct a robustness check using only information from the single-product plants. Results are reported in Figures 13 and 14. Reassuringly, also in this reduced sample, we find positive technique effects in a significant number of years, with particularly strong positive effects in the years 2009 and 2013, as in the full sample. Results from using single-product plants only also mimic the ones using all manufacturing plants in that energy intensities have mostly increased and thereby contributed to rising emission intensities, while fuel mix changes and the development of emission factors have counteracted this effect.[23]

[23] Note that the results seem somewhat more volatile than the ones from using all manufacturing plants which can be explained by the fact that approximately 11% of manufacturing plants switch between being a single- or a multiproduct plant in our observation period. Hence, there is a lot more movement in the sample with only singleproduct plants as compared to the complete sample which is why the estimated effects move less smoothly.



Source: Extracted from the goods catalogue of production statistics (DeStatis, 2011)

Figure 10: Industries, sectors and products

Fuel correction for administrative micro-data

Fuel consumption in the German manufacturing census is stated in terms of kWh and differentiated in energetic use (i.e. combusted) and non-energetic use (i.e. as a material input in the production process). These consumption numbers (for energetic use) amount to the "energy content" of the fuels, i.e. before the occurence of conversion losses in the combustion process. Using these numbers as a measure of energy consumption without applying any correction to them amounts to assuming that the manufacturing plants have a 100% efficiency in extracting the energy from the fuel, i.e. manage to extract all energy contained in the fuel without any losses. While this assumption is obviously implausible, it is also problematic because it is wrong to different extents for different fuels and electricity. Therefore, if one is interested in the final energy consumption of manufacturing plants (rather than the manufacturing plants' actual energy inputs), it is necessary to correct the fuel consumption for the occurrence of conversion losses.

For manufacturing plants not generating their own electricity and using fuels exclusively for heat production, we apply efficiency factors from the EU ("Harmonised efficiency reference values for separate production of electricity and heat") (EU, 2015) which separately present efficiency factors for converting fuels into heat and for converting them into electricity. The EU uses these efficiency reference values to identify highly efficient CHP-plants as CHP plants whose efficiency is significantly higher than the efficiency of comparable plants producing heat and electricity separately with identical fuels.

The breakdown in different fuels from this regulation 2015/2402 is not identical to the breakdown in the German manufacturing census. Table 3 shows the mapping between fuel categories in the administrative data and the EU factors we apply. If several efficiency factors fall into one category of the administrative data, we use simple arithmetic averages.[24]

Moreover, the EU regulation contains different emissions factors for heat production for hot water, steam and direct use of exhaust gases. Again, we make use of arithmetic averages of these three factors. Potential biases from this procedure should be small since the ordering of fuels remains intact in these three categories: If a fuel is more efficienct than another for hot water, it is generally also more efficient with regards to steam or exhaust gases.

For electricity self-generators, the issue is more complicated as the German manufacturing census does not distinguish between the share of fuels used for electricity production and the share used for heat production. Applying the efficiency factors for electricity production on all fuel consumption of self-generators will lead to a downward bias of self-generators' energy consumption as most likely, parts of self-generators' fuel consumption serves the purpose of heat production – for which efficiency factors are significantly higher, i.e. there are less conversion losses. Moreover, according to the *Survey of electricity producing units in manufacturing*, in 2018, around 96% of electricity self-generators in German manufacturing (with an electric bottleneck capacity of > 1 MW) made use of combined heat and power (CHP). In consequence, using electricity efficiency factors is inaccurate: CHP plants make use of the heat which is formed as a by-product of electricity generation which increases the efficiency of CHP plants as compared to the separate production of heat and electricity.

[24] For some fuels, the efficiency factors vary by year of construction of the installation. In case of heat production, this is the case for heavy fuel oil, bio liquids, waste liquids and biogas. Specifically, the factors differ if the installation has been built after 2016. We do not take this temporal variation into account as the administrative micro-data contain no information on the construction year of heating plants and electricity generation facilities. This should not lead to a big bias as the temporal variation in the efficiency factors is rather moderate.

Table 3: Mapping of fuel categories between EU (2015) and the German manufacturing census

Fuel in AFiD	**Fuel in EU (2015)**
natural gas	Natural gas, LPG, LNG and biomethane
light oil	Heavy fuel oil, gas/diesel oil, other oil products
hard coal	Hard coal including anthracite, bituminous coal, sub-bituminous coal, coke, semi-coke, pet coke
coke	Hard coal including anthracite, bituminous coal, sub-bituminous coal, coke, semi-coke, pet coke
raw lignite	lignite, lignite briquettes, shale oil
lignite briquettes	lignite, lignite briquettes, shale oil
heavy oil	Heavy fuel oil, gas/diesel oil, other oil products
other coal products	Hard coal including anthracite, bituminous coal, sub-bituminous coal, coke, semi-coke, pet coke;
	lignite, lignite briquettes, shale oil
liquid gas	natural gas, LPG, LNG and biomethane
other petroleum products	Heavy fuel oil, gas/diesel oil, other oil products;
	Hard coal including anthracite, bituminous coal, sub-bituminous coal, coke, semi-coke, pet coke;
	Refinery gases hydrogen and synthesis gas
renewables	Dry biomass including wood and other solid biomass including wood pellets and briquettes, dried
	woodchips, clean and dry waste wood, nut shells and olive and other stones;
	Other solid biomass including all wood not included under S4 and black and brown liquor;
	Bio-liquids including bio-methanol, bioethanol, bio-butanol, biodiesel and other bio-liquids;
	Biogas produced from anaerobic digestion, landfill, and sewage treatmetn
other gases	Refinery gases hydrogen and synthesis gas;
	Coke oven gas, blast furnace gas, mining gas, and other recovered gases (excluding refinery gas)
waste and others	Waste heat (including high temperature process exhaust gases, product from exothermic chemical reactions);
	Municipal and industrial waste (non-renewable) and renewable/bio- degradable waste

For self-generators, we therefore make use of the aforementioned *Survey of electricity producing units in manufacturing*. This survey contains information on the heat production, electricity production and the fuel input of installations with an electric bottleneck capacitify of more than 1 MW. We use this information to calculate average efficiency factors for electricity self-generators for four different fuels (coal, gas, oil and others) on the 2-digit sector level, by dividing the total energy generation of a fuel (i.e. heat production plus electricity production) in a 2-digit sector by the input of that fuel in that sector. This average efficiency factor reflects *both* the extent to which a sector uses a certain fuel for electricity versus heat production (if in a 2-digit sector a fuel is mostly used for electricity generation and less so for heat generation, the efficiency factor calculated this way will be lower reflecting the higher fuel input necessary to produce 1 kWh electricity than 1 kWh heat) *and* the prevalence of CHP in that sector for that fuel (if a sector does not make use of CHP at all for one particular fuel, the thus calculated average efficiency factor will be lower reflecting the higher fuel input necessary for the separate production of heat and electricity as compared to a combined production). This approach moreover has the advantage over weighting the electricity and heat efficiency factors of the EU in some way that it specifically reflects the German context in the manufacturing sector and not an EU average.

The EU efficiency factors for heat production and the calculated efficiency factors for electricity self-generators allow us to downwardly correct the fuel consumption numbers in the German manufacturing sector for the occurence of conversion losses on a fuel-specific basis.

Laspeyre and Paasche Indices

Table 4: Laspeyre and Paasche indices for the composition effect

Year	**Laspeyre**	**Paasche**	**Laspeyre**	**Paasche**
	9-digit	9-digit	3-digit	3-digit
2005	1	1	1	1
2006	0.980228	0.9751672	0.9976849	0.9972505
2007	0.9732357	0.950313	0.9719551	0.9673945
2008	0.9718257	0.9357771	0.9682478	0.956197
2009	1.01246	0.9737278	1.020659	1.012124
2010	1.008024	0.9845787	1.038043	1.027693
2011	0.958389	0.9279934	0.9780933	0.964179
2012	0.9251341	0.9196045	0.9571846	0.939608
2013	0.8958531	0.852989	0.9395387	0.9231052
2014	0.9141905	0.8806489	0.9488719	0.9305523
2015	0.927088	0.9128338	0.947798	0.9394875
2016	0.9056852	0.8915768	0.9240424	0.9131609
2017	0.9060092	0.8869469	0.9237183	0.908381

Source: Own calculations
The table shows the Laspeyre and Paasche indices for the composition effect calculated for the decomposition at the 9-digit product level (left) and the 3-digit sector level (right). Comparing the two shows, that the Paasche index is consistently smaller than the Laspeyre index indicating that industries with faster falling/more slowly growing carbon intensities grew at a faster rate. Moreover, the change in composition measured at the 3-digit level is smaller than at the more detailed 9-digit level.

Table 5: Laspeyre and Paasche indices for the technique effect

Year	**Laspeyre**	**Paasche**	**Laspeyre**	**Paasche**
	9-digit	9-digit	3-digit	3-digit
2005	1	1	1	1
2006	0.9731403	0.968116	0.9468003	0.9487606
2007	1.052598	1.027806	1.032359	1.027515
2008	1.047605	1.008746	1.018407	1.005732
2009	1.081799	1.040414	1.04182	1.033108
2010	1.024318	1.000494	0.9942686	0.9843548
2011	0.9964459	0.9648433	0.9711937	0.9573775
2012	1.025974	1.019842	1.016981	0.9983059
2013	1.10489	1.052024	1.032837	1.014772
2014	1.052639	1.014018	1.009323	0.9898364
2015	1.027436	1.011639	1.006439	0.9976141
2016	1.081609	1.06476	1.061815	1.049311
2017	1.044506	1.022529	1.025522	1.008494

Source: Own calculations The table shows the Laspeyre and Paasche indices for the technique effect calculated for the decomposition at the 9-digit product level (left) and the 3-digit sector level (right). Comparing the two shows, that the Paasche index is consistently smaller than the Laspeyre index indicating that industries with faster falling/more slowly growing carbon intensities grew at a faster rate. Moreover, the change in technique measured at the 3-digit level is smaller than at the more detailed 9-digit level.

Table 6: Laspeyre- and Paasche-indices of the technique effect for 2-digit sectors

Sector	Index	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
10: food	Laspeyre	1	1.012	1.002	1.055	1.027	1.027	1.009	1.046	1.289	1.217	1.160	1.172	1.147
	Paasche	1	0.995	0.991	0.986	0.975	0.956	0.923	0.967	1.031	1.002	0.948	0.966	0.939
11: beverages	Laspeyre	1	1.035	1.152	1.141	1.049	1.025	1.015	1.013	1.014	0.968	1.017	1.036	0.991
	Paasche	1	1.023	1.138	1.136	1.046	1.018	1.011	1.006	0.998	0.949	1.002	1.023	0.977
12: tobacco	Laspeyre	1	1.090	1.182	1.447	1.491	1.483	1.928	2.273	2.577	2.260	2.155	1.978	1.860
	Paasche	1	1.091	1.190	1.437	1.466	1.417	1.777	2.059	2.115	1.922	1.860	1.753	1.693
13: textiles	Laspeyre	1	1.003	1.012	0.998	1.079	0.978	0.957	1.006	1.105	1.033	0.898	0.881	0.816
	Paasche	1	0.988	1.004	0.964	1.043	1.083	1.041	1.122	1.174	0.988	1.038	1.019	0.895
14: wearing apparel	Laspeyre	1	1.028	1.126	1.296	1.384	1.626	1.730	1.782	1.891	1.788	1.766	2.152	2.014
	Paasche	1	0.949	0.956	1.010	1.063	1.036	0.968	0.958	0.987	0.933	0.876	0.836	0.813
15: leather	Laspeyre	1	0.951	0.839	0.822	0.892	0.680	0.619	0.683	0.720	0.635	0.658	0.690	0.691
	Paasche	1	1.004	0.820	0.815	0.882	0.730	0.652	0.706	0.738	0.630	0.669	0.698	0.741
16: wood	Laspeyre	1	0.998	0.989	0.959	1.031	1.029	0.979	1.001	1.137	0.929	0.849	0.843	0.799
	Paasche	1	0.995	0.985	0.952	1.011	0.996	0.928	0.914	1.029	0.910	0.847	0.842	0.805
17: pulp & paper	Laspeyre	1	0.982	1.011	0.983	1.046	0.913	0.899	0.918	1.009	0.952	0.915	0.942	0.909
	Paasche	1	0.985	1.006	0.974	1.041	0.902	0.901	0.913	1.002	0.949	0.926	0.939	0.895
18: printing	Laspeyre	1	0.985	0.991	0.922	0.905	0.883	0.838	0.870	0.923	0.844	0.825	0.834	0.791
	Paasche	1	0.980	0.989	0.924	0.904	0.888	0.866	0.891	0.945	0.861	0.829	0.828	0.785
19: coke	Laspeyre	1	1.043	1.209	1.233	1.364	1.010	1.095	1.038	1.070	1.134	1.095	1.232	1.315
	Paasche	1	1.044	1.139	1.066	1.250	0.861	0.901	0.870	0.910	0.970	0.893	1.047	1.094
20: chemicals	Laspeyre	1	0.940	1.056	1.018	1.172	1.139	1.312	1.471	1.561	1.491	1.447	1.546	1.595
	Paasche	1	0.944	1.016	0.971	1.106	1.058	1.170	1.294	1.290	1.228	1.237	1.328	1.285
21: pharmaceuticals	Laspeyre	1	1.036	0.981	1.053	1.124	1.283	1.196	1.027	1.150	0.983	1.011	1.076	0.952
	Paasche	1	1.053	1.002	1.051	1.041	1.159	1.124	1.019	1.024	0.880	0.954	0.990	0.907
22: rubber & plastics	Laspeyre	1	0.997	0.999	0.979	0.998	0.999	0.927	0.977	1.026	0.936	0.881	0.876	0.815
	Paasche	1	0.996	0.997	0.977	0.988	0.985	0.913	0.958	0.970	0.916	0.870	0.874	0.802
23: non-metallic minerals	Laspeyre	1	0.995	1.098	1.089	1.077	1.057	1.043	1.072	1.094	1.068	1.080	1.071	1.065
	Paasche	1	0.991	1.096	1.088	1.073	1.054	1.039	1.044	1.072	1.054	1.058	1.045	1.041
24: metal processing	Laspeyre	1	0.996	1.094	1.117	0.978	1.071	0.991	0.980	1.030	1.026	0.996	1.057	0.989
	Paasche	1	0.994	1.076	1.092	0.964	1.079	0.979	1.090	1.124	1.122	1.113	1.203	1.136
25: metal products	Laspeyre	1	0.985	0.990	0.971	1.154	1.032	0.950	1.015	1.046	0.978	0.928	0.917	0.861
	Paasche	1	0.981	0.974	0.958	1.134	1.022	0.933	0.991	1.026	0.950	0.969	0.958	0.890
26: computer	Laspeyre	1	0.843	0.756	0.720	0.763	0.615	0.569	0.597	0.569	0.498	0.460	0.469	0.405
	Paasche	1	0.822	0.702	0.574	0.542	0.489	0.410	0.408	0.363	0.318	0.322	0.321	0.285
27: electrical equipment	Laspeyre	1	0.960	1.028	0.950	1.091	0.952	1.030	1.140	1.693	0.901	0.881	1.014	0.806
	Paasche	1	0.950	1.025	0.928	1.023	0.918	0.997	1.055	1.308	0.887	0.866	0.873	0.781
28: machines	Laspeyre	1	0.959	0.901	0.886	1.020	0.952	0.855	0.867	0.904	0.848	0.908	0.836	0.778
	Paasche	1	0.947	0.884	0.862	1.079	1.049	0.945	0.966	1.011	0.961	0.975	0.933	0.869
29: motor vehicles	Laspeyre	1	0.977	0.959	0.955	1.133	0.992	0.834	0.874	0.880	0.733	1.058	1.156	1.074
	Paasche	1	0.970	0.950	0.942	1.054	0.937	0.797	0.827	0.839	0.704	0.847	0.895	0.847
30: other transport	Laspeyre	1	1.000	1.046	1.100	0.885	0.937	0.802	0.707	1.444	1.444	0.613	0.725	0.666
	Paasche	1	0.710	0.722	0.636	0.840	1.602	1.399	1.266	1.402	1.020	1.077	1.203	0.959
31: furniture	Laspeyre	1	0.958	1.076	1.352	4.295	0.922	1.153	1.153	1.278	0.866	0.845	0.837	0.872
	Paasche	1	0.949	1.071	1.403	1.053	0.946	0.983	0.926	1.003	0.868	0.855	0.849	0.800
32: other	Laspeyre	1	0.930	0.885	1.066	0.945	0.895	0.900	0.959	0.928	0.847	0.833	0.835	0.874
	Paasche	1	0.895	0.851	1.034	1.034	0.951	0.927	0.960	0.914	0.853	0.849	0.836	0.793
33: repair & installation	Laspeyre	1	0.502	0.397	0.463	0.756	0.382	0.262	0.289	0.236	0.265	0.264	0.324	0.233
	Paasche	1	0.525	0.491	0.578	0.333	15.55	12.16	8.405	9.028	10.46	15.21	12.67	13.15

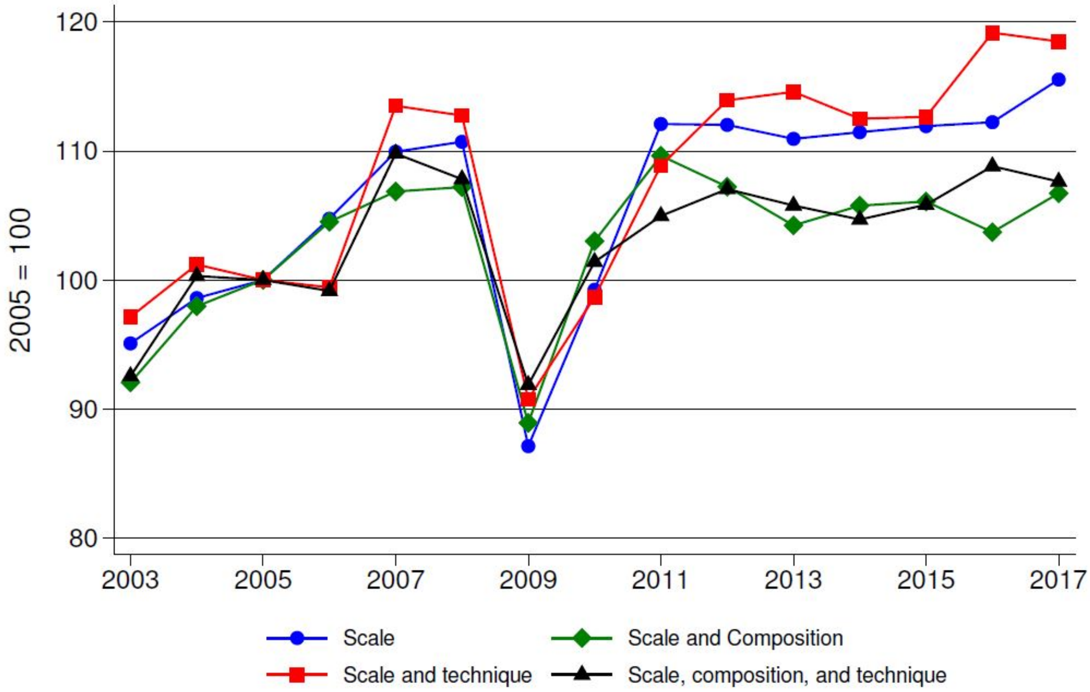
Source: Own calculations. Decomposition at the 9-digit product level.

Table 7: Laspeyre- and Paasche-indices of the composition effect for 2-digit sectors

Sector	**Index**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
10: food	Laspeyre	1	1.008	1.009	1.007	1.017	1.007	1.050	1.040	1.005	1.020	1.040	1.041	1.039
	Paasche	1	0.991	0.997	0.940	0.965	0.938	0.961	0.961	0.805	0.840	0.850	0.858	0.850
11: beverages	Laspeyre	1	0.994	0.994	0.985	0.997	0.954	0.934	0.955	0.953	0.965	0.998	1.002	1.002
	Paasche	1	0.983	0.981	0.980	0.994	0.948	0.930	0.948	0.937	0.946	0.983	0.990	0.987
12: tobacco	Laspeyre	1	1.001	1.016	1.020	1.018	1.042	1.045	1.048	1.072	1.071	1.066	1.064	1.062
	Paasche	1	1.002	1.023	1.012	1.001	0.995	0.963	0.949	0.880	0.911	0.919	0.943	0.967
13: textiles	Laspeyre	1	0.994	0.994	0.968	0.940	0.901	0.895	0.872	0.866	0.850	0.799	0.818	0.823
	Paasche	1	0.980	0.987	0.936	0.909	0.998	0.973	0.972	0.919	0.812	0.923	0.946	0.903
14: wearing apparel	Laspeyre	1	1.037	1.098	1.138	1.073	1.069	1.063	1.075	1.063	1.015	1.021	1.082	1.047
	Paasche	1	0.957	0.932	0.887	0.824	0.682	0.595	0.577	0.555	0.529	0.506	0.420	0.423
15: leather	Laspeyre	1	1.090	1.073	1.042	0.962	1.107	1.120	1.146	1.125	1.053	1.044	1.016	0.982
	Paasche	1	1.151	1.049	1.032	0.951	1.187	1.181	1.186	1.154	1.045	1.062	1.028	1.054
16: wood	Laspeyre	1	1.001	1.051	1.028	1.027	1.033	1.025	1.011	1.013	1.042	1.009	1.045	1.049
	Paasche	1	0.997	1.046	1.020	1.007	1.000	0.972	0.923	0.917	1.021	1.007	1.044	1.056
17: pulp & paper	Laspeyre	1	1.003	0.989	0.960	0.926	0.973	0.959	0.961	0.948	0.941	0.953	0.956	0.956
	Paasche	1	1.006	0.985	0.951	0.921	0.961	0.961	0.957	0.941	0.938	0.965	0.953	0.942
18: printing	Laspeyre	1	1.019	0.984	0.996	0.999	0.979	0.949	0.965	0.960	0.955	0.949	0.941	0.936
	Paasche	1	1.014	0.982	0.998	0.998	0.985	0.981	0.987	0.983	0.974	0.954	0.934	0.929
19: coke	Laspeyre	1	0.963	0.980	0.952	1.087	1.127	1.147	1.112	1.123	1.114	1.178	1.159	1.151
	Paasche	1	0.964	0.922	0.823	0.997	0.961	0.944	0.932	0.955	0.953	0.961	0.985	0.958
20: chemicals	Laspeyre	1	0.948	0.976	0.998	0.939	0.967	0.930	0.939	0.895	0.950	0.919	0.969	0.928
	Paasche	1	0.953	0.940	0.951	0.886	0.899	0.830	0.826	0.740	0.782	0.786	0.832	0.748
21: pharmaceuticals	Laspeyre	1	0.993	0.970	0.978	1.102	1.121	1.092	1.054	1.079	1.073	1.049	1.040	1.037
	Paasche	1	1.010	0.991	0.976	1.021	1.013	1.026	1.046	0.960	0.961	0.990	0.956	0.988
22: rubber & plastic	Laspeyre	1	0.998	1.002	1.003	1.002	1.013	0.994	0.990	0.993	1.005	1.001	1.003	0.996
	Paasche	1	0.996	1.000	1.000	0.992	0.999	0.979	0.971	0.939	0.984	0.988	1.000	0.979
23: non-metallic minerals	Laspeyre	1	0.952	1.002	1.023	1.047	1.026	1.014	1.014	1.010	1.003	0.981	0.968	0.963
	Paasche	1	0.948	1.000	1.022	1.043	1.023	1.009	0.988	0.989	0.989	0.962	0.945	0.941
24: metal processing	Laspeyre	1	0.975	0.967	0.957	1.001	0.975	1.044	0.971	0.940	0.925	0.912	0.891	0.899
	Paasche	1	0.973	0.951	0.936	0.987	0.982	1.032	1.080	1.026	1.011	1.020	1.012	1.032
25: metal products	Laspeyre	1	1.013	1.038	1.038	0.997	1.023	1.033	1.025	1.025	1.025	0.951	0.943	0.944
	Paasche	1	1.010	1.021	1.024	0.980	1.013	1.015	1.002	1.006	0.996	0.993	0.986	0.976
26: computer	Laspeyre	1	1.198	1.383	1.559	1.674	1.540	1.864	1.948	2.146	2.150	2.019	1.989	1.950
	Paasche	1	1.169	1.284	1.244	1.188	1.225	1.341	1.331	1.367	1.375	1.412	1.362	1.372
27: electrical equipment	Laspeyre	1	1.024	1.045	1.044	0.984	0.983	0.974	0.983	0.967	0.953	0.891	0.893	0.898
	Paasche	1	1.013	1.042	1.020	0.922	0.947	0.943	0.910	0.747	0.939	0.876	0.768	0.870
28: machines	Laspeyre	1	0.988	1.019	1.023	0.988	0.988	0.976	0.960	0.961	0.966	0.932	0.924	0.934
	Paasche	1	0.976	0.999	0.995	1.045	1.088	1.079	1.070	1.075	1.094	1.001	1.031	1.044
29: motor vehicles	Laspeyre	1	1.005	1.000	1.009	1.093	1.075	0.973	0.983	0.998	1.056	1.120	1.137	1.155
	Paasche	1	0.997	0.990	0.995	1.017	1.015	0.930	0.931	0.952	1.014	0.897	0.880	0.910
30: other transport	Laspeyre	1	1.525	1.382	1.555	1.428	1.081	0.945	0.936	1.038	0.955	1.138	1.095	1.080
	Paasche	1	1.082	0.954	0.899	1.355	1.847	1.648	1.676	1.008	0.674	2.000	1.818	1.555
31: furniture	Laspeyre	1	1.019	1.017	0.993	1.140	1.201	1.139	1.138	1.132	1.203	1.191	1.171	1.137
	Paasche	1	1.009	1.012	1.030	0.280	1.232	0.971	0.914	0.889	1.205	1.205	1.189	1.042
32: other	Laspeyre	1	1.030	1.028	1.037	1.076	1.051	1.057	1.062	1.083	1.076	1.054	1.066	1.087
	Paasche	1	0.992	0.988	1.005	1.178	1.116	1.089	1.062	1.066	1.084	1.075	1.067	0.986
33: repair & installation	Laspeyre	1	0.873	0.835	0.823	3.434	0.033	0.027	0.038	0.043	0.028	0.017	0.020	0.020
	Paasche	1	0.913	1.033	1.028	1.513	1.336	1.234	1.107	1.630	1.122	0.953	0.772	1.113

Source: Own calculations. Decomposition at the 9-digit product level.

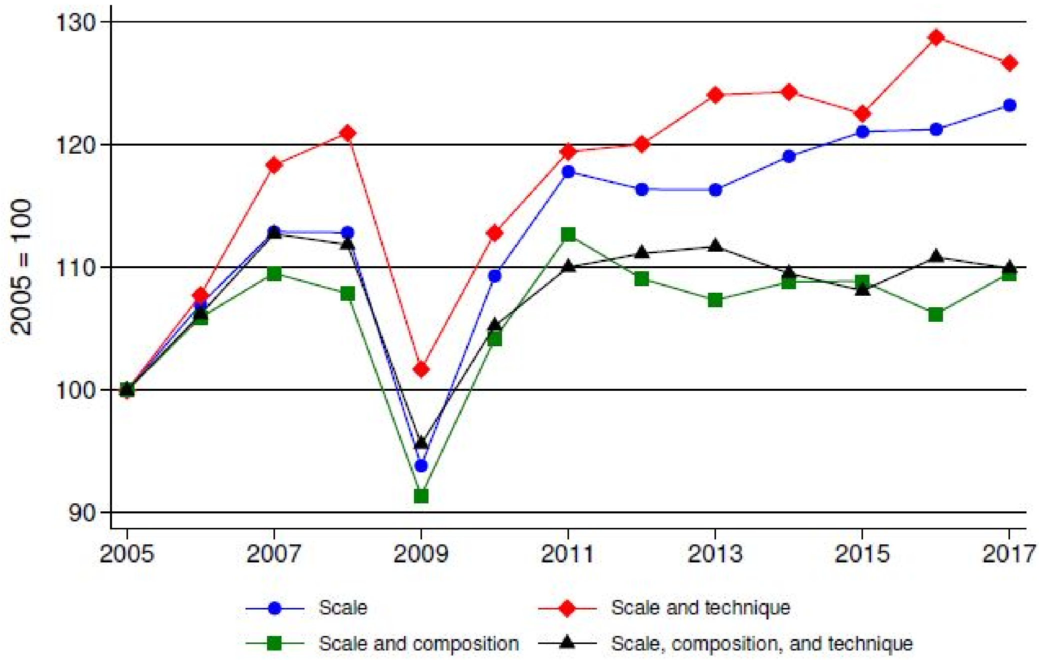
Robustness checks



Source: DOI 10.21242/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations

Figure 11: Decomposing carbon emissions in the German manufacturing sector, 3-digit sector level

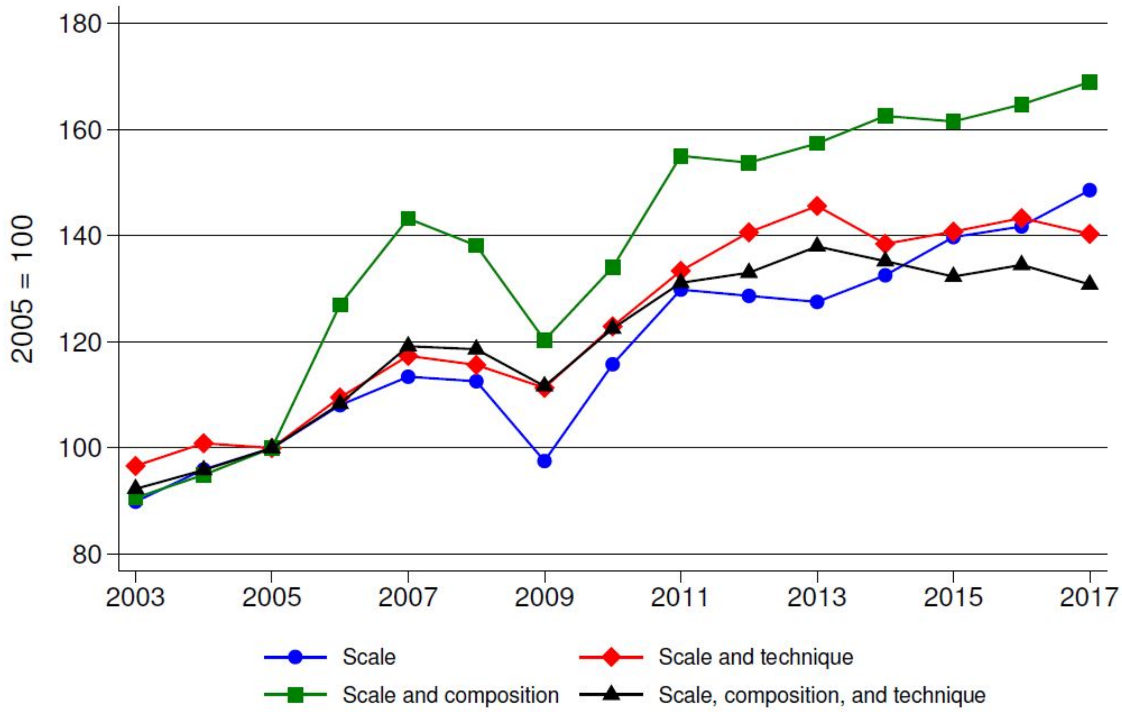
Notes: The figure shows the decomposition at the 3-digit sector level and is comparable to Figure 4 in the main text.



Source: DOI 10.21242/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations

Figure 12: Decomposing carbon emissions in the German manufacturing sector, 9-digit product level, balanced sample

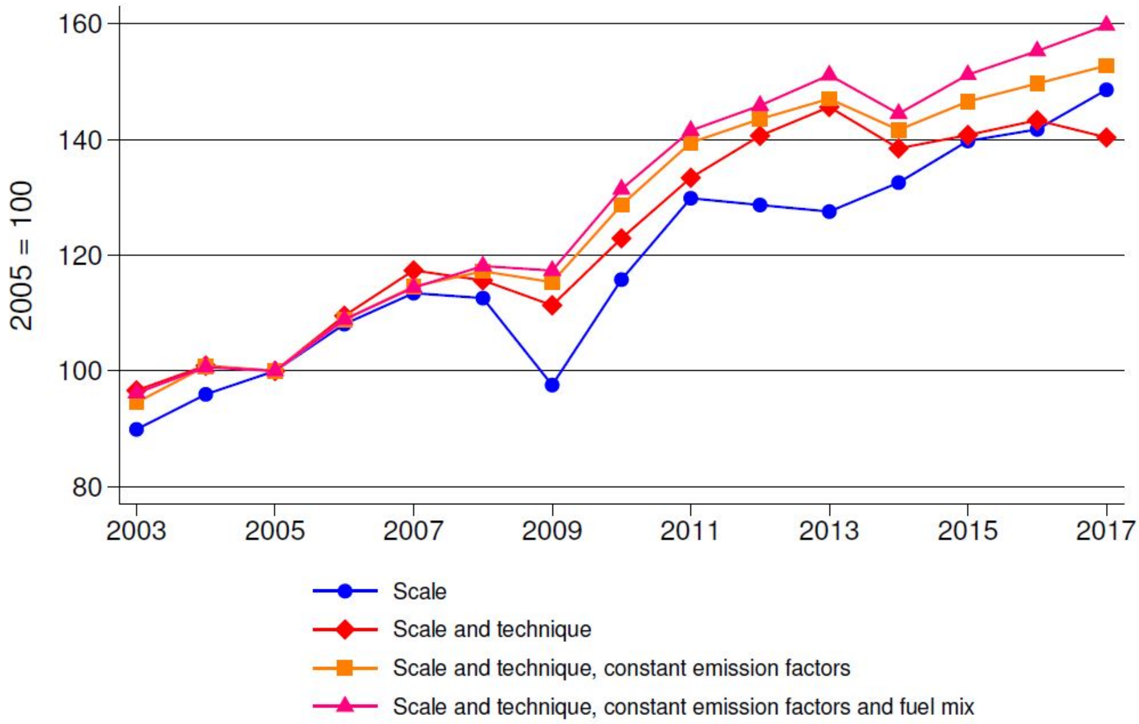
Notes: The figure shows the decomposition at the 9-digit product level for the balanced sample, and is comparable to Figure 4 in the main text.



Source: DOI 10.21242/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations

Figure 13: Decomposing carbon emissions in the German manufacturing sector, 9-digit product level, single-product plants

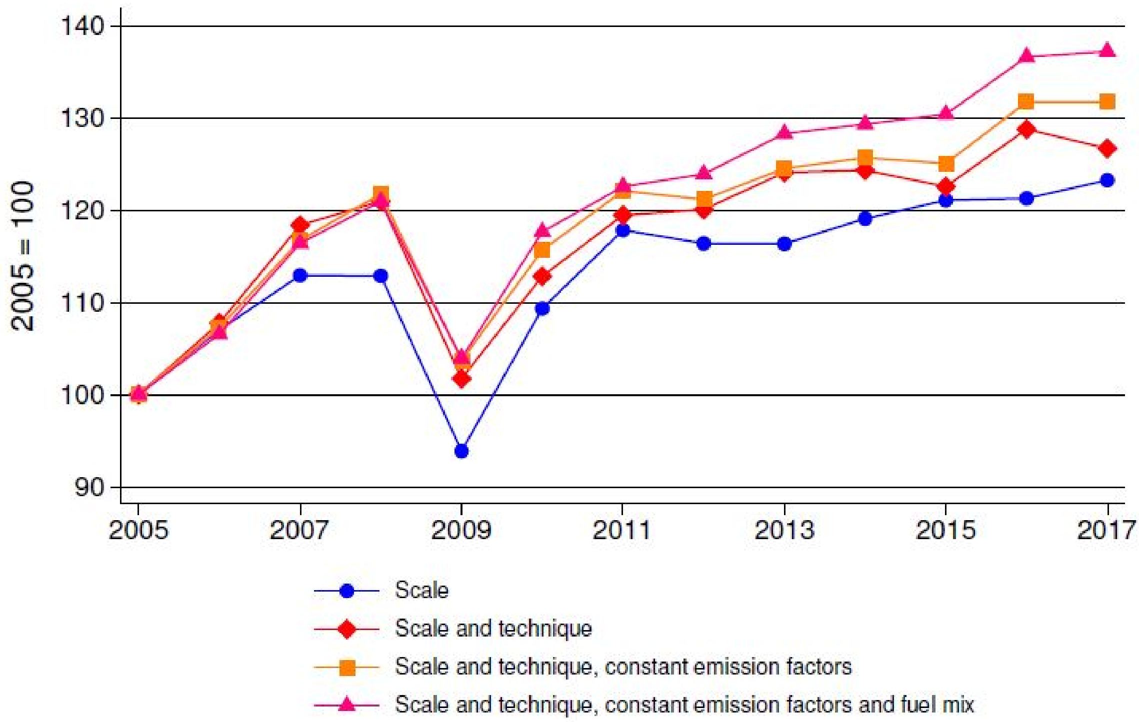
Notes: The figure shows the decomposition at the 9-digit product level using only data on single-product plants and is comparable to Figure 4 in the main text.



Source: DOI 10.21242/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations

Figure 14: Decomposing the technique effect in the German manufacturing sector, 9-digit product level, single-product plants

Notes: The figure shows the decomposition of the technique effect at the 9-digit product level for single product plants and is comparable to Figure 5 in the main text.



Source: DOI 10.21242/43531.2017.00.03.1.1.0, 10.21242/42111.2017.00.01.1.1.0 and 10.21242/42131.2017.00.03.1.1.0. Own calculations

Figure 15: Decomposing the technique effect in the German manufacturing sector, 9-digit product level, balanced sample

Notes: The figure shows the decomposition of the technique effect at the 9-digit product level for the balanced sample and is comparable to Figure 5 in the main text.

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ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de