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DISCUSSION PAPER

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

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

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Abstract

Carbon emissions from German manufacturing have increased over the past decade, while carbon intensity (emissions per Euro of gross output) has declined only slightly. We decompose changes in emissions between 2005 and 2017 into scale, composition (changes in the mix of goods produced) and technology (emission factors of production) effects. We find evidence that the production composition in the German manufacturing sector is increasingly shifting towards less carbon-intensive products. However, we also find evidence to suggest that the energy intensity of production has increased. These results are largely driven by a few energy intensive sectors.

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

JEL-Classification: D22, L60, Q41, Q48

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1 Introduction

Climate policies in Germany have long been on the rise: Beginning with the introduction of ecotaxes in 1999, numerous policy measures targeted at the reduction of fossil fuel consumption have been introduced. Feed-in-tariffs for renewable energy sources financed through the Renewable Energy Surcharge were introduced in 2003 to incentivize the expansion of renewable energies. In 2005, the EU Emissions Trading Scheme (EU ETS) was established, which prices the carbon emissions of certain sectors in the EU.

While the EU ETS is a policy measure at the EU-level, most climate policies remain a national affair. Many countries around the world are less stringent with regard to greenhouse gas emissions or even leave emissions completely unregulated. Therefore, the introduction of climate policies, which tend to increase the cost of fossil energy have been accompanied by debates about their potential adverse effects on competitiveness and labour market outcomes. Moreover, concerns about potential carbon leakage, i.e. the extent to which unilateral climate policies merely result in a relocation of carbon emissions to countries exempt from stringent emissions regulation, have been raised.

This paper sheds light on how carbon emissions and carbon intensities evolved in the German manufacturing sector between 2005 and 2017. The manufacturing sector is of particular interest in the German context as it is responsible both for a large share of the country's GDP (roughly 25% in 2018) and a large share of the country's carbon emissions (23% in 2018). 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. Our study period spans the introduction of several important climate policies, most notably, the Renewable Energy Surcharge and the EU ETS.

We find that the German manufacturing sector is shifting towards a cleaner production composition from 2011 onwards. However, even though different climate policies have been introduced during our observation period, we mostly find positive technique effects, 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 intense. 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 most energy and emission intensive sectors, while various less emission intensive sectors display opposing patterns.

The paper contributes to two strands of literature. First, it 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; Petrick and Wagner, 2014). While this literature has focused on identifying causal links of specific policies on specific subsets of firms by exploiting quasi-natural experiments, this paper provides descriptive evidence of how the manufacturing sector as a whole has responded to the joint introduction of different policies.

Second, this paper contributes to the literature using decomposition tools to study emissions developments (e.g. Shapiro and Walker, 2018; Brunel, 2017; Levinson, 2009, 2015, 2016; Petrick, 2013 and Kube and Petrick, 2019). We contribute to that literature by providing evidence on Germany which is still scarce with the papers by Petrick, 2013; Kube and Petrick, 2019 being the only previous analysis based on detailed micro data. We conduct the decomposition at an exceptionally granular level: While most of the existing studies use aggregate sector-level data, we conduct our decomposition at the product-level, distinguishing between more than 4,600 products. In doing so our analysis exceeds even the granularity of the study by Shapiro and Walker (2018) who distinguish between roughly 1,400 products. Our analysis is closest in spirit to Petrick (2013) and Kube and Petrick (2019) who also decompose carbon emissions of the German manufacturing sector. However, Petrick (2013) and Kube and Petrick (2019) use a different methodology and a broader sector disaggregation to identify production composition changes. Moreover, our study differs from past research based on the German manufacturing census in that we implement a novel and more accurate method to correct fuel consumption in the German manufacturing census for the occurrence of conversion losses. This is important as onsite generation has become increasingly important in the last 15 years and failure to adjust for conversion losses would make the manufacturing sector appear more energy intensive than it actually is.

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. Visual inspection of the data reveals that in the first two years of the new energy survey, emission intensities follow a notably different path than gross output, while the two variables move pretty much in parallel afterwards.

Our analysis requires information on aggregate emissions, total output, each industry's output share, each industry's emission intensities and each industry'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 time-varying. 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.

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.[1]

Aggregate output is calculated by summing up gross output of the products produced by each manufacturing plant.[2] We deflate gross output numbers using producer price indices from Destatis (DeStatis, 2018).[3] 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 8 in the appendix shows an example of the breakdown 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 comoposition 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. The relevant procedure is described in Section 7 in the Appendix. 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.

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[1] 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.

[2] 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.

[3] 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.

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

Figure 1 shows the development of aggregate energy consumption, i.e. the source of carbon emissions, and carbon emissions in the German manufacturing sector between 2003 and 2017.[4] As depicted in the figure, both energy consumption and carbon emissions in the German manufacturing sector 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 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.

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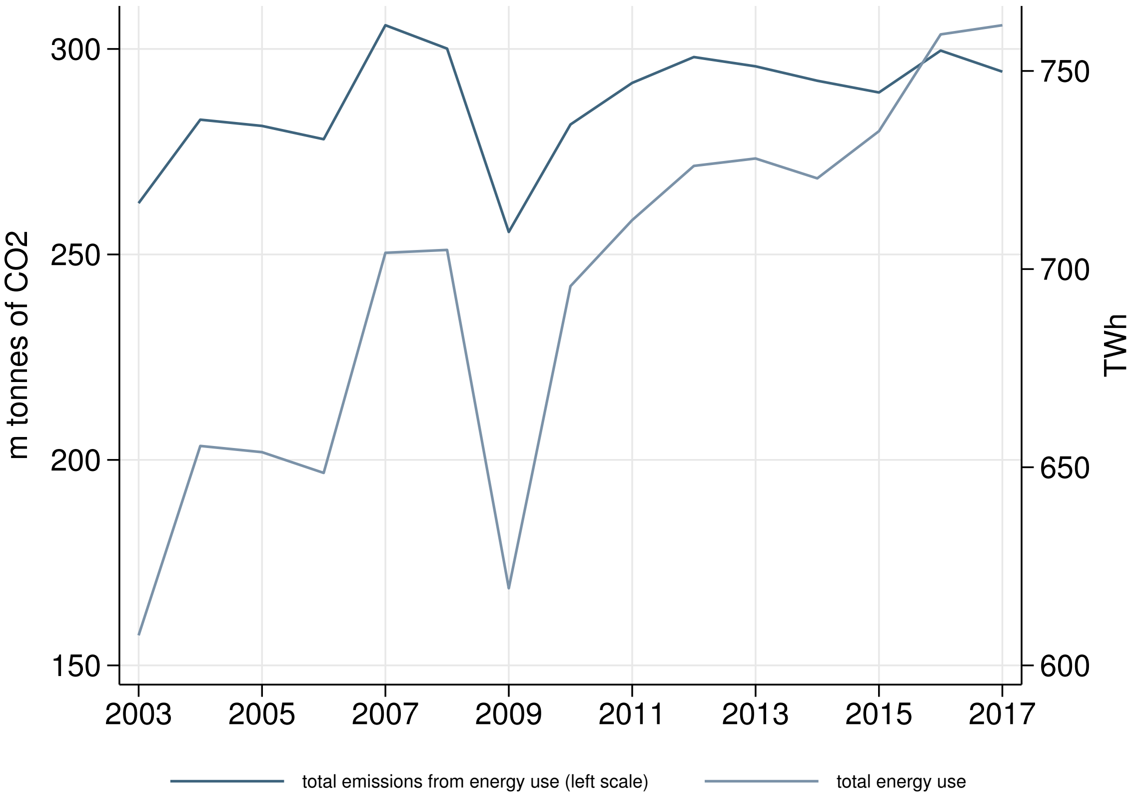
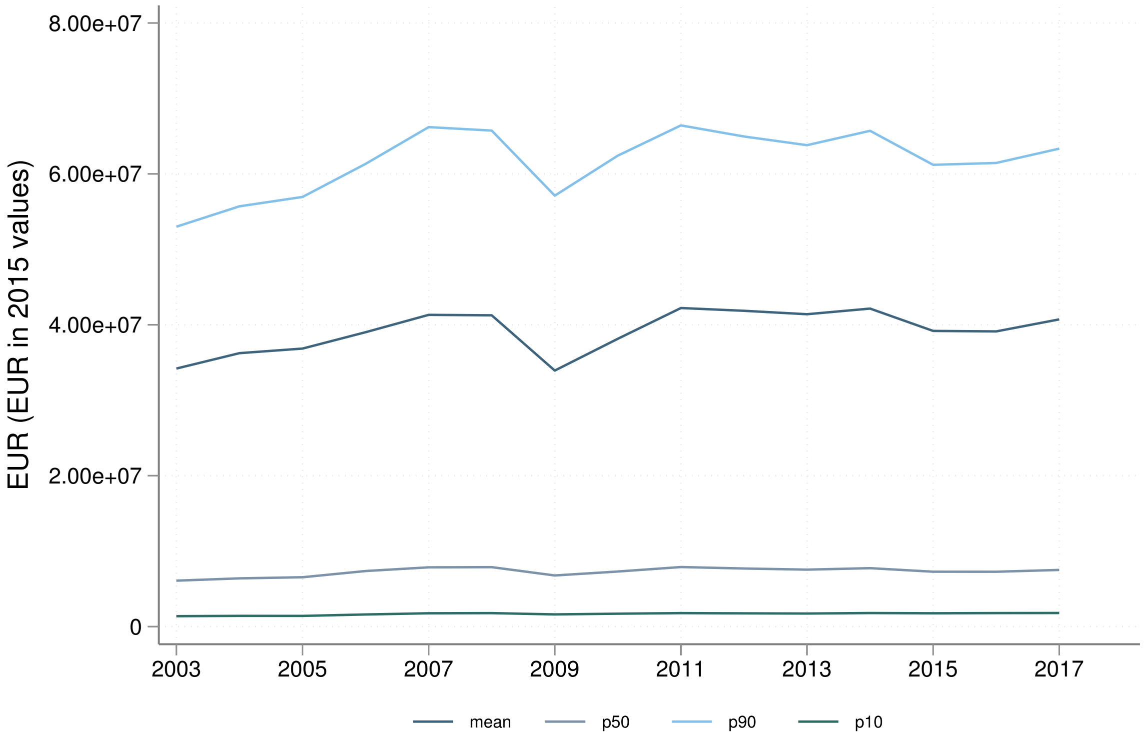
[4] All figures and numbers in this section are based on data from the German manufacturing census covering all German manufacturing plants with more than 20 employees. Process emissions are not included in the analysis due to data limitations.



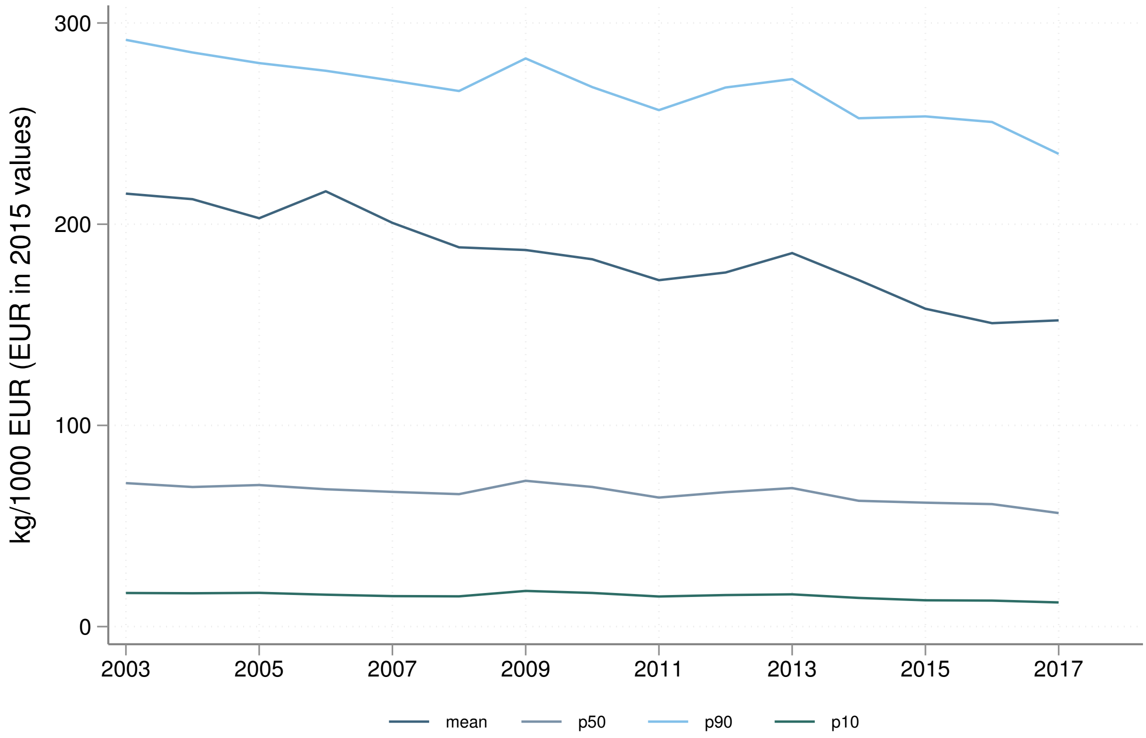
Source: DOI 10.21242/43531.2017.00.03.1.1.0. Own calculations.

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



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

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 decline resulting from decreasing 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 point this potential might be exhausted (namely once all manufacturing plants switched from burning coal to using renewable energy sources and gas); technology changes improving energy efficiency of production might be expected to offer more potential in terms of widespread reduction of emission intensities. Improving energy efficiency is also a declared policy goal both nationally and at the EU level with specific targets to be achieved by 2030.

To disentangle the channels through which both carbon emissions and carbon intensities 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, 2016) 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 (2020) local pollutants in Canada.[5]

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, CO2 in the German manufacturing sector at a given point in time, as the sum of emissions from S different sectors in manufacturing. In each sector, emissions are determined by the product of output produced, v_{st}, and the emission intensity of that sector z_{st}. Hence, total emissions from manufacturing can be written as a function of aggregate output V_t of the manufacturing sector as a whole, the share of each sector from aggregate output θ_{st} and the emission factors of production in each sector.

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

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):

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

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[5] 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 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.

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. 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:

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

Effectively, the technique effect is then given by the following Laspeyre-like index:[6]

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

where 0 indicates the base year to which emission intensity changes are compared.[7]

In this case, the composition effect is 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 notes 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.[8]

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

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

[7] 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.

[8] 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 has shifted towards or away from sectors in which pollution intensities declined the most. The comparison does not capture all possible interactions between scale, composition and technique effect. We report comparisons between

The level of sectoral disaggregation is decisive 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. In particular, since production composition changes were invisible, all emission changes resulting from 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 towards an accurate calculation of the effects.[9]

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.

[9] 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.

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. As a comparison, Figure 9 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 dark green line and labeled ”Scale, composition and technique”. The dark blue line 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. The light blue line shows the combined scale and composition effect (obtained by holding 2005 emission intensities constant), the grey line shows the combined scale and technique effect (obtained by holding the 2005 production composition constant). Hence, the difference between the light blue (grey) line and the dark blue line constitutes the directly estimated composition (technique) effect, while the difference between the light blue (grey) line and the line depicting the actual emissions development (dark green) shows the technique (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.[10]

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 incorporat-

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[10] The corresponding Laspeyre- and Paasche-indices for the technique effect are reported in Table 4 in the appendix.

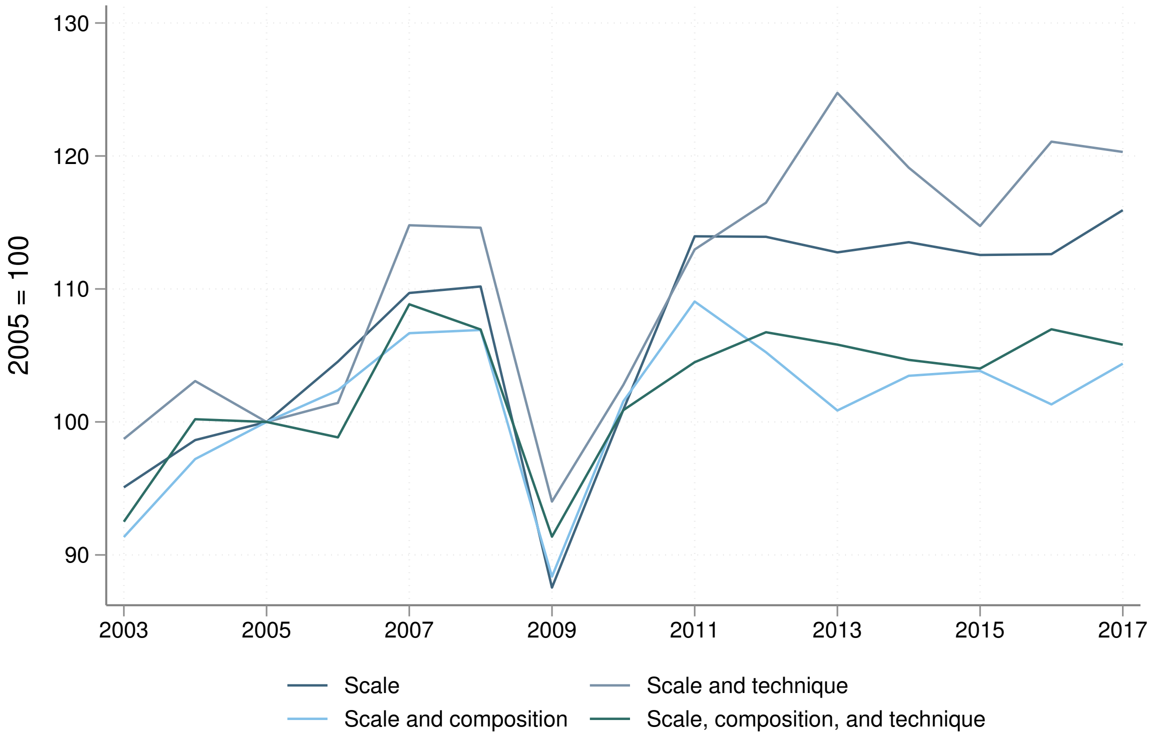

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Figure 4: Decomposing carbon emissions in the German manufacturing sector

ing 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 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.

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 4 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 cannot downwardly adjust energy consumption at the same pace as production.[11]

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.

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[11] Note that these results are not driven by manufacturing plants' entries and exits: Figures 10 and 13 in the Appendix show that these patterns also hold in a balanced sample of manufacturing plants.

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.[12]

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

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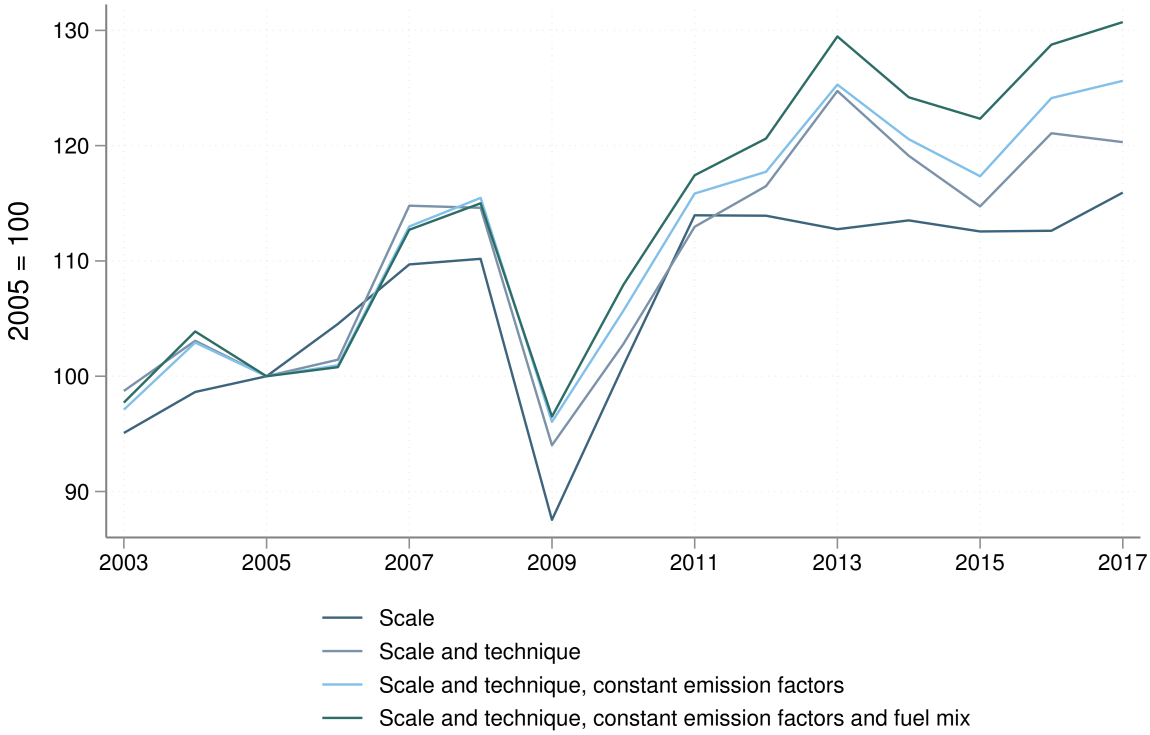
[12] To hold fuel mix constant, we divide each product's 2005-emissions by the 2005-energy input for that product to obtain an average emission factor applicable in 2005 which is then used to calculate emissions in the following years.

the other emission factors did not change much. 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 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 plays 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. Levinson (2016) e.g. documents a declining trend in the energy intensity of US manufacturing, albeit along a more extended time period between 1982 and 2007. He offers two potential explanations for the US case, namely policies and energy prices. Since, unlike his study, we cannot make use of cross-sectional variation in energy prices and policies across states, we cannot test to which extent these factors correlate with the rising energy-intensity of production we observe.

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. 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 13 in the Appendix.



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

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 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 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.[13]

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, production composition became significantly less carbon-intense over time, but a huge 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. Table 5 reports the Laspeyre-indices of the technique effect (see equation 7) for each 2-digit sector.[14] Despite the positive technique effect in 2017 for the manufacturing sector overall, as

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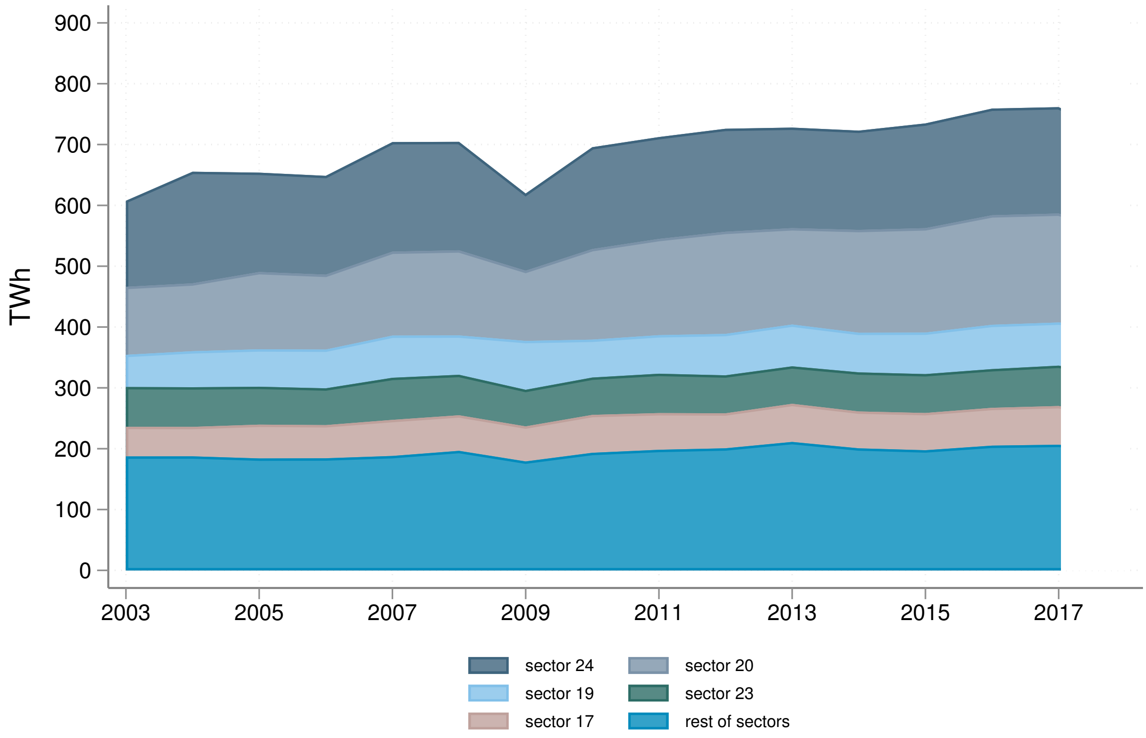
[13] We are aware that there are also process emissions associated with manufacturing. However, as we have no data on these, we were not able to include them in the analysis. According to the EEA (2015) process emissions made up about 1 % of overall German emissions regulated under the EU Emissions Trading Scheme in 2013.

[14] Accompanying Paasche-indices for each sector are reported 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

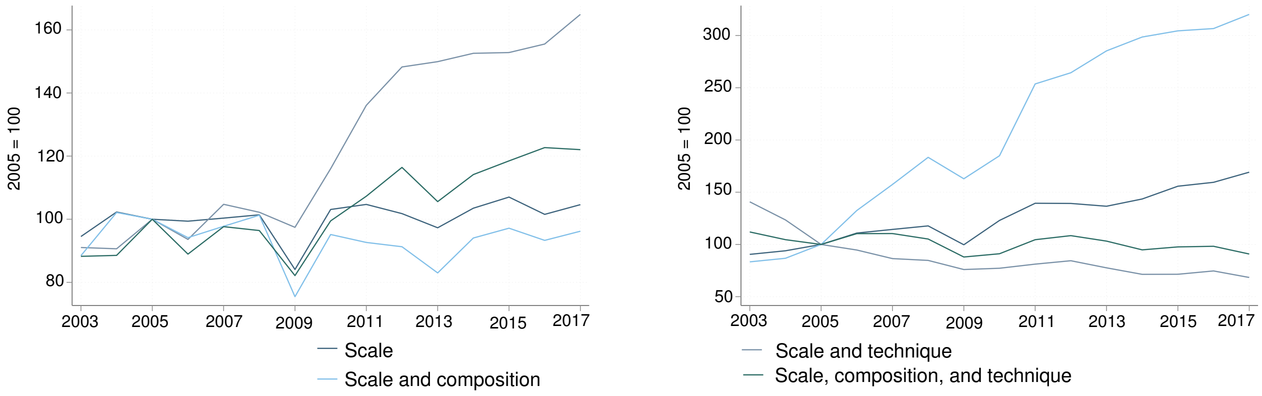
can be seen, in the same year, negative technique effects prevail when it comes to the 2-digit sectors. Several sectors experienced continuous improvements in terms of their emission intensity (among others, NACE 15: manufacture of leather and related products, NACE 18: printing and reproduction of recorded media, and NACE 26: manufacture of computer, electronic and optical products).

Table 2: Laspeyre-indices of the technique effect for 2-digit sectors in German manufacturing

Sector	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
10	1	1.012	1.005	1.073	1.031	1.027	1.009	1.046	1.288	1.216	1.159	1.171	1.146
11	1	1.034	1.152	1.140	1.049	1.025	1.015	1.013	1.014	0.967	1.017	1.036	0.991
12	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
13	1	0.939	1.007	0.945	1.027	0.917	0.900	0.940	1.034	0.971	0.840	0.819	0.759
14	1	1.025	1.126	1.290	1.367	1.593	1.701	1.738	1.891	1.788	1.766	2.15	2.01
15	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
16	1	0.998	0.989	0.959	1.031	1.029	0.979	1.001	1.137	0.930	0.849	0.843	0.799
17	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
18	1	0.752	0.756	0.703	0.691	0.674	0.640	0.779	0.772	0.644	0.629	0.699	0.664
19	1	1.043	1.209	1.233	1.364	1.010	1.095	1.038	1.135	1.134	1.094	1.232	1.314
20	1	0.942	1.044	1.008	1.159	1.125	1.300	1.457	1.541	1.474	1.428	1.532	1.576
21	1	1.036	0.981	1.053	1.124	1.283	1.202	1.027	1.150	0.983	1.011	1.076	0.952
22	1	0.997	0.998	0.979	0.997	0.998	0.926	0.977	1.025	0.935	0.880	0.875	0.815
23	1	0.994	1.125	1.089	1.078	1.056	1.043	1.071	1.094	1.068	1.079	1.070	1.064
24	1	0.996	1.083	1.106	0.968	1.060	0.981	0.970	1.020	1.015	0.986	1.046	0.979
25	1	0.988	0.994	0.971	1.154	1.065	0.0997	1.065	1.163	1.122	0.927	0.917	0.860
26	1	0.854	0.756	0.720	0.762	0.628	0.582	0.606	0.568	0.497	0.459	0.468	0.404
27	1	0.960	1.028	0.950	1.091	0.952	1.030	1.140	1.693	0.901	0.880	1.013	0.805
28	1	0.953	0.896	0.891	1.028	0.955	0.849	0.870	0.898	0.842	0.902	0.830	0.772
29	1	0.978	0.960	0.956	1.136	1.017	0.834	0.874	0.880	0.733	1.058	1.156	1.074
30	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
31	1	0.959	1.076	1.352	4.295	0.923	1.153	1.153	1.278	0.866	0.843	0.836	0.871
32	1	0.930	0.885	1.066	0.945	0.895	0.900	0.959	0.928	0.847	0.832	0.835	0.874
33	1	0.504	0.399	0.463	0.751	0.381	0.262	0.289	0.235	0.265	0.264	0.323	0.232

Laspeyre-Indices for all 2-digit industries in the German manufacturing sector. Source: Own calculations.

Table 5 shows that sectoral heterogeneity in both sign and magnitude of the technique effects is large. In parts, the differing effects might be grounded in climate policy exemptions (e.g. special treatment of sectors exposed to a significant risk of carbon leakage under the EU ETS, exemptions from the Renewable Energy Surcharge) that apply to



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

different extents to manufacturing plants in the different sectors. In fact, we do not find large negative technique effects in the most energy-intensive sectors in which more plants are likely subject to exemptions or other compensating measures with regard to existing climate policies.

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 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.

6 Conclusion

The introduction of several climate policies in Germany in the period between 2005 and 2014 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. From 2011 onwards, we find that the German manufacturing sector is shifting towards a less carbon-intensive production composition. Surprisingly, we also find that 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 intensities. We also provide evidence that within-plant energy-intensities have increased.

Results however display large degrees of sectoral heterogeneity some of which might be attributed to exemptions from climate policies which affect sectors to differing degrees.

These results imply that most improvements in the emission performance of the German manufacturing sector have been rooted in fuel switching which has a limited potential for future emission reductions, and the Greening of the German electricity sector, which cannot be attributed to the manufacturing sector. Our results suggests that carbon leakage might be of concern in the German manufacturing sector, since from 2011 onwards, carbon-intensive products seem to have decreased their production shares in Germany. Nevertheless, within existing plants surprisingly little seems to have changed with regard to energy intensity and emissions reductions. Therefore, the German manufacturing sector is still far from achieving the substantial emission reductions necessary to reach Germany's ambitious climate goals. More research is needed to identify the impacts and interactions of climate policies and potential improvements of climate policy design.

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References

BMWi (2014). Altmaier: Energieeffizienz und Wettbewerbsfähigkeit gehören zusammen . Further information (only available in German): https://www.bmwi.de/Redaktion/DE/Pressemitteilungen/2019/20191218-energieeffizienz-und-wettbewerbsfaehigkeit-gehoeren-zusammen.html.

Brunel, C. (2017). Pollution Offshoring and Emission Reductions in EU and US Manufacturing. *Environmental and Resource Economics*, **68**, 621–641.

DeStatis (2011). Güterverzeichnis für Produktionsstatistiken (GP 2009). Further information: https://www.destatis.de/DE/Methoden/Klassifikationen/Gueter-Wirtschaftsklassifikationen/klassifikation-gp-19.html.

— (2018). Erzeugerpreisindex gewerblicher Produkte. Further information: https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Erzeugerpreisindex-gewerbliche-Produkte-inhalt.html.

Ederington, J., Levinson, A. and Minier, J. (2004). Trade Liberalization and Pollution Havens. *B.E. Journal of Economic Analysis & 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*.

EU (2015). Commission delegated Regulation 2015/2402 of 12 October 2015 reviewing harmonised efficiency reference values for separate production of electricity and heat in application of Directive 2012/27/EU of the European Parliament and of the Council and repealing Commission Implementing Decision 2011/877/EU.

Flues, F. and Lutz, B. J. (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. and Ulltveit-Moe, K. H. (2018). Why are Firms that Export Cleaner? International Trade, Abatement, and Environmental Emissions. *Journal of Environmental Economics and Management*, **91**, 166–183.

Gerster, A. and Lamp, S. (2020). Energy Tax Exemptions and Industrial Production. *Working Paper*.

Kube, R. and 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*.

Levinson, A. (2009). Technology, International Trade, and Pollution from US Manufacturing. *American Economic Review*, **99** (5), 2177–2192.

— (2015). A Direct Estimate of the Technique Effect: Changes in the Pollution Intensity of US Manufacturing, 1900–2008. *Journal of the Association of Environmental and Resource Economists*, **2** (1), 43–56.

— (2016). Energy Intensity: Prices, Poliy, or Composition in US States. *Working Paper*.

Najjar, N. and Cherniwchan, J. (2020). Environmental Regulations and the Clean-Up of Manufacturing: Plant-Level Evidence. *Review of Eonomics and Statistics*, **forthcoming**.

Petrick, S. (2013). Carbon Efficiency, Technology, and the Role of Innovation Patterns: Evidence from German Plant-Level Microdata. *Kiel Working Papers 1833*.

— and Wagner, U. (2014). The Impact of Carbon Trading on Industry: Evidence from German Manufacturing Firms. *Kiel Working Papers 1912*.

Shapiro, J. S. and Walker, R. (2018). Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade. *American Economic Review*, **108** (12), 3814–3854.

Umweltbundesamt (2008). Bestimmung spezifischer Treibhausgas-Emissionsfaktoren für Fernwärme. *Climate Change*, **08/08**.

— (2020a). Carbon Dioxide Emissions for the German Atmospheric Emission Reporting 1900–2018.

— (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. and Rottner, E. (2020). Energy Use Patterns in German Manufacturing since 2003. *ZEW Discussion Paper 20-008*.

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 11 and 12. 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.[15]

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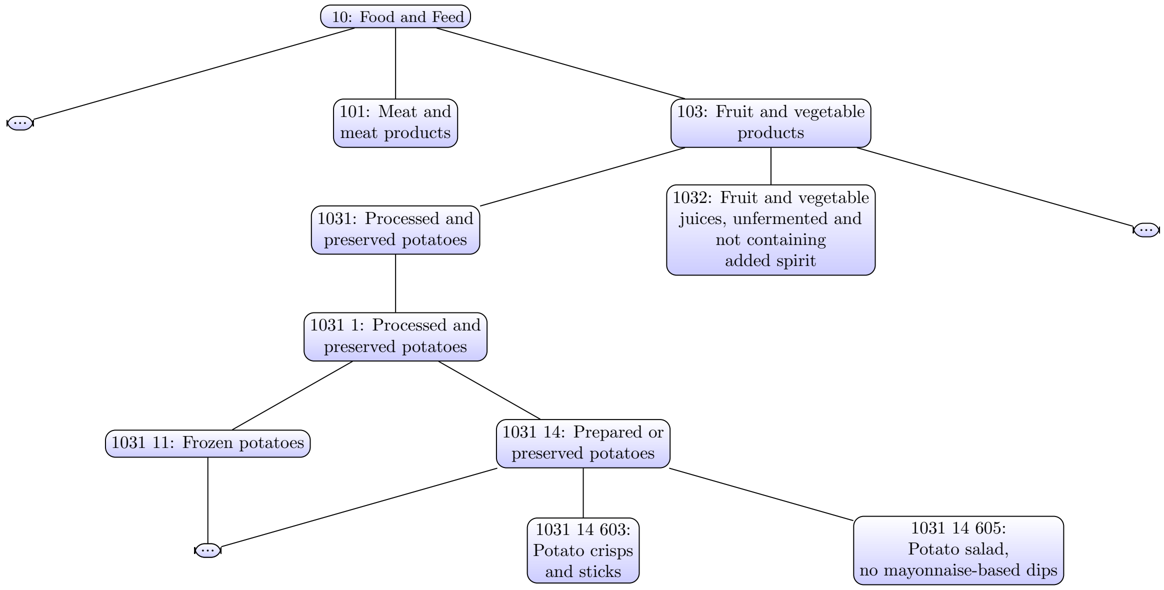
[15] Note that the results seem somewhat more volatile than the ones from using all manufacturing plants which can be explained by the fact that approximately 11% of manufacturing plants switch between being a single- or a multiproduct plant in our observation period. Hence, there is a lot more movement in the



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

Figure 8: 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 obviously is implausible, it only becomes problematic because it is true 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 numbers 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 effi-

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sample with only singleproduct plants as compared to the complete sample which is why the estimated effects move less smoothly.

ciency 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. These efficiency reference values serve the EU 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.[16]

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 a second one 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 allow to distinguish 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 larger, 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) which again means that using electricity efficiency factors is inaccurate: CHP plants make use of the heat which is formed as

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[16] 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

a by-product of electricity generation which increases the efficiency of CHP plants as compared to the separate production of heat and electricity.

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 these 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

Year	**Laspeyre**	**Paasche**	**Laspeyre**	**Paasche**
	9-digit	9-digit	3-digit	3-digit
2005	1	1	1	1
2006	0.9703103	0.9653555	0.9468003	0.9465285
2007	1.046423	1.020367	1.025827	1.021098
2008	1.040145	1.000346	1.010342	0.9977838
2009	1.07392	1.033983	1.034662	1.026432
2010	1.018528	0.993503	0.9869201	0.9769639
2011	0.9912825	0.9581422	0.963658	0.9501157
2012	1.022516	1.014293	1.011061	0.9925314
2013	1.106374	1.049103	1.03016	1.013408
2014	1.049363	1.011546	1.004379	0.9859755
2015	1.019357	1.001738	0.9975459	0.9886464
2016	1.075109	1.055763	1.053349	1.040666
2017	1.037769	1.013678	1.017489	1.000202

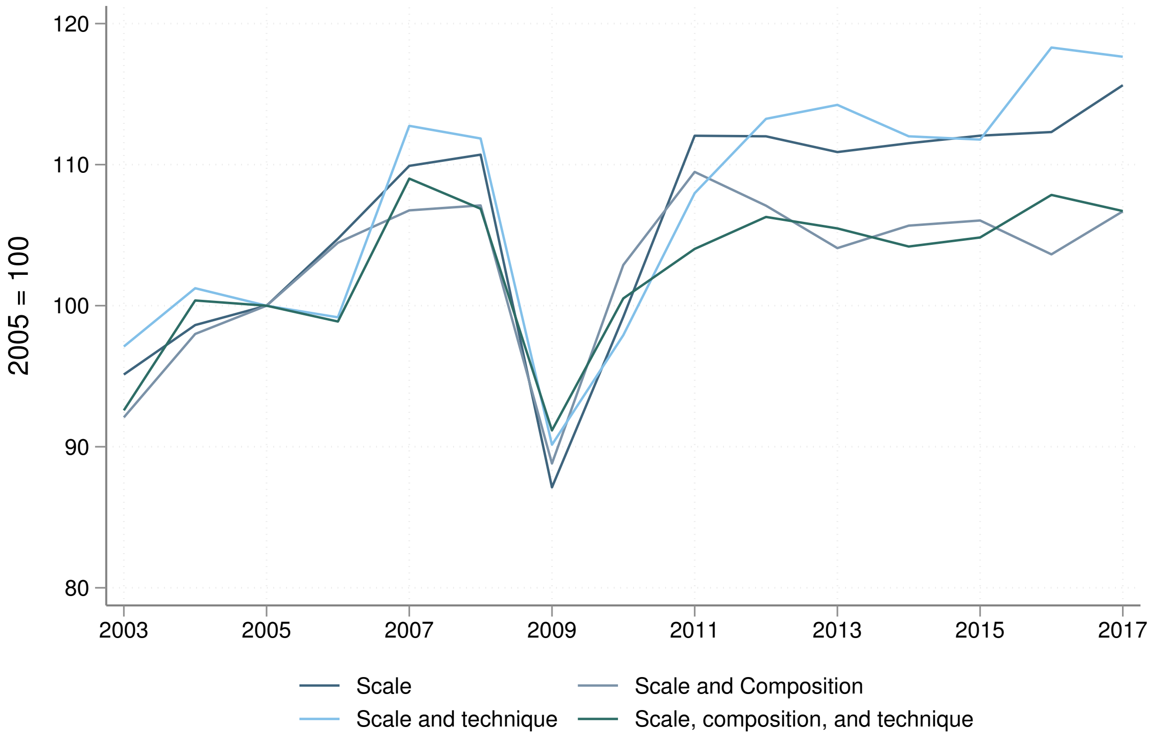
Source: Own calculations

Table 5: 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	Laspeyre	1	1.012	1.005	1.073	1.031	1.027	1.009	1.046	1.288	1.216	1.159	1.171	1.146
	Paasche	1	0.995	0.993	1.006	0.999	0.956	0.923	0.967	1.031	1.000	0.946	0.964	0.937
11	Laspeyre	1	1.036	1.152	1.140	1.049	1.025	1.015	1.013	1.014	0.967	1.017	1.036	0.991
	Paasche	1	1.024	1.138	1.135	1.046	1.019	1.010	1.006	0.997	0.949	1.002	1.023	0.977
12	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	Laspeyre	1	0.939	1.007	0.945	1.027	0.917	0.900	0.940	1.034	0.971	0.840	0.819	0.759
	Paasche	1	0.974	1.055	0.935	1.017	1.045	0.993	1.087	1.126	0.946	0.974	0.976	0.864
14	Laspeyre	1	1.025	1.126	1.290	1.367	1.593	1.701	1.738	1.891	1.788	1.766	2.15	2.01
	Paasche	1	0.947	0.956	1.009	1.060	1.033	0.964	0.954	0.987	0.933	0.876	0.836	0.813
15	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	Laspeyre	1	0.998	0.989	0.959	1.031	1.029	0.979	1.001	1.137	0.930	0.849	0.843	0.799
	Paasche	1	0.995	0.985	0.952	1.011	0.996	0.928	0.914	1.029	0.911	0.847	0.842	0.805
17	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	Laspeyre	1	0.752	0.756	0.703	0.691	0.674	0.640	0.779	0.772	0.644	0.629	0.699	0.664
	Paasche	1	0.737	0.725	0.694	0.661	0.639	0.616	0.768	0.710	0.595	0.581	0.650	0.617
19	Laspeyre	1	1.043	1.209	1.233	1.364	1.010	1.095	1.038	1.135	1.134	1.094	1.232	1.314
	Paasche	1	1.044	1.139	1.066	1.250	0.861	0.901	0.870	0.927	0.970	0.893	1.047	1.094
20	Laspeyre	1	0.942	1.044	1.008	1.159	1.125	1.300	1.457	1.541	1.474	1.428	1.532	1.576
	Paasche	1	0.945	0.999	0.952	1.089	1.045	1.158	1.275	1.272	1.214	1.220	1.315	1.269
21	Laspeyre	1	1.036	0.981	1.053	1.124	1.283	1.202	1.027	1.150	0.983	1.011	1.076	0.952
	Paasche	1	1.053	1.002	1.051	1.041	1.159	1.129	1.019	1.024	0.880	0.954	0.990	0.907
22	Laspeyre	1	0.997	0.998	0.979	0.997	0.998	0.926	0.977	1.025	0.935	0.880	0.875	0.815
	Paasche	1	0.995	0.996	0.977	0.987	0.984	0.912	0.958	0.970	0.915	0.868	0.872	0.800
23	Laspeyre	1	0.994	1.125	1.089	1.078	1.056	1.043	1.071	1.094	1.068	1.079	1.070	1.064
	Paasche	1	0.990	1.121	1.088	1.074	1.053	1.038	1.044	1.072	1.054	1.058	1.045	1.041
24	Laspeyre	1	0.996	1.083	1.106	0.968	1.060	0.981	0.970	1.020	1.015	0.986	1.046	0.979
	Paasche	1	0.994	1.063	1.082	0.957	1.065	0.966	1.075	1.108	1.110	1.097	1.183	1.119
25	Laspeyre	1	0.988	0.994	0.971	1.154	1.065	0.997	1.065	1.163	1.122	0.927	0.917	0.860
	Paasche	1	0.985	0.977	0.958	1.134	1.055	0.980	1.040	1.157	1.115	0.969	0.958	0.889
26	Laspeyre	1	0.854	0.756	0.720	0.762	0.628	0.582	0.606	0.568	0.497	0.459	0.468	0.404
	Paasche	1	0.833	0.702	0.574	0.540	0.493	0.412	0.410	0.362	0.318	0.321	0.320	0.284
27	Laspeyre	1	0.960	1.028	0.950	1.091	0.952	1.030	1.140	1.693	0.901	0.880	1.013	0.805
	Paasche	1	0.950	1.025	0.928	1.023	0.918	0.998	1.055	1.308	0.887	0.865	0.872	0.781
28	Laspeyre	1	0.953	0.896	0.891	1.028	0.955	0.849	0.870	0.898	0.842	0.902	0.830	0.772
	Paasche	1	0.942	0.879	0.867	1.088	1.052	0.940	0.966	1.005	0.955	0.968	0.925	0.863
29	Laspeyre	1	0.978	0.960	0.956	1.136	1.017	0.834	0.874	0.880	0.733	1.058	1.156	1.074
	Paasche	1	0.970	0.950	0.942	1.060	0.963	0.797	0.828	0.839	0.704	0.847	0.895	0.846
30	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	0.708	0.722	0.636	0.840	1.602	1.399	1.266	1.402	1.020	1.077	1.203	0.959
31	Laspeyre	1	0.959	1.076	1.352	4.295	0.923	1.153	1.153	1.278	0.866	0.843	0.836	0.871
	Paasche	1	0.949	1.070	1.403	1.053	0.947	0.983	0.925	1.003	0.867	0.853	0.847	0.797
32	Laspeyre	1	0.930	0.885	1.066	0.945	0.895	0.900	0.959	0.928	0.847	0.832	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	Laspeyre	1	0.504	0.399	0.463	0.751	0.381	0.262	0.289	0.235	0.265	0.264	0.323	0.232
	Paasche	1	0.527	0.492	0.577	0.336	15.48	12.17	9.281	9.036	10.41	15.10	12.63	13.03

Source: Own calculations.

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

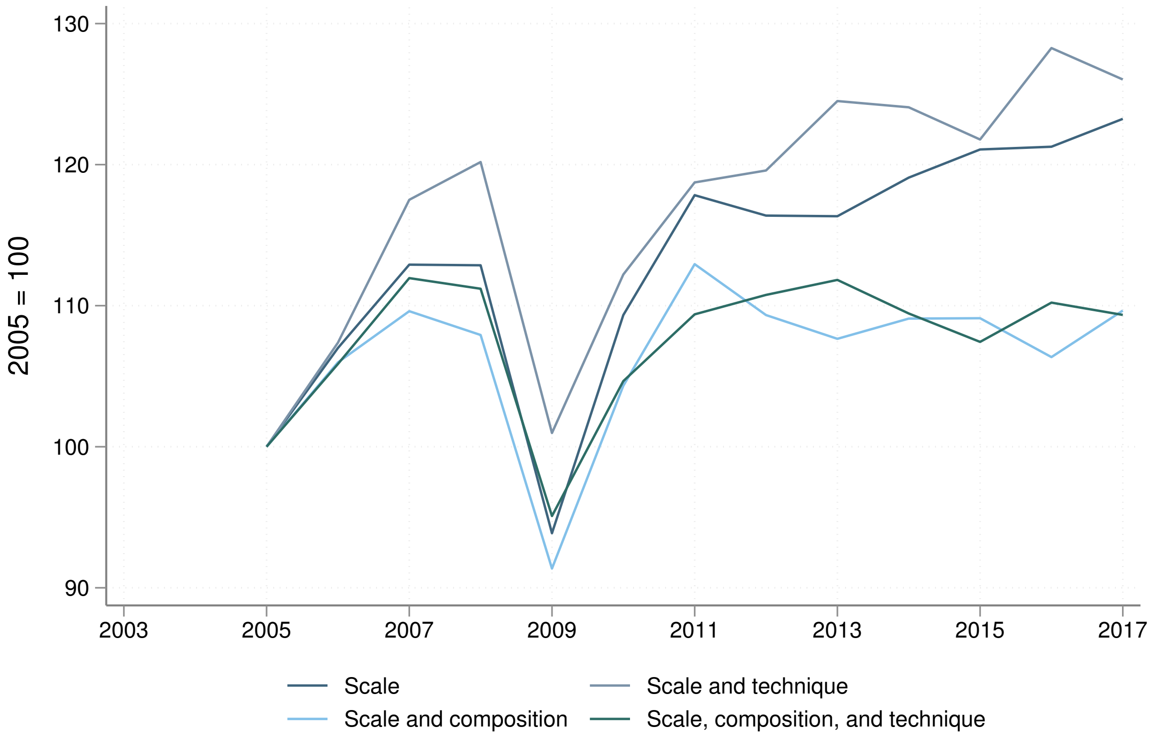


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Figure 10: Decomposing carbon emissions in the German manufacturing sector, 9-digit product level, balanced sample

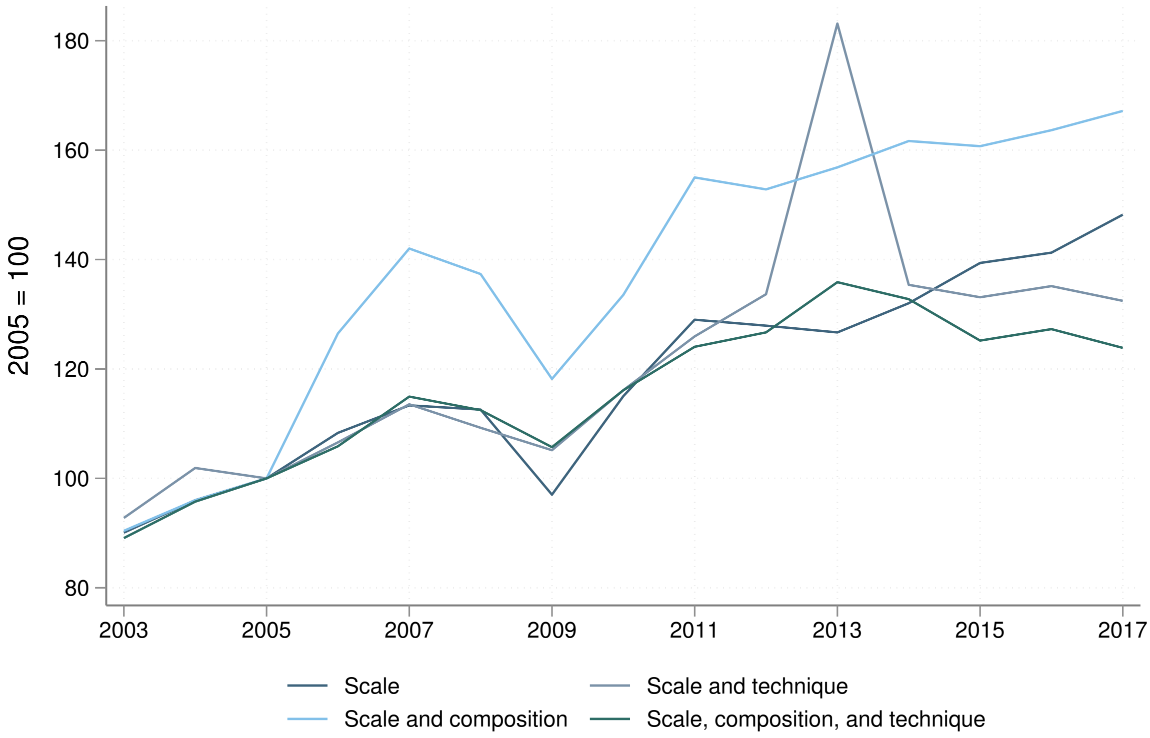

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Figure 11: Decomposing carbon emissions in the German manufacturing sector, 9-digit product level, single-product plants

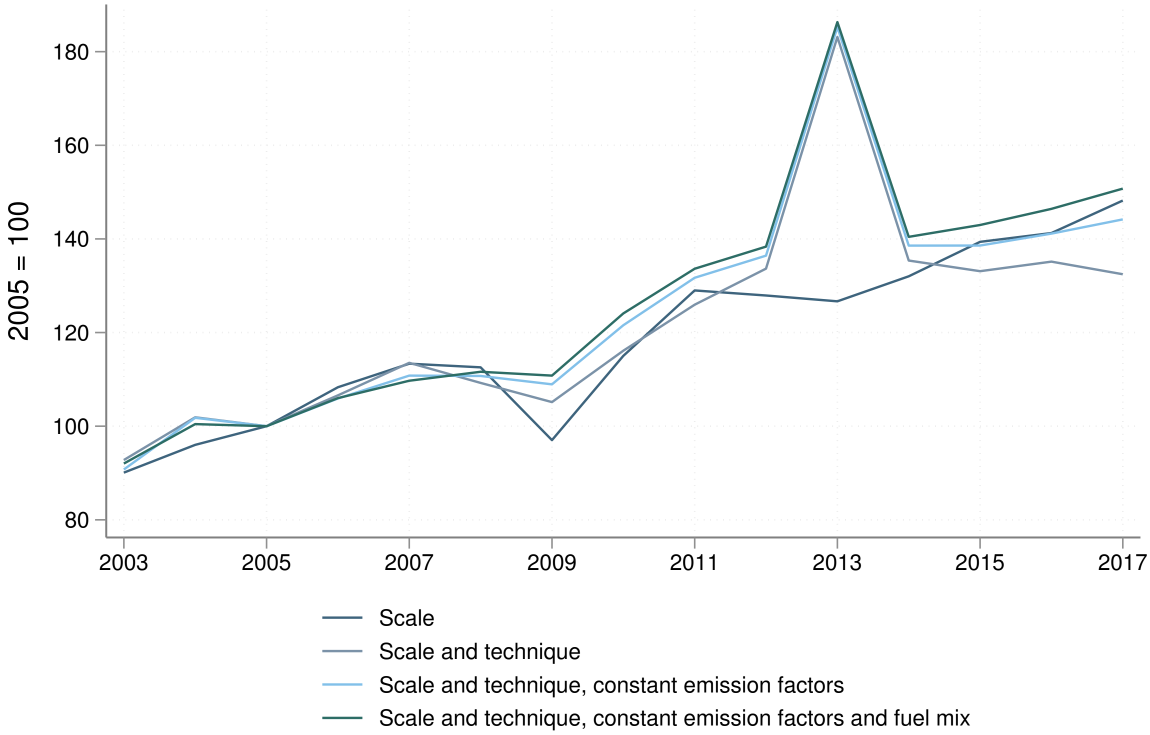

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Figure 12: Decomposing the technique effect in the German manufacturing sector, 9-digit product level, single-product plants

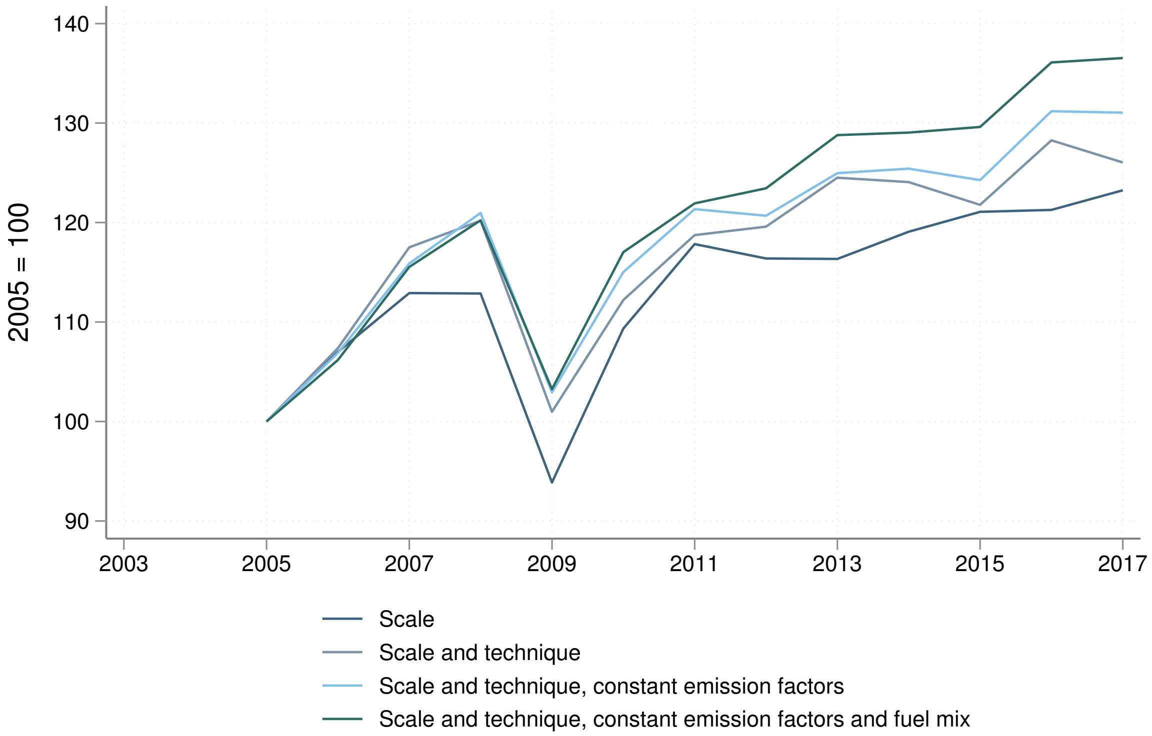

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Figure 13: Decomposing carbon emissions in the German manufacturing sector, 9-digit product level, balanced sample

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