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The Effect of Temperature on Energy Use and CO₂ Emissions in the German Industry

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The Effect of Temperature on Energy Use and CO₂ Emissions in the German Industry

February 24, 2021

PRELIMINARY DRAFT, PLEASE DO NOT CITE

Abstract

This paper adds to the scarce empirical evidence related to the impact of climate change on the manufacturing sector. To study the effect of temperature on energy use and CO₂ emissions daily temperature information from 11.000 German municipalities are combined with the census of the manufacturing industry. The census data covers the universe of German manufacturing plants with more than 20 employees, close to 40.000 plants annually, and spans across more than two decades from 1995 to 2017. We find large and significant effects on CO₂ emissions from cold days reflecting heating demand, while higher emissions from electricity consumption result from cooling needs. The increase in electricity related emissions from hot days is approximately twice as high among labor-intensive plants as it is among less labor-intensive plants. The response of direct emissions to cold days is roughly one third larger for old plants compared to new plants. When our estimates are combined with climate projections, direct emissions would decrease by about 12% by the end of the century due to rising temperatures under a business-as-usual scenario. The respective changes under the emission reduction scenario are about one-third of the changes under the business-as-usual scenario.

Keywords: Temperature, Climate Change, Manufacturing, Panel data, Energy use, Carbon emissions

¹We acknowledge the World Climate Research Programme's Working Group on Regional Climate, and the Working Group on Coupled Modelling, former coordinating body of CORDEX and responsible panel for CMIP5. We also thank the climate modelling groups (listed in Table XX of this paper) for producing and making available their model output. We also acknowledge the Earth System Grid Federation infrastructure an international effort led by the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison, the European Network for Earth System Modelling and other partners in the Global Organisation for Earth System Science Portals (GO-ESSP). We acknowledge the E-OBS dataset from the EU-FP6 project UERRA (<http://www.uerra.eu>) and the Copernicus Climate Change Service, and the data providers in the ECA& D project (<https://www.ecad.eu>)

1 Introduction

Among the various economic consequences of climate change, the impact of global temperature rise on energy consumption is of particular importance (e.g., Auffhammer and Mansur (2014)). Energy consumption affects and is affected by both climate change and climate policy. In the short term, climate change will affect energy consumption through weather variability and extreme events; in the longer term, adaptation measures could limit the impact.

In this paper we add to the scarce empirical evidence related to the impact of climate change on the manufacturing sector, by analyzing how temperature affects energy use and related CO₂ emissions in the German manufacturing sector. The manufacturing sector in Germany itself accounts for approximately 200 million tons of CO₂ emissions per year, which is approximately one quarter of total emissions in Germany¹. If indirect emissions are taken into account, i.e. emissions resulting from the generation of electricity that the manufacturing firms purchase from the grid system, this share is even much higher. Despite its relevance to economic development and its contribution to climate change, there is little empirical evidence for the effect of temperature on the manufacturing sector on the plant level. There are a few recent papers that provide evidence for the effect of temperature on economic activity at the plant level. Zhang et al. (2017) focused on temperature effects on productivity and factor reallocation in China similarly to Chen and Yang (2019). Sudarshan et al. (2018) study the effects for manufacturing in India and Addoum et al. (2020) focus on the United States. We are not aware of any paper, that addresses specifically the question how temperature affects carbon emissions in the manufacturing sector.

To study the effect of temperature on energy use and CO₂ emissions we combine daily temperature information from 11.000 municipalities with the German census of the manufacturing industry. The census data covers the universe of German manufacturing plants with more than 20 employees and spans across more than two decades from 1995 to 2017. Annually, we observe close to 40000 plants. Methodologically, similar to for example Barreca et al. (2016) we regression relate plants' yearly CO₂ emissions to the discretized temperature distribution. In line with what one would expect, our estimates imply a large and significant increase of CO₂ emissions in response to low

¹Compare for example information from "Umwelt Bundesamt" (Umweltbundesamt, Nationale Trendtabellen für die deutsche Berichterstattung atmosphärischer Emissionen seit 1990, Emissionsentwicklung 1990 bis 2018).

temperatures presumably reflecting heating needs. The effect of hot days on emissions is less clear: we do find some evidence for increased electricity consumption, which could plausibly be related to use of air conditioning. We also look at the effect of temperature on gross output as a measure of plants economic performance. At the macro level previous studies have documented a negative relationship between high temperatures and economic performance in poor or developing countries but not in advanced economies (Dell et al., 2012). In line with this literature, we do not find a detrimental effect of high temperatures on gross output. In contrast, we find small positive and significant effects of hot days on gross output. The previously mentioned positive effect of high temperatures on electricity use is most likely in parts related to the positive association between gross output and high temperatures.

Further, in order to investigate effect heterogeneities, existing adjustments to current climate conditions and the mitigating role of technological advancement we slice the sample in subsamples. First, we divide between more and less labor-intensive plants to test the hypothesis that more labor intensive plants' respond stronger to extreme temperatures. If the productivity of labor is more sensitive to temperature fluctuations than productivity of other factor inputs, labor-intensive firms will find it more profitable to invest in heating and cooling. Second, we split the sample between plants located in northern federal states and plants in federal states further south. The former tend to experience more moderate climate. This gives some indication of adjustment to existing climatic conditions. For instance, plants exposed to more frequent cold days may be more inclined to invest in insulation. This would result in a dampened response of direct emissions to low temperature. Third, we split the sample between older plants, i.e. those that we observed in 1995 already and those established only after 1995 to get an indication for the role of technological progress and changed expectations. Technologies such as insulation material or air conditioning have improved over time and become cheaper. In addition, expectations regarding future climate conditions may have changed. Newly built plants are more likely to be designed to reflect these changes as retrofitting old plants with better insulation, for example, is often not worthwhile from a company's perspective. Changing expectations about future climate conditions are expected to discourage investment in insulation while improved quality and lower prices for insulation and higher energy prices will work in the opposite direction.

Finally, we link our estimates to projections for different climate change scenarios and calculate the changes in emissions that our estimates imply.

The remainder of this paper is structured as follows: Section (2) reviews the related

literature, in section (3) we introduce the datasets and provide some summary statistics and in section (4) the empirical approach and results are presented. Section (5) links the empirical estimates with climate projections and section (6) discusses the results and concludes.

2 Literature Review

At the country level, a negative and significant association between high temperatures and aggregate economic outcomes such as economic growth or production has been documented. Dell et al. (2012) for example, show that temperatures that are 1°C above the long run mean, lead to a reduction of per capita income by 1.5 percent in poor countries. Using international trade data, Jones and Olken (2010) study the effect of higher temperatures on a country's exporting activities. In line with Dell et al. (2012) they find that being 1°C warmer reduces export growth in poor countries by 2 to 5.7 percentage points. Furthermore, they find that the impacts are concentrated in exports of agricultural products and light manufacturing. In a panel for twenty-eight Caribbean countries, Hsiang (2010) find a negative temperature effect in three out of six non-agricultural sectors with output losses occurring in nonagricultural production substantially exceeding losses occurring in agricultural production. More recently, Kalkuhl and Wenz (2020) use global subnational data for 1500 regions in 77 countries from 1900 - 2014 to estimate the effect of climate conditions on productivity. Their estimates imply that temperature affects productivity levels but not the growth rate². A growing body of literature analysis the effect of climate change on energy consumption (for an overview see Auffhammer and Mansur (2014)). These studies were primarily focused on households'. Most closely related to our work Deschênes and Greenstone (2011) or Auffhammer and Aroonruengsawat (2011) use panel data to study households' adoption to climate change by analyzing how residential electricity consumption responds to temperature.

Despite its relevance for economic development and contribution to climate change, there is little evidence related to the impact of climate change on the manufacturing sector and associated adaptations. Few studies look at plants exposure to extreme events; for example, Elliott et al. (2019) find strong but short lived negative effects of typhoons on manufacturing plants' sales in China. Plant level evidence for the effect of tempera-

²In spite of the studies referred to, studies at the sectoral level have mostly focused on agriculture (e.g., (Mendelsohn et al., 1994) or Deschênes and Greenstone (2007)). These studies have used cross-sectoral or panel data and analyzed data for a specific country or region or made cross-country comparisons.

ture on Total Factor Productivity (TFP) in the manufacturing sector is provided by Zhang et al. (2017). They combine daily mean temperatures with a panel of Chinese plants for the period 1998 till 2007. The authors document strong and non-linear negative effects on output from temperatures at the tails of the temperature distribution. The negative effect on output appears to be driven by a negative effect of temperature on TFP. Their estimates imply that the negative effect of a 1°C shift in the annual distribution of daily temperature on the manufacturing sector will cause a reduction of approximately 0.5% of Chinese GDP. Using climate projections for the middle of the 21st century these estimates imply an annual output loss of 12% in the Chinese manufacturing sector. Based on the same data as Zhang et al. (2017); Chen and Yang (2019) also find U-shaped relation between temperature and output. Their estimates imply that daily mean temperatures between 21°C and 24°C maximize output. In line with these relatively high optimal temperatures, they find that above average temperatures in spring have a positive effect on sales whereas high summer temperatures depress economic activity. The detrimental effect of high summer temperatures is stronger in relatively cool regions which is suggestive evidence for adaption by firms. Results from Sudarshan et al. (2018) who use a panel of Indian manufacturing firms broadly confirm the negative effects of high temperature on output estimated by Zhang et al. (2017) and Chen and Yang (2019). However, Sudarshan et al. (2018) estimates suggest that declining output due to extreme temperature can be fully explained by decreased labor productivity. Lower labor productivity is caused by increased absenteeism and heat stress at the workplace. Evidence for temperature effects on plants performance in developed countries is mixed: Addoum et al. (2020) find no effect of temperature on firms in the US while Kabore and Rivers (2020) document a negative effect of temperature extremes among Canadian manufacturer. Their estimates imply that daily mean temperatures below -18°C and above 24°C reduce output by 0.18% and 0.11% relative to a day with mean temperature between 12°C and 18°C.

We add to this scarce evidence on the effect of temperature on firm behavior in multiple ways. First, our main variable of interest are carbon emissions which has not been analyzed in previous studies. Second, we address the need for further research on the effect of temperature on firm level energy use that was emphasized by Auffhammer and Mansur (2014). We use a unique panel dataset for the manufacturing sector in Germany, a major industrial country. Third, we extent our analysis to the effect of temperature on measures of plants' economic performance. While this has been studied for developing countries such as India and China, we focus on an industrialized country. Among industrialized countries, Germany is a particularly interesting case since its

climate is mostly temperate but varies by the geographical and topographical characteristics of its regions. Due to the effect of the sea the climate of the North German plain and the Baltic coast varies comparatively little over the seasons. The climate in Central and Southern Germany is more varied due in part to the topographical features of these regions. In Bavaria the climate is similar to the Austrian Alps with cold winters and frequent snowfall whereas in Rhineland Palatine and Saarland in South Western Germany the climate is held to be particularly pleasant.

3 Data and Descriptive Statistics

3.1 AFiD Panel - Manufacturing Firms

The main data source is the German census of manufacturer (AFiD), in particular the so called "energy use module" ("Energieverwendung") which covers the universe of German manufacturing plants with more than 20 employees. The energy use module contains detailed information of plant specific fuel use in physical units (kWh) which allows calculating CO_2 emissions at the plant level based on fuel specific conversion factors³. The dataset spans more than two decades from 1995 to 2017. However, for the most part we restrict ourselves to data from 2003 onward due to a major change in the reporting of energy variables between 2002 and 2003⁴. Besides energy related variables, the data contains a rich set of further plant level information such as sales, the number of employees, export share and investment. In panel A of Table (1) we provide some summary statistics from indicators of economic performance. For example, the average plant in the sample has approximately 110 employees, a turnover of 22 million Euro per year and an export share of roughly 20%. Comparing the mean plant with the median plant indicates right skewed distributions. Panel B of Table (1) provides summary statistics of plants' total carbon emissions as well as their emissions by fuel type. It can be seen, that indirect emissions from electricity consumption account for more than one third of total emissions. Together, oil and gas make up for another third and coal consumption is approximately one quarter of total emissions⁵. Again the distributions are heavily skewed to the right. For example, coal consumption is

³To calculate the plant level CO_2 emissions we rely on the conversion factors provided by the Umwelt Bundesamt (a Table with the respective information can be found here). The table gives the fuel specific time varying CO_2 content per Terajoule. This can be converted to CO_2 per kWh. We then multiply the fuel use in kWh with the respective conversion factor to get the CO_2 emissions.

⁴For a detailed description of the dataset as well as the change in the reporting requirements see (Wagner et al., 2010)

⁵Total emissions also include emissions from some additional sources of energy such as heat. All of which play a minor role.

Table 1 Economic Characteristics and Carbon Emissions from Different Fuel Types

Variable	Mean	Std. Dev	p10	p50 (Median)	p90	N
<i>A. Economic Performance</i>						
Number of Employees	109	164.44	24	53	238	599128
Gross Output	22831.48	48862.62	1803.69	7086.95	54152.29	599128
Export Share	0.21	0.26	0	.09	0.61	599128
Total Energy Use	6926.84	25185.76	174.83	988.10	13356.04	599128
<i>B. Carbon Emissions</i>						
Total CO2 Emissions	6616.17	141270.1	47.71	354.18	5371.16	676169
CO2 Emissions - Coal	1455.08	106815	0	0	0	676169
CO2 Emissions - Gas	1496.75	30482.05	0	21.30	911.23	676169
CO2 Emissions - Oil	746.86	40861.09	0	0	183.74	676169
CO2 Emissions - electricity	2613.60	24332.08	25.58	237.97	3465.96	676169

Notes: Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturhebung und Energieverwendung, 2003-2017, own calculations.

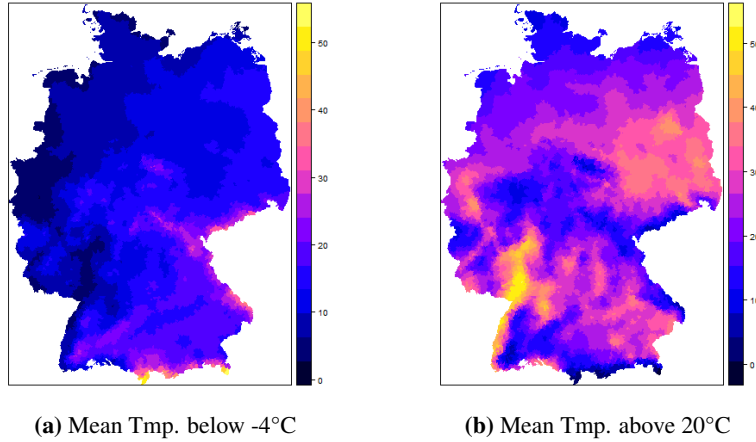
zero at the 90th percentile because coal is generally used in only a few energy-intensive industrial processes, but hardly ever for heating. Most plants use either gas or oil for heating.

3.2 Temperature Data

We supplement the plant data with temperature information that we collected from the German Meteorological Service ("Deutscher Wetterdienst") and the "European Climate Assessment & Dataset project". We downloaded gridded daily mean temperatures to calculate the mean temperature in all 11.000 German municipalities⁶. From the daily means, we construct temperature bins, i.e we count the number of days per temperature bin for each year and municipality. This information is then merged to the plant level data using the official municipality identifier. Figure (A1) in the appendix summarizes the temperature distribution over Germany for the period 1995 to 2017. On average about three-quarters of the days in a year have a mean temperature between zero and 20°C. The bins in Figure (A1) are an unweighted average across municipalities and years, thus, masking all spatial variation in climate conditions. Figure (1a) and (1b) show the spatial variation at the community level for the average number of days below -4°C and above 20°C. In contrast, days with mean temperature below -4°C barely occur in regions with climates mediated by the sea. Hot days with mean temperature above 20°C are most frequent along the Rhine, especially in the metropolitan area around Frankfurt. Metropolitan areas in general appear to be warmer than their neighboring regions which could be due to geographical characteristics but also because daytime heat is stored in the city (e.g. in buildings and concrete), emitted at night and therefore

⁶The median municipality has approximately 1.800 inhabitants and a size of 19km².

Figure 1 Average Number of Cold and Hot Days per Year



Notes: Subfigure 1a plots the average number of days with mean temperature below -4°C for the period 1995 until 2017. Subfigure 1b shows with average number of days with mean temperature above 20°C for the period 1995 until 2017. Both maps show information at the municipality level. Source: E-OBS dataset from the EU-FP6 project UERRA (<https://www.uerra.eu>) and the Copernicus Climate Change Service

increasing the daily mean. With some knowledge of Germany's geography Berlin, Stuttgart or Cologne can be spotted easily in Figure (1b). Figure (A2) in the appendix shows the annual mean temperature in municipalities for the period 1995 to 2017.

3.3 Climate Projections

To project the effect of climate change on CO_2 emissions and energy consumption in the manufacturing sector we use end of century climate projections for Germany. These projections can be downloaded from the World Climate Research Program (WCRP) and were produced under the ReKiEs-De Project. We use projections from two different climate models and for two representative concentration pathways (RCP). The first projection is based on the global climate model MPI-ESM-LR and the regional downscaling model CCLM. The second projection is based on the global model EC-Earth but the same downscaling model, i.e CCLM. Both models yield projections for the "climate-protection-scenario" (RCP2.6) and the "business-as-usual" scenario (RCP8.5)⁷. The projections start in 2006 and run until 2100. We discretize the annual projected temperature distribution at the federal state level using the same temperature bins that

⁷ReKiEs-De stands for Regionale Klimaprojektionen Ensemble für Deutschland. Background information regarding the different climate projections, their underlying global and regional models as well as general information on the ReKiEs Project is available in the User Handbook.

we used for the historical temperature information. Figure (A3) in the appendix shows the discretized distribution of projected mean temperatures (red bars) under the RCP8.5 scenario alongside the historical distribution (blue bars)⁸. It can be seen easily that the distribution of projected temperatures is shifted to the right.

4 Econometric Strategy and Empirical Results

We are interested in the effect of daily temperatures on plant level outcomes. The latter is observed annually. To align frequencies we discretize the annual distribution of daily mean temperatures into temperature bins as described in Section (3). This approach has been widely used in the literature for example Deschênes and Greenstone (2011), Zhang et al. (2017) or Barreca et al. (2016). Concretely, T_{mt}^j is the number of days in municipality m in year t with a mean temperature that lies in bin j . In total we define 10 bins with each interior bin having a width of 4°C. All days with a mean temperature below -8°C are collected in T^1 . T^{10} is the count of days with mean temperature above 24°C. Figure (A1) shows the average number of days per bin across municipalities and years. The estimation equation we take to the data reads as follows:

$$y_{imt} = \beta x_{imt} + \sum_{j \neq z} \theta^j T_{mt}^j + v_{st} + \lambda_{rt} + \tau_i + \varepsilon_{imt} \quad (1)$$

The dependent variable y_{imt} can be the logarithm of any outcome of plant i , located in municipality m in year t . The vector x_{imt} contains strictly exogenous plant level controls. Annual shocks common to subsectors are purged via year-by-sector fixed effects v_{st} , time varying sub-region specific shocks are controlled for by λ_{rt} and time-invariant plant characteristics are controlled for by the plant fixed effect τ_i . Finally, ε_{imt} is a random disturbance term. The coefficients of interest are the semi-elasticities θ . Each coefficient θ^j captures the effect of an additional day in bin j relative to another day in the leave-out-bin z . In our application it gives the percentage change in the outcome that results from an additional day in bin j instead of that day being in bin z . With this approach the effect of temperature on the outcome is assumed to be constant within bins while the effect across bins can take any form. Coefficient θ^j is consistently estimated if the year to year temperature fluctuations experienced by plant i are exogenous which is arguably true for a weather variable.

⁸For the historical temperature distribution we use the daily mean temperatures at the federal state level. We then calculate the weighted average across federal states. Weights are the share in total CO₂ emissions in the manufacturing sector that originate in the respective federal state.

4.1 Main Results - CO₂ Emissions

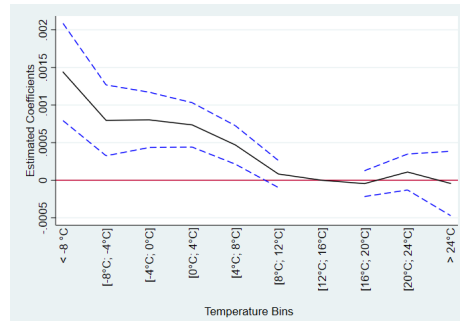
In practice we estimate variants of equation (1). The most parsimonious specification includes only firm and year-sector fixed effects. We consecutively add further fixed effects. Our preferred specification includes sizeclass-year fixed effects, exporter-year fixed effects and east-west-year fixed effects⁹. With this specification we purge shocks that are specific to plants located in federal states that were part of the former GDR which is important as these federal states are still different in their economic structure. We also control for shocks that might occur in export markets as well as for differential shocks along the plant size distribution. We omit the number of days with a mean temperature between 12°C and 16°C, thus, our coefficient estimates have to be interpreted relative to this leave out bin. In Figure (2) we show the estimated effect of an additional day in bin j relative to the leave out bin on total CO₂ emission as estimated from our baseline specification.

The solid line in Figure (2) connects the point estimates, i.e. the semi elasticities and the two dashed lines correspond to the 95th confidence intervals. Robust standard errors are clustered at the firm level. The Figure shows that cold days cause an increase in CO₂ emissions. Concretely, an additional day with temperature below -8°C induces an increase in annual CO₂ emissions by approximately 0.15% relative to a day with a mean temperature between 12°C and 16°C. The effects flatten out towards higher temperature bins. An additional day with mean temperature between 8°C and 12°C has an effect on total emissions that is indistinguishable from zero. As temperatures rise further, total CO₂ emissions do not change relative to a day with mean temperature between 12 and 16°C. Results from alternative specifications are shown in Table (A2) in the appendix. Across specifications the results remain qualitatively the same.

The effect of temperature on total emissions combines the effect of temperature on emissions from different sources of energy. We separately investigate the response of indirect emissions, i.e. the emissions contained in the electricity that plants buy as well as direct emissions, i.e. emissions resulting from plants burning fossil fuels. Corresponding results are shown in Figure (3a) and Figure (3b). One can see that the positive effect of low temperatures on total emissions as documented above is driven by direct emissions. The point estimate from the lowest temperature bin implies an increase in direct emissions by about 0.5% from a day with mean temperature

⁹All firms that export part of their sales are classified as exporter. Sizeclasses are five categories predefined in the data based on the number of employees: 20 - 49 employees, 50-99 employees, 100 - 249 employees, 250-499 employees and more than 499 employees. A plant is assigned to the east if it is located in a federal state that belonged to the former GDR.

Figure 2 Estimated effect of a day in 9 temperature bins on annual CO₂ emissions relative to a day in the 16°C to 20°C bin

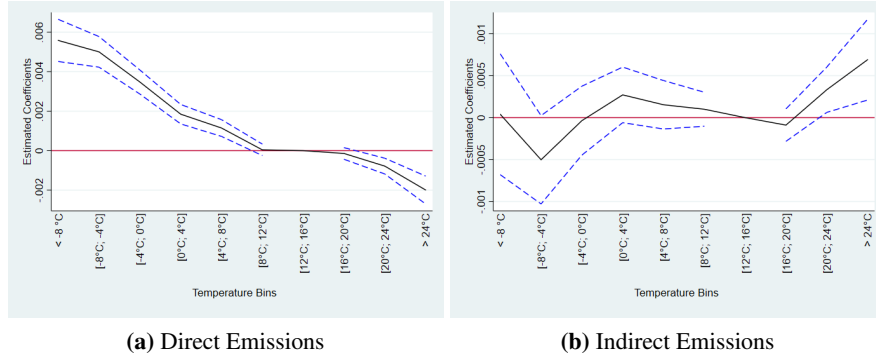


Notes: The effects are estimated on an unbalanced panel covering the period 2003 until 2017. The number of observations is 598576. Dashed lines show the 95th confidence interval. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 1995-2017, own calculations.

below -8°C relative to a day with mean temperature between 12°C and 16°C. The effect declines almost linearly towards the leave out bin. Looking at the right end of the temperature distribution one can see that direct emissions decrease further when temperatures rise, probably related to even lower heating needs. Electricity consumption appears largely unaffected by low temperatures (compare Figure (3b)) but increases when temperatures rise. For example, a day with mean temperature above 24°C causes emissions from electricity use to increase by approximately 0.07% relative to a day with mean temperature in the leave out bin. The positive effect of hot temperatures on electricity related emissions and the negative effect of hot days on direct emissions combined, result in the null effect of hot temperatures on total emissions as shown in Figure (2).

The effect on direct emissions could be decomposed further by looking at different primary sources of energy such as coal, gas and oil (compare Table 1). While there exists a sufficient number of observations with a non zero use of gas and oil only a few hundred plants use coal on a regular basis. In Table (A6) and Table (A5) in the appendix we show the respective point estimates. These are qualitatively very similar to the combined effect on direct emissions.

Figure 3 Estimated effect of a day in 9 temperature bins on annual CO_2 emissions relative to a day in the 16°C to 20°C bin by energy source

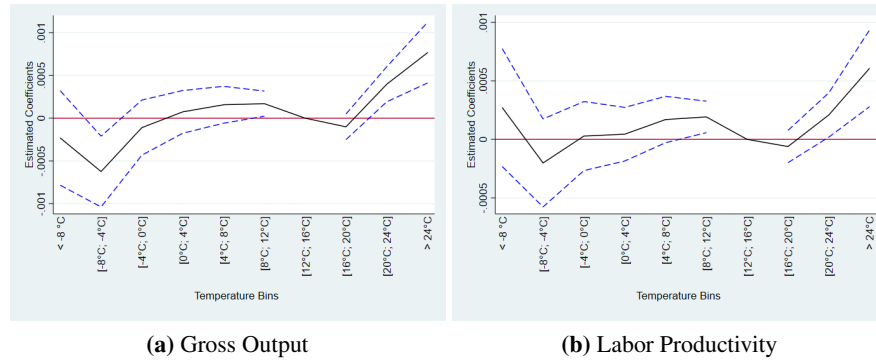


Notes: The effects are estimated on an unbalanced panel covering the period 2003 until 2017. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 1995-2017, own calculations.

4.2 Additional Results: Effect on Gross Output

We estimate the effect of temperature on gross output and labor productivity measured as gross output per worker. While this is interesting in itself it is also relevant for the interpretation of the effect of temperature on carbon emissions. If output was boosted by low temperatures, this could be an explanation for increased energy use. To investigate the effect of temperature on gross output we rely on the same baseline specification as for the effect on CO_2 emissions. The estimated semi elasticities are shown in Figure (4). We do not detect a systematic effect of cold temperatures on gross output. Only the number of days with a mean temperature between -8°C and -4°C has a negative and statistically significant effect. The pattern shown in Figure (4a) closely resembles the one for electricity related CO_2 emissions as shown in Figure (3b) suggesting a high correlation between electricity use and gross output. This is very plausible as electricity is an almost fully flexible input. Again similarly to electricity use there exists a positive effect of high temperatures on gross output. Hence, the positive effect of high temperatures on gross output could be an additional or alternative explanation for higher electricity consumption on hot days. We therefore re-estimate the effect of temperature on CO_2 emissions from electricity controlling for gross output (compare Table (A7) in the appendix). While this introduces a bad control problem it is informative regarding the mere cooling effect. The respective point estimate decreases and remains only marginally significant suggesting that the positive effect of hot temperatures on output does play an important role in explaining the increase in electricity use. We further

Figure 4 Estimated effect of a day in 9 temperature bins on gross output and labor productivity relative to a day in the 12°C to 16°C bin



Notes: The effects are estimated on an unbalanced panel covering the period 2003 until 2017. The number of observations is 590605. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 1995-2017, own calculations.

investigate this issue in the subsample analysis (Subsection 4.3)).

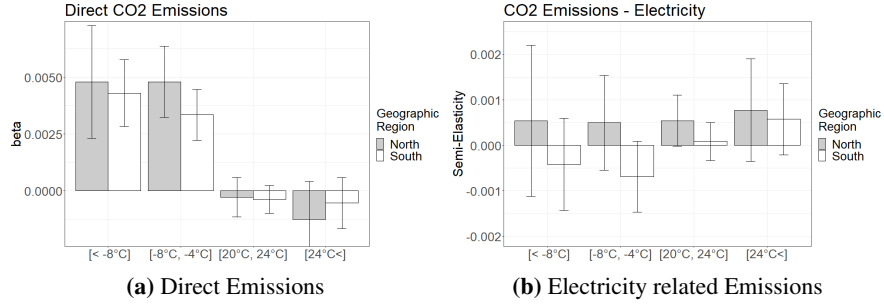
We scale gross output with the number of employees as a measure of labor productivity. Its response to temperature is qualitatively similar to that of gross output. The marginally significant dip of gross output resulting from days with mean temperature between -8°C and -4°C is insignificant but the positive effect at the right tail remains. We will investigate this effect in more detail by looking at subsectors (4.3.4). For example, the effect could be driven by sectors that are closely linked to the construction sector where economic activity is higher during the summer.

4.3 Effect Heterogeneity

4.3.1 Split by Region

Depending on prevailing climate conditions one would expect different strategies by firms to respond. In regions that experience cold winters frequently, it might be profitable from a firms perspective to insulate buildings. This should lead to a smaller increase in CO₂ emissions in response to cold days. Regions in which hot periods are more likely firms might invest in air conditioning causing a larger increase in electricity related CO₂ emissions when temperatures are high. To investigate this adjustment behavior we split the sample between plants located in the north and those located in the south. The north of Germany experiences more moderate temperatures, i.e mild winters and relatively cool summers. Thus, investing in insulation might appear less profitable in the north

Figure 5 North South Split: Effect at the Tails



Notes: The effects are estimated on an unbalanced panel covering the period 2003 until 2017. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 1995-2017, own calculations.

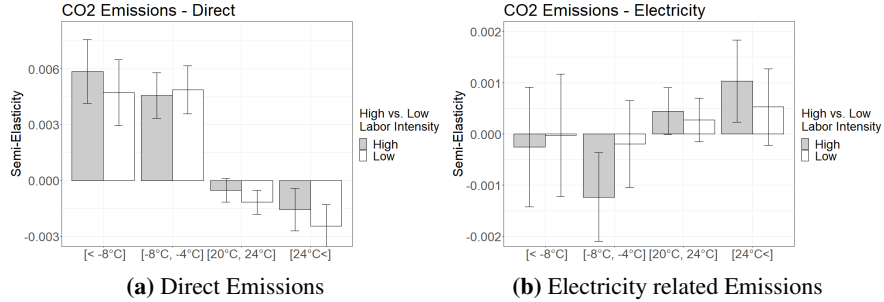
resulting in a larger CO₂ response to cold days. Similarly, firms in the north might not find it profitable to install air conditioning. In Figure (5) we plot the coefficient estimates from the four outer temperature bins estimated on the respective subsamples. The height of the bars give the point estimates and the vertical lines indicate the 95th confidence intervals. Grey bars are the coefficients estimated from plants located in the north and white bars the corresponding estimates from plants in the south. Figure (5a) shows the effect on the log of direct emissions and Figure (5b) the effect on the log of electricity consumption. The point estimates that capture the effect of cold days on direct emissions are somewhat higher for plants in the north. All point estimates capturing the effect of hot days on direct emissions are statistically indistinguishable from zero. Taken together the difference in point estimates are small and neither the effect of cold days nor the effect of hot days on direct CO₂ emissions are statistically significantly different between plants in the north and plants in the south. Thus, these estimates do not support the hypothesis that firms adaption to climate conditions within Germany alters the response of direct emissions on low temperatures in important ways. The same holds true when turning to the effect of temperature on CO₂ emissions resulting from electricity use. All point estimates are statistically indistinguishable from zero. The negative point estimate for the number of days with mean temperature between -8°C and -4°C estimated on the full sample (compare Figure (3b)) is found only for firms in the south. Probably, this effect operates through the negative effect on gross output which is also present only in the subsample of plants located south (compare Table A8). Again, none of the estimates is statistically different from the corresponding effect in the other subsample (confidence intervals overlap).

4.3.2 Split by Labor Intensity

To analyze the extent to which the response of emissions to temperature varies by the labor intensity of plants, we split the sample by plants average labor intensity. Labor intensity is calculated as the ratio of the number of employees to gross output. All plants with an average labor intensity below the 40th percentile are classified as low labor intensive plants. Plants with labor intensity above the 60th percentile are classified as high labor intensive plants. One might expect that labor productivity is stronger affected by temperature fluctuations than for example productivity of capital. If firms balance the marginal productivity gains from heating against marginal cost of heating, plants with a relatively high labor intensity will respond stronger to temperature fluctuations. In other words: for the same outside temperature a more labor intensive plant will spent more on heating than a less labor intensive plant¹⁰. Figure (6a) shows the point estimates and corresponding confidence intervals from the effect on direct emissions in both subsamples. The same for electricity related emissions is shown in Figure (6b). The point estimates suggest that the percentage increase in direct emissions resulting from cold days is somewhat higher in the group of more labor intensive plants. Still, these differences are neither large relative to each other nor statistically significant. Turning to the effect of temperature on electricity related emissions as shown in Figure (6b), one can see that the effect from hot days is more pronounced among highly labor intensive plants. Despite not being statistically significantly different from each other, the point estimates suggest that the response of CO₂ emissions from a hot day by a labor intensive plant is roughly twice the response of a low labor intensive plant. As discussed in Subsection (4.2), the increase in electricity consumption resulting from hot days is most likely in parts related to the increase in sales. In Table (A8) in the appendix we report the results from all sample splits with the logarithm of sales as the left hand side variable. As one can see from Table (A8), the increase in sales at the right tail of the temperature distribution is concentrated among plants with low labor intensity. This indicates that cooling needs are driving the pronounced increase in electricity related emissions in the group of plants with high labor intensity. This is also plausible, since workers are likely to suffer more from high temperatures than machinery.

¹⁰Interestingly, this kind of differential effect would also open further adjustment options. Relocating the vulnerable part of the economy, e.g. labor intensive production to geographic regions with more suitable climatic conditions could cushion the overall effect of changed climatic conditions.

Figure 6 Labor Intensity Split: Effect at the Tails



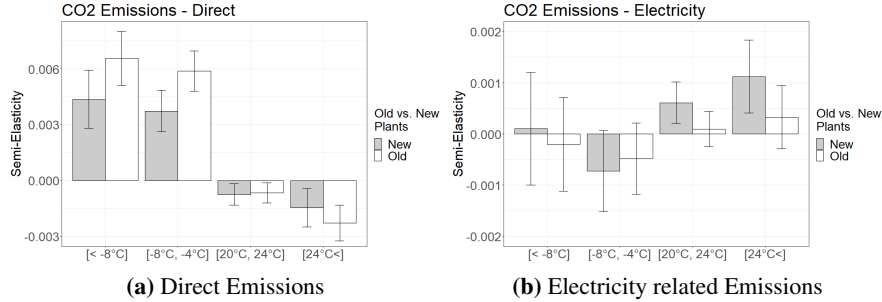
Notes: The effects are estimated on an unbalanced panel covering the period 2003 until 2017. Plants with an average labor intensity (number of workers per unit of sales) below the 40th percentile are classified as low labor intensive plants. Plants with an average labor intensity above the 60th percentile are classified as high labor intensive plants. There are 241972 observations with low labor intensity and 215996 observation with a high labor intensity to estimate the effect on electricity related emissions. The corresponding numbers for direct emissions 22257 and 12973 respectively. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 1995-2017, own calculations.

4.3.3 Split by Plant Age

Besides adoption to region specific conditions and across plant heterogeneity one would also expect a general time trend in the response of CO₂ emissions to temperature e.g. resulting from technological progress. Improved insulation material has been developed and is available at lower cost. Moreover, expectation regarding future climate conditions are different today from what they were decades ago changing firms calculations with respect to the profitability of investments e.g in air conditioning. Newly established plants are arguably more likely to adopt these new technologies or adjust to changes in expectations as retrofitting old plants will most likely be more expansive than installing new technologies when a plant is built. Therefore, we split the sample between plants we observe in 1995 already and the rest¹¹. The effect of days with cold and hot average temperatures on direct emissions and emissions resulting from electricity use are shown in Figure (7). The estimates imply that the response of direct CO₂ emissions from cold days is weaker among newly established plants. For example, a day with mean temperature below -8°C causes an increase in emissions among old plants by 0.66% relative to the leave out bin. The corresponding increase among newly established plants is 0.43%. Days with a mean temperature between -8°C and -4°C cause an increase

¹¹Unfortunately, we do not observe the data at which a plant came into being. The fact that we did not observe some plant in 1995 does not necessarily imply that it did not exist in 1995. For example if a plant has less than 20 employees it is not included in the sample. Moreover, plants sometimes change the economic sector. If a plant changes from a sector outside manufacturing into manufacturing this could also explain why it appears in the data only later.

Figure 7 Age Split: Effect at the Tails



Notes: The effects are estimated on an unbalanced panel covering the period 2003 until 2017. Plants that we observe in 1995 already are classified as old plants (17940 of which emit CO_2 directly and 258772 emit CO_2 indirectly via electricity use). Plants observed only later are classified as new plants (24889 of which emit CO_2 directly and 328495 emit CO_2 indirectly via electricity use). Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 1995-2017, own calculations.

in emissions by 0.59% among old plants and by 0.378°C among new plants. These differences could be a result of the availability of better or cheaper insulation material. Note, that changes in the expectation of future climate conditions would rather result in fewer investment in insulation, since cold periods are expected to be less likely. Turning to the effect of hot days on electricity related emissions, one can see from Figure (7b), that the effect among old plants is small and indistinguishable from zero. In the sample of newly established plants the estimated increase in electricity related CO_2 emissions caused by a day with mean temperature between 20°C and 24°C is 0.06% and from a day with mean temperature above 24°C the increase amounts to 0.11%. Looking at the effect of temperature on gross output for old and new plants separately (Table (A8) in the appendix) one can see that the positive effect on sales from hot days is stronger among old plants. This indicates that other factors contribute to the increase in electricity related CO_2 emissions among new plants when daily mean temperatures are high. This is in line with anecdotal evidence of increased adoption of air conditioning in recent years which could be caused by firms expecting high temperatures to occur more frequently.

4.3.4 Effects by Economic Sector

Due to the closure of the statistical office for guest researchers (because of Covid) we could not yet get the results for the sectoral analysis.

5 Projections

We combine the estimated relationship between temperature and CO₂ emissions with end of century climate projections which were introduced in subsection (3.3). Figure A3 in the appendix shows the average number of days per temperature bin for the historical temperature distribution (blue bars) and the days per bin from the projected temperatures (red bar) in the end of the century (average day count between 2080 and 2099). The day count in each bin is done at the federal state level. To aggregate up federal states we weight them by the respective share of carbon emissions in the manufacturing sector as observed in the AFiD data. We follow Deschênes and Greenstone (2011) and implement their error-correction method in order to correct for systematic errors in the projections¹². To calculate the implied change in carbon emissions one has to multiply each regression coefficient with the respective difference in the number of days per bin, i.e the difference in the height of the bars. In Table (2) we report the projected change in emissions under a business as usual scenario and a emission reduction scenario (RCP2.6) for two climate models. For each model-scenario combination we calculate the change in total emissions, direct emissions and electricity related emissions for the middle of this century (average across 2050 - 2069) as well as the end of the century (average across 2080 - 2099).

Table 2 Projected Change of Carbon Emissions in Percent

Source - CO ₂ Emissions	Time Horizon	EC-EARTH-RCA4	EC-EARTH-RCA4 (RCP26)	MPI-ESM-LR-CCLM	MPI-ESM-LR-CCLM (RCP26)
CO ₂ -Total	Mid Century	-0.81	-0.54	-0.80	-0.73
CO ₂ -Total	End Century	-2.08	-0.52	-1.70	-0.83
CO ₂ -Electricity	Mid Century	0.65	-0.14	0.73	0.25
CO ₂ -Electricity	End Century	1.55	-0.00	1.59	0.27
CO ₂ -Direct	Mid Century	-5.22	-1.59	-5.40	-3.64
CO ₂ -Direct	End Century	-12.80	-2.15	-11.13	-4.05

The table shows the change in CO₂ emissions that results from combining the regression estimates from the baseline model with the projected change in temperatures. Mid century refers to the average of 2050-2069 and end century to the average of 2080-2099. The columns are different combinations of climate models and CO₂ emission scenarios.

From the signs of the point estimates, it is obvious that linking them with climate change projections will generate a decrease in direct emissions and an increase in electricity related emissions. Across almost all model-scenario combinations both effects grow larger over time (end century vs. mid century). Combining baseline estimates for direct emissions with climate projections under a no reduction scenario implies a decrease in direct emissions by approximately 5% in the middle of this century and by 11-12% by the end of the century. The respective changes under the emission reduction scenario are roughly one third the changes under the business as

¹²We use the period from 2006 to 2018 to compare the simulated mean temperatures in each federal state with the actual temperature realization. For each day we take the average of the differences between projected mean temperature and actual mean temperature. These day specific average projection errors are then added to the projected temperatures on each day.

usual scenario. For CO₂ emissions from electricity we calculate a moderate increase under the no reduction scenario by approximately 1.5% for the end of the century. It needs to be emphasized that this exercise should not be seen as a prediction but rather as an interpretation of the empirical results against the backdrop of projected climate change. For these calculations to be valid predictions, firms' response to temperature has to remain constant over time and the distribution of firms across regions is not allowed to change depending on climate. In other words, the economy is not allowed to adjust in any way to climate change. The results from the subsample analysis presented earlier invalidate these assumptions already. Splitting the sample by plant age indicated that the response of emissions to hot days is likely to become larger while the response to cold days tends to be dampened. In Table (3) we recalculate the changes in emissions using the coefficient estimates from the subsample of plants built more recently. Their response to temperature will plausibly be a closer approximation to the future response of plants to climate shocks. Emissions from electricity use increase by approximately 3% by the end of the century while direct emissions fall by approximately 9%. The calculated net effect on emissions is then very close to zero.

Table 3 Projected Change of Carbon Emissions in Percent - Coefficients from Subsample of New Plants

Source - CO ₂ Emissions	Time Horizon	EC-EARTH-RCA4	EC-EARTH-RCA4 (RCP26)	MPI-ESM-LR-CCLM	MPI-ESM-LR-CCLM (RCP26)
CO ₂ -Total	Mid Century	-0.02	-0.26	-0.01	-0.29
CO ₂ -Total	End Century	-0.19	-0.27	-0.09	-0.39
CO ₂ -Electricity	Mid Century	1.38	0.09	1.44	0.58
CO ₂ -Electricity	End Century	3.23	0.16	3.00	0.59
CO ₂ -Direct	Mid Century	-3.88	-1.07	-4.07	-2.74
CO ₂ -Direct	End Century	-9.68	-1.45	-8.60	-3.25

The table shows the change in CO₂ emissions that results from combining the regression estimates from the baseline model on the sample of plants erected after 1995 with the projected change in temperatures. Mid century refers to the average of 2050-2069 and end century to the average of 2080-2099. The columns are different combinations of climate models and CO₂ emission scenarios.

6 Conclusion and Discussion

In this paper, we estimate the effect of temperature on energy use and carbon emissions on the German manufacturing sector. We find large and significant effects on CO₂ emissions by cold days presumably reflecting heating needs. For example, a day with mean temperature below -8°C causes an increase in CO₂ emissions at the plant level by about 0.5% relative to a day with a mean temperature between 12°C and 16°C. This effect is driven by the responses of CO₂ emissions from gas and oil. Indirect carbon emissions resulting from electricity use do not respond to low temperatures. In contrast, electricity related emissions increase slightly when temperatures are high. Our baseline estimates imply that an additional day with mean temperature above 24°C increases

annual emissions from electricity use by 0.07% relative to a day with mean temperature between 12°C and 16°C. This reaction could plausibly reflect increased electricity use resulting from cooling needs.

To investigate effect heterogeneities, we split the sample by plants' labor intensity, between geographic regions and plants age. We find that the increase in electricity related emissions from hot days is approximately twice as high among labor intensive plants as it is among less labor intensive plants. However, the response of direct emissions to cold days indicates hardly any difference. This result suggests that labor intensive firms invest more in order to mitigate high temperatures which would be in line with adverse economic effects from high temperatures being larger when labor intensity is high. By splitting the sample between plants located in the north of Germany and those in the south we seek to understand adjustments to different climatic conditions. The coefficient estimates that describe the responsiveness of direct emissions to cold days are somewhat larger for plants in the north. There exist no systematic differences between plants in different regions with respect to the responsiveness of electricity related emissions to hot days. The absence of regional adjustment as indicated by our estimates could be due to comparably little variation in climatic conditions within Germany. Last, we split the sample by plants' age. The response of direct emissions to cold days is estimated to be roughly one third larger among old plants compared to new plants. Similarly, the increase in electricity related emissions is comparably large among newly established plants while it is small and statistically indistinguishable from zero among old plants. The dampened response to cold days by new plants could be explained by the availability of better materials for example to insulate buildings. This also gives an indication of the energy savings potential if old plants were retrofitted. The stronger response of new plants' electricity consumption to high temperatures is in line with anecdotal evidence for increased adoption of air conditioning.

We extend our analysis to the effect of temperature on gross output. In line with the existing literature (for example Dell et al., 2012), we do not find a detrimental effect of high temperatures on gross output. In contrast, we find small positive and significant effects of hot days on gross output. The previously mentioned positive effect of high temperatures on electricity use is partly related to the positive association between gross output and high temperatures.

Our analysis suggests that warmer temperatures will make it somewhat easier for Germany as a whole to reduce its emissions. We link our estimates to climate projections

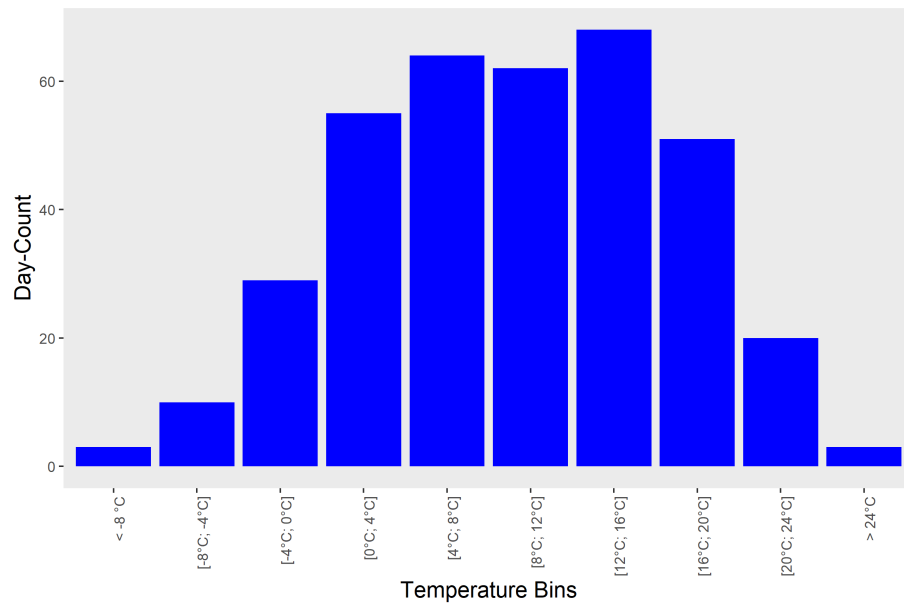
to calculate the implied future changes in emissions. On the one hand, these calculations yield a decrease in direct emissions by approximately 12% under a business-as-usual scenario by the end of the century. On the other hand, more frequent occurrence of hot days will most likely increase electricity demand for cooling. The net effect as we calculate it is still negative. Moreover, cooling needs are likely to coincide with the availability of low carbon electricity (PV) and thus our projections will rather overstate the increase in CO₂ emissions from air conditioning.

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Figure A1 Annual Average of Days per Temperature-Bin



Notes: The bar plot shows the average number of days per temperature bin in Germany. The average is calculated over time and space, i.e. over the period 1995 until 2017 and across all municipalities. Note that municipalities are not weighted by their geographic size. Source: E-OBS dataset from the EU-FP6 project UERRA (<https://www.uerra.eu>) and the Copernicus Climate Change Service

Table A1 Effect of Temperature on Gross Output

	Log Gross Output			
	(1)	(2)	(3)	(4)
$[Temp < -8C]$	-.00041 (.00031)	-.0002 (.00028)	-.00046 (.00031)	-.00023 (.00028)
$[-8C < Temp < -4C]$	-.0008 (.00023)	-.00059 (.00021)	-.00083 (.00023)	-.00062 (.00021)
$[-4C < Temp < 0C]$	-.00003 (.00018)	-.00007 (.00016)	-.00008 (.00018)	-.00011 (.00016)
$[0C < Temp < 4C]$.00017 (.00014)	.00009 (.00013)	.00015 (.00014)	.00007 (.00013)
$[4C < Temp < 8C]$.00026 (.00012)	.00017 (.00011)	.00025 (.00012)	.00016 (.00011)
$[8C < Temp < 12C]$.00019 (.00008)	.00017 (.00008)	.00019 (.00008)	.00017 (.00008)
$[16C < Temp < 20C]$	-.00016 (.00008)	-.00012 (.00008)	-.00013 (.00008)	-.0001 (.00008)
$[20C < Temp < 24C]$.00052 (.00011)	.00037 (.00011)	.00054 (.00011)	.0004 (.0001)
$[24C < Temp]$.00084 (.0002)	.00078 (.00018)	.00081 (.0002)	.00077 (.00018)
Year-Sizeclass Fixed Effects	No	Yes	No	Yes
Year-Export Fixed Effects	No	No	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
N	590605	590605	590605	590605

Notes: The table reports the coefficient estimates for all temperature bins using different specifications. The dependent variable is the logarithm of gross output. Standard errors clustered at the firm level are reported in parenthesis. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturhebung und Energieverwendung, 2003-2017, own calculations.

Table A2 Effect of Temperature on CO2 Emissions

	Log of Total CO2 Emissions			
	(1)	(2)	(3)	(4)
$[Temp < -8C]$.00126 (.00034)	.00146 (.00033)	.00124 (.00034)	.00144 (.00033)
$[-8C < Temp < -4C]$.00067 (.00025)	.00081 (.00024)	.00065 (.00025)	.0008 (.00024)
$[-4C < Temp < 0C]$.00086 (.0002)	.00082 (.00019)	.00084 (.0002)	.0008 (.00019)
$[0C < Temp < 4C]$.00082 (.00016)	.00074 (.00015)	.0008 (.00016)	.00074 (.00015)
$[4C < Temp < 8C]$.00055 (.00013)	.00047 (.00013)	.00055 (.00013)	.00047 (.00013)
$[8C < Temp < 12C]$.0001 (.00009)	.00009 (.00009)	.00009 (.00009)	.00008 (.00009)
$[16C < Temp < 20C]$	-.00007 (.00009)	-.00005 (.00009)	-.00007 (.00009)	-.00005 (.00009)
$[20C < Temp < 24C]$.00022 (.00013)	.0001 (.00012)	.00023 (.00013)	.00011 (.00012)
$[24C < Temp]$.00001 (.00023)	-.00003 (.00022)	0 (.00023)	-.00004 (.00022)
Year-Sizeclass Fixed Effects	No	Yes	No	Yes
Year-Export Fixed Effects	No	No	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
N	590195	590195	590195	590195

Notes: The table reports the coefficient estimates for all temperature bins using different specifications. The dependent variable is the logarithm of total carbon emissions. Standard errors clustered at the firm level are reported in parenthesis. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturhebung und Energieverwendung, 2003-2017, own calculations.

Table A3 Effect of Temperature on Direct CO2 Emissions

	Log of Direct CO2 Emissions			
	(1)	(2)	(3)	(4)
$[Temp < -8C]$.00545 (.00055)	.0056 (.00054)	.00542 (.00055)	.00558 (.00054)
$[-8C < Temp < -4C]$.00485 (.0004)	.00502 (.00039)	.00485 (.0004)	.005 (.0004)
$[-4C < Temp < 0C]$.00351 (.00031)	.00349 (.00031)	.00349 (.00031)	.00348 (.00031)
$[0C < Temp < 4C]$.0019 (.00025)	.00185 (.00025)	.00189 (.00025)	.00185 (.00025)
$[4C < Temp < 8C]$.0012 (.00022)	.00115 (.00022)	.0012 (.00022)	.00115 (.00022)
$[8C < Temp < 12C]$.00007 (.00015)	.00004 (.00015)	.00006 (.00015)	.00004 (.00015)
$[16C < Temp < 20C]$	-.00016 (.00015)	-.00015 (.00015)	-.00016 (.00015)	-.00014 (.00015)
$[20C < Temp < 24C]$	-.00069 (.0002)	-.00078 (.0002)	-.00069 (.0002)	-.00078 (.0002)
$[24C < Temp]$	-.00194 (.00036)	-.00199 (.00036)	-.00195 (.00036)	-.00199 (.00036)
Year-Sizeclass Fixed Effects	No	Yes	No	Yes
Year-Export Fixed Effects	No	No	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
N	546362	546362	546362	546362

Notes: The table reports the coefficient estimates for all temperature bins using different specifications. The dependent variable is the logarithm of direct carbon emissions, i.e. total emissions minus emissions resulting from electricity bought from the grid system. Standard errors clustered at the firm level are reported in parenthesis.

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturhebung und Energieverwendung, 2003-2017, own calculations.

Table A4 Effect of Temperature on CO2 Emissions from Electricity Use

	Log of CO2 Emissions from Electricity Use			
	(1)	(2)	(3)	(4)
$[Temp < -8C]$	-.00015 (.00038)	.00006 (.00037)	-.00018 (.00038)	.00004 (.00037)
$[-8C < Temp < -4C]$	-.00062 (.00028)	-.00048 (.00027)	-.00064 (.00028)	-.00005 (.00027)
$[-4C < Temp < 0C]$.00003 (.00022)	-.00002 (.00021)	0 (.00022)	-.00004 (.00021)
$[0C < Temp < 4C]$.00036 (.00017)	.00028 (.00017)	.00034 (.00018)	.00027 (.00017)
$[4C < Temp < 8C]$.00023 (.00015)	.00016 (.00015)	.00023 (.00015)	.00015 (.00015)
$[8C < Temp < 12C]$.0001 (.00011)	.0001 (.0001)	.0001 (.00011)	.0001 (.0001)
$[16C < Temp < 20C]$	-.00012 (.0001)	-.0001 (.0001)	-.00012 (.0001)	-.00009 (.0001)
$[20C < Temp < 24C]$.00044 (.00014)	.00032 (.00014)	.00045 (.00014)	.00033 (.00014)
$[24C < Temp]$.00074 (.00025)	.00069 (.00025)	.00073 (.00025)	.00069 (.00025)
Year-Sizeclass Fixed Effects	No	Yes	No	Yes
Year-Export Fixed Effects	No	No	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
N	587267	587267	587267	587267

Notes: The table reports the coefficient estimates for all temperature bins using different specifications. The dependent variable is the logarithm of carbon emissions from electricity bought from the grid system. Standard errors clustered at the firm level are reported in parenthesis. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturhebung und Energieverwendung, 2003-2017, own calculations.

Table A5 Effect of Temperature on CO2 Emissions from Oil Use

	Log of CO2 Emissions from Oil Use			
	(1)	(2)	(3)	(4)
$[Temp < -8C]$.00671 (.001)	.00652 (.00099)	.0067 (.001)	.00653 (.00099)
$[-8C < Temp < -4C]$.00394 (.00072)	.00358 (.00072)	.00388 (.00072)	.00356 (.00072)
$[-4C < Temp < 0C]$.00388 (.00056)	.00378 (.00056)	.00392 (.00056)	.0038 (.00056)
$[0C < Temp < 4C]$.00214 (.00048)	.00208 (.00048)	.00222 (.00048)	.00214 (.00048)
$[4C < Temp < 8C]$.0016 (.00041)	.00159 (.00041)	.00165 (.00041)	.00162 (.00041)
$[8C < Temp < 12C]$.00039 (.00028)	.00047 (.00028)	.00045 (.00028)	.00051 (.00028)
$[16C < Temp < 20C]$	-.00076 (.00027)	-.00067 (.00027)	-.00078 (.00027)	-.00068 (.00027)
$[20C < Temp < 24C]$	-.00103 (.00039)	-.00101 (.00039)	-.00107 (.00039)	-.00104 (.00039)
$[24C < Temp]$	-.00093 (.00068)	-.0008 (.00067)	-.00093 (.00068)	-.0008 (.00067)
Year-Sizeclass Fixed Effects	No	Yes	No	Yes
Year-Export Fixed Effects	No	No	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
N	232659	232659	232659	232659

Notes: The table reports the coefficient estimates for all temperature bins using different specifications. The dependent variable is the logarithm carbon emissions resulting from oil use. Standard errors clustered at the firm level are reported in parenthesis. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturerhebung und Energieverwendung, 2003-2017, own calculations.

Table A6 Effect of Temperature on CO2 Emissions from Gas Use

	Log of CO2 Emissions from Gas Use			
	(1)	(2)	(3)	(4)
$[Temp < -8C]$.00406 (.00074)	.00412 (.00074)	.00405 (.00074)	.00411 (.00074)
$[-8C < Temp < -4C]$.0029 (.00053)	.00298 (.00053)	.00292 (.00053)	.003 (.00053)
$[-4C < Temp < 0C]$.00285 (.00042)	.00277 (.00041)	.00283 (.00042)	.00277 (.00041)
$[0C < Temp < 4C]$.00189 (.00033)	.00179 (.00033)	.00188 (.00033)	.00178 (.00033)
$[4C < Temp < 8C]$.00122 (.00029)	.00113 (.00028)	.00122 (.00029)	.00113 (.00028)
$[8C < Temp < 12C]$.00045 (.0002)	.00042 (.0002)	.00043 (.0002)	.00041 (.0002)
$[16C < Temp < 20C]$	-.00025 (.0002)	-.00021 (.0002)	-.00024 (.0002)	-.0002 (.0002)
$[20C < Temp < 24C]$	-.00008 (.00027)	-.00019 (.00027)	-.00007 (.00027)	-.00017 (.00027)
$[24C < Temp]$	-.00058 (.00048)	-.00064 (.00048)	-.0006 (.00048)	-.00065 (.00048)
Year-Sizeclass Fixed Effects	No	Yes	No	Yes
Year-Export Fixed Effects	No	No	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
N	389079	389079	389079	389079

Notes: The table reports the coefficient estimates for all temperature bins using different specifications. The dependent variable is the logarithm of carbon emissions resulting from gas use. Standard errors clustered at the firm level are reported in parenthesis. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturhebung und Energieverwendung, 2003-2017, own calculations.

Table A7 Effect of Temperature on CO2 Emissions with Log of Sales as Control

	Total Emissions	Direct Emissions	Indirect Emissions
$[Temp < -8C]$.0015 (.00032)	.00563 (.00054)	.00011 (.00036)
$[-8C < Temp < -4C]$.00098 (.00023)	.00511 (.00039)	-.00031 (.00026)
$[-4C < Temp < 0C]$.00083 (.00018)	.00349 (.00031)	0 (.0002)
$[0C < Temp < 4C]$.00072 (.00015)	.00184 (.00025)	.00025 (.00016)
$[4C < Temp < 8C]$.00042 (.00013)	.00111 (.00022)	.0001 (.00014)
$[8C < Temp < 12C]$.00004 (.00009)	.00001 (.00015)	.00005 (.0001)
$[16C < Temp < 20C]$	-.00002 (.00008)	-.00012 (.00015)	-.00006 (.0001)
$[20C < Temp < 24C]$	0 (.00012)	-.00085 (.0002)	.0002 (.00013)
$[24C < Temp]$	-.00026 (.00021)	-.00212 (.00036)	.00045 (.00024)
Control Log of Gross Output	Yes	Yes	Yes
Year-Sizeclass Fixed Effects	Yes	Yes	Yes
Year-Export Fixed Effects	Yes	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
N	590195	546362	587267

Notes: The table reports the coefficient estimates for all temperature bins using different specifications. The dependent variable is the logarithm of carbon emissions resulting from gas use. Standard errors clustered at the firm level are reported in parenthesis. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturhebung und Energieverwendung, 2003-2017, own calculations.

Table A8 Impact on Gross Output

	Log of Gross Output					
	North vs. South		Old vs. New		Labor Intensity	
	North	South	Old	New	High	Low
[<i>Temp</i> < −8 <i>C</i>]	.00054 (.00063)	-.00089 (.0004)	-.00062 (.00037)	.00017 (.00043)	-.00046 (.00045)	.00016 (.00047)
[−8 <i>C</i> < <i>Temp</i> < −4 <i>C</i>]	.00009 (.00041)	-.00101 (.00031)	-.00137 (.00028)	-.00002 (.00031)	-.00063 (.00033)	-.00075 (.00035)
[−4 <i>C</i> < <i>Temp</i> < 0 <i>C</i>]	-.00018 (.00033)	-.00051 (.00024)	-.00044 (.00022)	.00016 (.00024)	-.00002 (.00026)	-.00038 (.00027)
[0 <i>C</i> < <i>Temp</i> < 4 <i>C</i>]	-.0003 (.00024)	-.00005 (.0002)	-.00012 (.00017)	.00025 (.00019)	.00009 (.0002)	-.00008 (.00021)
[4 <i>C</i> < <i>Temp</i> < 8 <i>C</i>]	-.00037 (.00023)	.00021 (.00016)	.00006 (.00014)	.00021 (.00017)	.00018 (.00018)	.00005 (.00018)
[8 <i>C</i> < <i>Temp</i> < 12 <i>C</i>]	-.00065 (.00015)	.00017 (.00011)	.00015 (.0001)	.00018 (.00011)	.00017 (.00012)	.00005 (.00013)
[16 <i>C</i> < <i>Temp</i> < 20 <i>C</i>]	.00023 (.00018)	-.00005 (.00011)	.00002 (.0001)	-.00018 (.00011)	-.00017 (.00012)	-.00002 (.00013)
[20 <i>C</i> < <i>Temp</i> < 24 <i>C</i>]	.00044 (.00022)	.00022 (.00017)	.00061 (.00014)	.00029 (.00015)	.00012 (.00016)	.00061 (.00018)
[24 <i>C</i> < <i>Temp</i>]	.0003 (.00043)	.00026 (.0003)	.00097 (.00025)	.00063 (.00026)	.00033 (.00028)	.0011 (.0003)
Year-Sizeclass Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Export Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	357060	233545	330551	260054	217247	243492

Notes: The table reports the coefficient estimates for all temperature bins (obviously except for the leave out bin) from the baseline model estimated on subsamples with the logarithm of gross output as the lhs variable. Standard errors are clustered at the firm level and reported in parenthesis. Plants observed in 1995 already are classified as old plants. Plants are those with a labor to sales ratio above the 60th percentile are classified as "high labor intensity". Plants with a labor to sales ratio below the 40th percentile are classified as low labor intensity plants. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AfID-Panel Industriebetriebe, 2003-2017, own calculations.

Table A9 Impact on Direct CO2 Emissions

	Log of Direct CO2 Emissions					
	North vs. South		Old vs. New		Labor Intensity	
	North	South	Old	New	High	Low
[<i>Temp</i> < -8C]	.00479 (.00126)	.0043 (.00075)	.00657 (.00074)	.00437 (.0008)	.00586 (.00087)	.00473 (.0009)
[-8C < <i>Temp</i> < -4C]	.0048 (.0008)	.00334 (.00057)	.00588 (.00055)	.00373 (.00057)	.00458 (.00062)	.00488 (.00066)
[-4C < <i>Temp</i> < 0C]	.0035 (.00063)	.00237 (.00046)	.0044 (.00043)	.00235 (.00045)	.00316 (.0005)	.00323 (.00051)
[0C < <i>Temp</i> < 4C]	.00227 (.00049)	.00149 (.00038)	.00235 (.00034)	.00127 (.00037)	.00173 (.00041)	.00138 (.00041)
[4C < <i>Temp</i> < 8C]	.00156 (.00045)	.00061 (.0003)	.00151 (.00029)	.00072 (.00032)	.00092 (.00035)	.00105 (.00036)
[8C < <i>Temp</i> < 12C]	-.00012 (.0003)	.00012 (.0002)	.00037 (.00021)	-.00027 (.00022)	-.00002 (.00024)	-.00022 (.00024)
[16C < <i>Temp</i> < 20C]	.00037 (.00036)	-.00002 (.00021)	-.00031 (.0002)	.00001 (.00023)	-.00005 (.00025)	-.00049 (.00024)
[20C < <i>Temp</i> < 24C]	-.00028 (.00044)	-.00037 (.00031)	-.00066 (.00028)	-.00075 (.00029)	-.00052 (.00032)	-.00116 (.00033)
[24C < <i>Temp</i>]	-.00126 (.00086)	-.00053 (.00057)	-.00229 (.00049)	-.00146 (.00053)	-.00156 (.00058)	-.00244 (.00059)
Year-Sizeclass Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Export Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	216445	329917	248619	297743	198850	226893

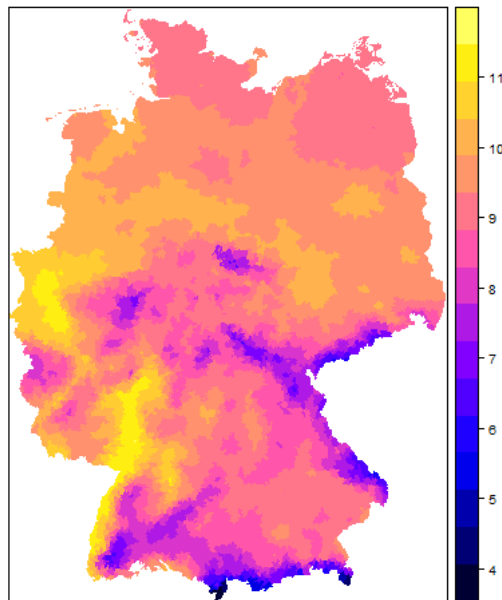
Notes: The table reports the coefficient estimates for all temperature bins (obviously except for the leave out bin) from the baseline model estimated on subsamples with the logarithm of direct carbon emissions as the lhs variable. Standard errors are clustered at the firm level and reported in parenthesis. Plants observed in 1995 already are classified as old plants. Plants are those with a labor to sales ratio above the 60th percentile are classified as "high labor intensity". Plants with a labor to sales ratio below the 40th percentile are classified as low labor intensity plants. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2003-2017, own calculations.

Table A10 Impact on CO2 from Electricity Use

	Log of CO2 Emissions from Electricity					
	North vs. South		Old vs. New		Labor Intensity	
	North	South	Old	New	High	Low
[<i>Temp</i> < −8C]	.00054 (.00085)	-.00041 (.00052)	-.0002 (.00047)	.0001 (.00056)	-.00025 (.0006)	-.00002 (.00061)
[−8C < <i>Temp</i> < −4C]	.0005 (.00053)	-.00069 (.0004)	-.00048 (.00036)	-.00072 (.0004)	-.00123 (.00044)	-.0002 (.00043)
[−4C < <i>Temp</i> < 0C]	.00029 (.00041)	-.00028 (.00031)	-.00006 (.00027)	-.00014 (.00032)	-.00052 (.00035)	.00002 (.00034)
[0C < <i>Temp</i> < 4C]	.00014 (.00032)	.00013 (.00026)	.00024 (.00023)	.00027 (.00025)	0 (.00029)	.00024 (.00027)
[4C < <i>Temp</i> < 8C]	.00004 (.00031)	.00021 (.00021)	.00011 (.00019)	.00011 (.00022)	.00004 (.00025)	.00011 (.00023)
[8C < <i>Temp</i> < 12C]	-.00035 (.00021)	.00002 (.00014)	.00001 (.00014)	.00017 (.00015)	.00017 (.00017)	-.00012 (.00017)
[16C < <i>Temp</i> < 20C]	.00031 (.00024)	.00004 (.00014)	-.00022 (.00012)	.00004 (.00015)	.00014 (.00017)	-.00033 (.00015)
[20C < <i>Temp</i> < 24C]	.00054 (.00029)	.00009 (.00022)	.0001 (.00018)	.00061 (.00021)	.00045 (.00023)	.00027 (.00022)
[24C < <i>Temp</i>]	.00078 (.00058)	.00058 (.0004)	.00033 (.00032)	.00112 (.00036)	.00103 (.00041)	.00053 (.00038)
Year-Sizeclass Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Export Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-East-West Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	232544	354723	258772	328495	215996	241972

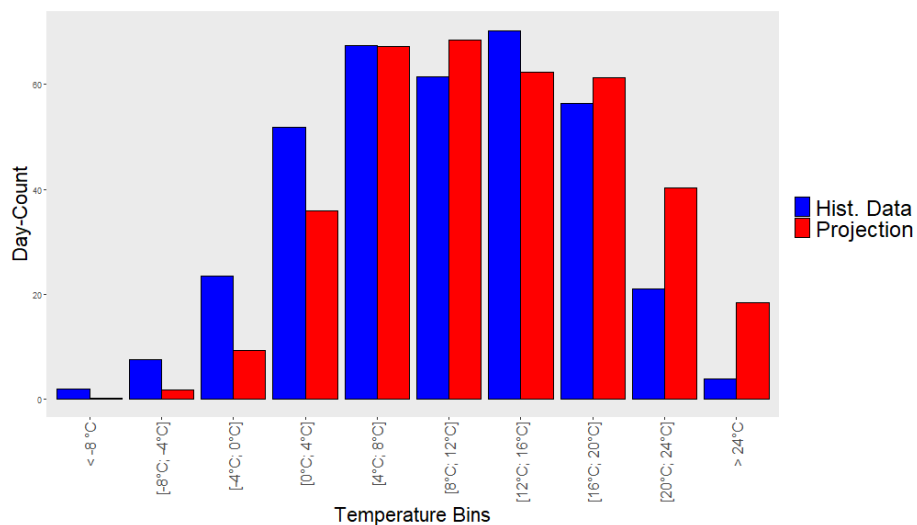
Notes: The table reports the coefficient estimates for all temperature bins (obviously except for the leave out bin) from the baseline model estimated on subsamples with the logarithm of carbon emissions resulting from electricity use as the lhs variable. Standard errors are clustered at the firm level and reported in parenthesis. Plants observed in 1995 already are classified as old plants. Plants are those with a labor to sales ratio above the 60th percentile are classified as "high labor intensity". Plants with a labor to sales ratio below the 40th percentile are classified as low labor intensity plants. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2003-2017, own calculations.

Figure A2 Mean Temperature



Notes: The temperature is the mean of the annual means from 1995 until 2017 at the municipality level. Source: E-OBS dataset from the EU-FP6 project UERRA (<https://www.uerra.eu>) and the Copernicus Climate Change Service

Figure A3 Average Number of Days per Temperature-Bin: Historical and Projected Distribution



Notes: The height of the bars give the average number of days per temperature bin. The average is a weighted average across federal states with weights being a federal state's share in total CO₂ emissions in the manufacturing industry. The blue bars are historical temperatures and the red bars the projected temperatures for the end of the century (2080-2099). Source: E-OBS dataset from the EU-FP6 project UERRA (<https://www.uerra.eu>) for the historical data. The projection has been produced by the Copernicus Climate Change Service. The projections result from the business as usual scenario (RCP8.5).