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The Effect of Temperature on Energy Use, CO2 Emissions, and Economic Performance in German Industry

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The Effect of Temperature on Energy Use, CO_2 Emissions, and Economic Performance in German Industry

Jakob Lehr,* and Katrin Rehdanz,†

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Abstract

This paper represents an addition to the scanty empirical evidence relating to the impact of temperature on the manufacturing sector. To study the effect of temperature on CO_2 emissions (energy use) and plants' economic performance, we combine daily temperature information from 11,000 German municipalities with the German census of the manufacturing industry for the period 2004 - 2017. We find that temperature affects industrial emissions significantly. Low temperatures cause a large and robust increase in CO_2 emissions as a reflection of heating requirements. For example, one additional day with a mean temperature below -6°C increases the average plant's emissions by $\approx 0.15\%$ or 6t CO_2 relative to a day with mean temperatures between 12°C and 15°C. Evidence for increased emissions from electricity consumption due to cooling needs is less consistent. We extend our analysis to encompass the effect of temperature on economic performance. While finding consistent evidence for a negative effect of cold days on gross output and labor productivity, results for hot days are mixed. Finally, we interpret our estimates against the backdrop of climate projections.

Keywords: Temperature, Manufacturing, Climate Change, Energy Use, CO_2 Emissions, Gross Output, Germany

JEL Classification: Q41, Q54, D22, L60

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1 Introduction

Among the various economic consequences of climate change, the impact of global temperature increase 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. Climate change affects energy consumption in the short term through weather variability and extreme events; in the long term, adaptation measures may restrict or even amplify this impact.

In this paper we provide new empirical evidence relating to the impact of extreme temperatures on energy use and related CO_2 emissions in the German manufacturing sector. The prevalence of extreme temperatures will increase due to climate change. The number of days with extreme temperatures from both ends of the temperature distribution will plausibly affect energy demand: low temperatures require more energy for heating and high temperatures increase cooling needs (Graff Zivin and Kahn, 2016). Moreover, the energy needed for industrial processes could also depend on outside conditions. In addition to estimating the temperature-emission relationship, we also analyze how temperature affects manufacturing plants' economic performance. Our paper thus adds to a recent literature that analyzes the effect of temperature on manufacturing plants (Zhang et al., 2018; Chen and Yang, 2019; Addoum et al., 2020; Somanathan et al., 2021; Kabore and Rivers, 2023). These studies focus on plants' economic performance, measured e.g. by output, output per worker or total factor productivity. Studies examining the temperature-energy use relationship exist only for household-level energy consumption (Deschênes and Greenstone, 2011; Auffhammer and Aroonruengsawat, 2011). Our paper thus makes two main contributions.[1]

First, we extend the literature on the effects of temperature on manufacturing plants by examining how plants' CO_2 emissions respond to temperature (and implicitly their energy use). Despite its relevance for economic development and its contribution to climate change, no micro-level empirical evidence exists concerning temperature's effect on manufacturing sector emissions. The need for further research on the effect of temperature on energy consumption at the firm/plant-level has also been foregrounded by Auffhammer and Mansur (2014). Germany, as Europe's industrial powerhouse, provides an ideal setting to study this question with industrial emissions amounting to approximately 200 million tons of CO_2 annually, which is about one-quarter of Germany's total emissions.[2] Taking indirect emissions into account, i.e. emissions arising from the generation of electricity that the manufacturing firms purchase from the grid system, the share is significantly higher.

Second, by looking at the effect of temperature on gross output and gross output per worker as a measure of industrial plants' economic performance, we contribute to the literature that analyzes the effect of temperature on economic activity. At the macro-level, previous studies have established a negative relationship between high temperatures and economic performance in poor/developing countries but not in advanced economies (e.g. Dell et al., 2012). A growing body

[1] Dell et al. (2014) provide a comprehensive survey of multiple branches of the literature that studies the impact of weather.

[2] See, for example, the information from Germany's principal environmental protection agency ("Umwelt Bundesamt") as published in Umweltbundesamt (2018).

of literature provides evidence of the effect of temperature on economic activity at the plant-level. For example, Zhang et al. (2018) and Chen and Yang (2019) focus on how temperature affects productivity and factor reallocation in China. Similarly, Somanathan et al. (2021) study the effects of temperature on manufacturing firms in India, Addoum et al. (2020) focus on the United States, and Kabore and Rivers (2023) conduct such an analysis for Canada. For advanced economies, the evidence concerning the effect of temperature on economic performance is mixed. While Addoum et al. (2020) document a flat relationship between sales and temperature for the US, Kabore and Rivers (2023) find adverse temperature effects at the tails of the temperature distribution for Canadian firms. We add to this yet inconclusive literature by studying the case of Germany, a country in which the manufacturing sector is of particular significance for the overall economy: the manufacturing sector in Germany absorbs more than 15% of Germany's labor force and, in recent years, has contributed approximately one quarter to Germany's gross domestic product.[3] Against this background, studying the effect of temperature on the economic performance of plants in the manufacturing sector is of particular relevance.

For our analysis, we draw on comprehensive census data which covers the universe of German manufacturing plants with more than 20 employees, spans more than two decades from 1995 to 2017, and specifies such factors as plant-specific fuel use. We observe close to 40,000 plants on an annual basis. Thanks to detailed reporting of fuel use by fuel type (more than 20 categories), we can calculate CO_2 emissions at the plant level. We combine the census data with daily temperature information from 11,000 municipalities.

In our baseline specification, we relate the yearly CO_2 emissions of plants to a discretized temperature distribution by using temperature bins similar to, for example, Barreca et al. (2016). To check the robustness of our results, we also test an alternative temperature specification based on seasonal averages (cf. Chen and Yang, 2019). We investigate effect heterogeneities in terms of factor intensities, plants' age and location. As in prior literature, causal identification rests on the assumption that conditional on plant and year-by-sector fixed effects, daily temperature variation is quasi-random.

In line with what one would expect, our estimates show a large and significant increase of CO_2 emissions in response to more days with low temperatures, presumably reflecting the increase in heating requirements. Specifically, we find that an additional day with a mean temperature below -6°C increases the average plant's annual total CO_2 emissions by 0.15% and its direct emissions by 0.42% relative to a day with a mean temperature between 12°C and 15°C degrees. Both effects decline towards higher temperature bins but remain quantitatively and statistically significant. We do not find robust evidence of increased electricity consumption that could be related to air conditioning. Our results are qualitatively and quantitatively similar in specifications with dependent variables in levels instead of logs. We find some indication for adaptation and a decline in the temperature sensitivity of emissions over time, but overall effect heterogeneities, e.g. in terms of factor intensities, are limited. To interpret the effect size and

[3] See, for example, Statistisches Bundesamt (2020).

implied magnitudes, we take the most recent years from 2018 until 2022, which, except 2021, were abnormally warm, and ask the question of how average plant's emissions would have looked like, based on our estimates, if temperatures matched the average from the period 2004-2017. These calculations show that the estimated emission-temperature relation implies that (direct) emissions were reduced by (4-7%) 1-2% for the average plant due to warm temperatures in recent years. To further interpret the size of our estimates, we pair them with projections for different climate change scenarios and calculate the implied changes in emissions. Under a business-as-usual scenario and based on c.p. assumptions, the average plants' direct emissions from fuel combustion will decrease by approximately 12-14% until the end of the century, while electricity-related emissions will not change.

We find small but significant and robust adverse effects from low temperatures on gross output and gross output per worker. These results are quantitatively in line with the estimates from Kabore and Rivers (2023) for Canada and qualitatively with the results from Chen and Yang (2019) for China. We find mixed results for high temperatures: the baseline specification indicates a negative effect on gross output but not on gross output per worker.

The remainder of this paper is structured as follows: Section 2 reviews the related literature, in section 3 we introduce the datasets and provide summary statistics, and section 4 discusses the empirical approach. The main results are presented in section 5 and section 6 discusses the results and concludes.

2 Literature Review

At the country level, there is documentation of a negative and significant association between high temperatures and aggregate economic outcomes such as economic growth or production. Dell et al. (2012), for example, show that in poor countries temperatures 1°C above the long-term mean lead to a reduction of per-capita income by 1.5%. Hsiang et al. (2015) document non-linear adverse effects of high temperatures on productivity with an annual average temperature of 13°C being optimal. Drawing upon international trading data, Jones and Olken (2010) study the effect of higher temperatures on a country's export activities. In line with Dell et al. (2012), they find that an increase of 1°C in poor countries reduces export growth by 2 to 5.7 percentage points. They also find that this impact primarily affects the export of agricultural products and light manufacturing. In general, much of the literature on the link between economic activity and temperature focuses on the agricultural sector (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016). Among the more recent papers focusing on the agricultural sector, Aragón et al. (2021) pay special attention to farmers' adaptation behavior by drawing upon household data. Miller et al. (2021) consider the effect of prolonged exposure to heat (i.e. heat waves).[4]

Based on a panel of 28 Caribbean countries, Hsiang (2010) finds a negative temperature effect

[4] In a related literature Jia et al. (2022) and Lin et al. (2021) explore medium to long run impacts (e.g. firm entry and exit) of floods.

on three out of six non-agricultural sectors, with output losses in non-agricultural production substantially exceeding losses in agricultural production. More recently, Kalkuhl and Wenz (2020) used global subnational data for 1500 regions in 77 countries from 1900 to 2014 to estimate the effect of climate conditions on productivity. Their estimates indicate that temperature affects productivity levels but not the growth rate.

A growing body of literature analyzes the effect of extreme weather conditions on the manufacturing sector at the plant-level. Elliott et al. (2019), for example, find strong but short-lived adverse effects of typhoons on the sales figures of manufacturing plants in China. For plant-level evidence on the effect of temperature on Total Factor Productivity (TFP), see Zhang et al. (2018). They combine daily mean temperatures with a panel of Chinese plants for the period 1998 to 2007. The authors document strong and non-linear negative effects on output from temperatures at the tails of the temperature distribution, which is driven by a negative effect of temperature on TFP. Their estimates indicate that a 1°C shift in the annual distribution of daily temperature causes a reduction of about 0.5% of China's GDP. Based on climate projections for the mid-21st century, these estimates imply an annual output loss of 12% in the Chinese manufacturing sector. Using the same data as Zhang et al. (2018), Chen and Yang (2019) also find a U-shaped relationship between temperature and output, which they measure as value added per worker. 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 positively affect sales, whereas high summer temperatures dampen economic activity. The detrimental effect of high summer temperatures is stronger in relatively cool regions, suggesting that firms are adapting. The results produced by Somanathan et al. (2021), who use a panel of Indian manufacturing firms, broadly confirm the adverse effects of high temperature on output estimated by Zhang et al. (2018) and Chen and Yang (2019). However, the findings by Somanathan et al. (2021) suggest that the decline in output due to extreme temperatures can be fully explained by the lower labor productivity caused by increased absenteeism and heat stress at the workplace.[5] Mixed evidence exists for the effect of temperature on plant performance in developed countries. Addoum et al. (2020) find that temperature does not affect firms in the USA, while Kabore and Rivers (2023) document an adverse effect of extreme temperatures on Canadian manufacturers. 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 temperatures between 12°C and 18°C.

Few studies analyze the effect of climate change on energy consumption (for an overview see Auffhammer and Mansur, 2014). These studies have primarily focused on households. The ones most closely related to our work are Deschênes and Greenstone (2011) or Auffhammer and Aroonruengsawat (2011), who use panel data to study households' adaptation to climate change by analyzing how residential energy / electricity consumption responds to temperature. Deschênes and Greenstone (2011) find that an additional day with mean temperatures below

[5]Indeed, other studies confirm that temperature affects labor market outcomes such as labor productivity and labor supply (cf. Heal and Park, 2016; Zivin and Neidell, 2014.

-12°C increases annual residential energy consumption by 0.32% relative to a day with mean temperature between 10 and 15°C. For the right end of the temperature distribution they find that an additional day with mean temperature above 32°C increase energy consumption by 0.37%. Combing theese estimates with climate projections under a business as usual scenario yields an 11% increase in residential energy consumption by the end of the century. Auffhammer and Aroonruengsawat (2011) use data from different climate zones within California to estimate how residential electricity consumption responds to weather conditions. Their findings indicate sizable differences between climate zones. Extrapolations of their estimates based on climate change scenarios imply a 55% increase in electricity consumption.

3 Data and Descriptive Statistics

3.1 AFiD Panel - Manufacturing Plants

Our primary data source is the German census of the manufacturing industry called AFiD ("Amtliche Firmendaten für Deutschland"), which covers the universe of German manufacturing plants with more than 20 employees. The census data consists of different data modules that can be merged based on plant identifiers. For our analysis, we combine the modules "energy-use" ("Energieverwendung") and "industrial plants" ("Industriebetriebe"). *"AFiD Modul Industriebetriebe"* (industrial plants module) with *"AFiD Modul Energieverbrauch"* (energy use module).[6] In principle, the AFiD panel covers more than two decades, from 1995 to 2017. However, we restrict ourselves to data from 2004 onward due to a major change in the reporting of energy variables between 2002 and 2003.[7] To allow for the fact that it may have taken time for companies to adjust their reporting, we only use energy data from 2004 onward.[8]

Energy-use module: The energy-use module contains detailed information about plants' fuel-specific energy use in physical units (kWh) (more than 20 different fuel categories). This information allows calculating CO_2 emissions at the plant-level based on fuel-specific conversion factors.[9] To calculate indirect emissions from electricity purchased from the grid system we apply the average carbon content, which we also obtain from the "Umwelt Bundesamt" (Umweltbundesamt, 2018).

Industrial-plants module: We supplement the energy-use module with the industrial-plants module, which contains a rich fund of plant-level economic performance indicators such as gross output, number of employees, export share, wagebill and investment behavior. It also provides the plants' economic sector at the four-digit level and, importantly, the plant's geographic

[6] AFiD-Modul Industriebetriebe: Source: DOI: 10.21242/42111.2021.00.01.1.1.0, own calculations.
AFiD-Modul Energieverbrauch: Source: DOI: 10.21242/43531.2021.00.03.1.1.0, own calculations.

[7] For a detailed description of the dataset as well as the change in the reporting requirements see (Petrick et al., 2011).

[8] Our results are, however, also robust to the longer period from 2003 onwards.

[9] To calculate plant-level CO_2 emissions, we draw upon the conversion factors provided by the Umwelt Bundesamt (a table with the relevant information can be found using the following link https://www.umweltbundesamt.de/themen/klima-energie/treibhausgas-emissionen, last retrieved 18.11.2020). The table gives the fuel-specific time-varying CO_2 content per terajoule, which we convert to CO_2 per kWh. We then multiply the fuel use in kWh with the respective conversion factor to obtain the CO_2 emissions.

location at the municipality level.

Table 1 provides summary statistics of the raw data. Panel A of Table 1 shows summary statistics for economic performance indicators. It can be seen that the average plant in the sample has approximately 111 employees, a turnover of 24 million euros per year, an export share of 21%, pays an average annual wage per worker of $\approx$ 33 thousand euros and invests roughly 640 thousand in buildings or machinery. Comparison of mean plant with median plant reveals mostly right-skewed distributions.

Panel B of Table 1 contains summary statistics on the plants' total energy use, CO_2 emissions and emissions by fuel type. The average plant's annual energy consumption is almost 8000 MWh, associated with more than 2600 tons of CO_2 emissions. The distributions of energy use and emissions are even more skewed to the right with median values being around one-seventh of the means. Looking at fuel-specific emissions it becomes apparent that indirect emissions from electricity consumption account for more than half of total emissions. The average plant causes indirect emissions of almost 1600 tons per year. Gas is the most critical direct energy source, causing approximately 25% of total emissions. Coal and oil are equally important and jointly account for about 10% of total emissions.[10] Coal use appears mainly concentrated as consumption at the 90^{th} percentile is zero, which can be explained by the fact that coal is generally used in a few energy-intensive industrial processes but hardly ever for heating. To characterize emission intensities we take the ratio of (direct) carbon emissions to gross output as shown in the last two rows of Table 1. One can see that the average plant emits approximately 115kg CO_2 in order to produce gross output worth thousand euros. The direct emission intensity of the average plant amounts to $\approx$ 44 kg CO_2 per thousand euros gross output.

3.2 Temperature and Weather Data

We supplement the plant data with temperature information collected from the German Meteorological Service ("Deutscher Wetterdienst") and the "European Climate Assessment & Dataset project".[11] We downloaded gridded daily mean temperatures to calculate the mean temperature for all 11,000 German municipalities.[12] 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. In addition to the daily temperature information, we collect data from the German Meteorological Service on average annual rainfall, the number of days with snowcover and information about the incidence of droughts.[13] We use those variables as controls in the regression analysis.

To provide an overview of the binned temperature data, the histogram in Figure 1 summarizes the temperature distribution by federal state for the period 2004 to 2017. The bins in Figure 1

[10] Total emissions include emissions from some additional sources of energy such as heat, all of which play a minor role.

[11] 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).

[12] The median municipality has approximately 1800 inhabitants and an area of 19km^2.

[13] The data can be downloaded by clicking on this link.

Table 1: Economic performance indicators and CO_2 Emissions by Fuel (2004 - 2017)

Variable	Mean	Std. Dev	p10	p50 (Median)	p90	N
A. Economic Performance Indicators						
Number of Employees	111	161.74	25	56	247	485619
Gross Output (in 1000€)	23868.67	49259.57	1943.06	7672.15	57621.76	485619
Export Share (in %)	21	26	0	10	62	485619
Average Wage (in 1000€)	32.58	12.27	17.81	31.57	48.22	485619
Investment (in 1000€)	638.89	1509.62	0	119.72	1652.72	485619
B. CO_2 Emissions / Energy Use						
Total Energy (in MWh)	7767.68	30003.83	196.48	1065.52	14247.37	485619
Total CO_2 Emissions (in t)	2612.86	9386.05	69.90	415.86	5299.60	485619
CO_2 Emissions - Coal (in t)	109.04	2551.33	0	0	0	485619
CO_2 Emissions - Gas (in t)	694.76	3757.82	0	30.15	961.71	485619
CO_2 Emissions - Oil (in t)	126.60	1308.93	0	0	189.12	485619
CO_2 Emissions - Electricity (in t)	1586.90	5827.39	38.66	284.18	3470.46	485619
CO_2 Emission Intensity (kg/1000€)	114.63	324.59	12.80	58.20	222.38	485619
Direct CO_2 Emission Intensity (kg/1000€)	43.99	201.25	1.30	11.70	75.27	485619

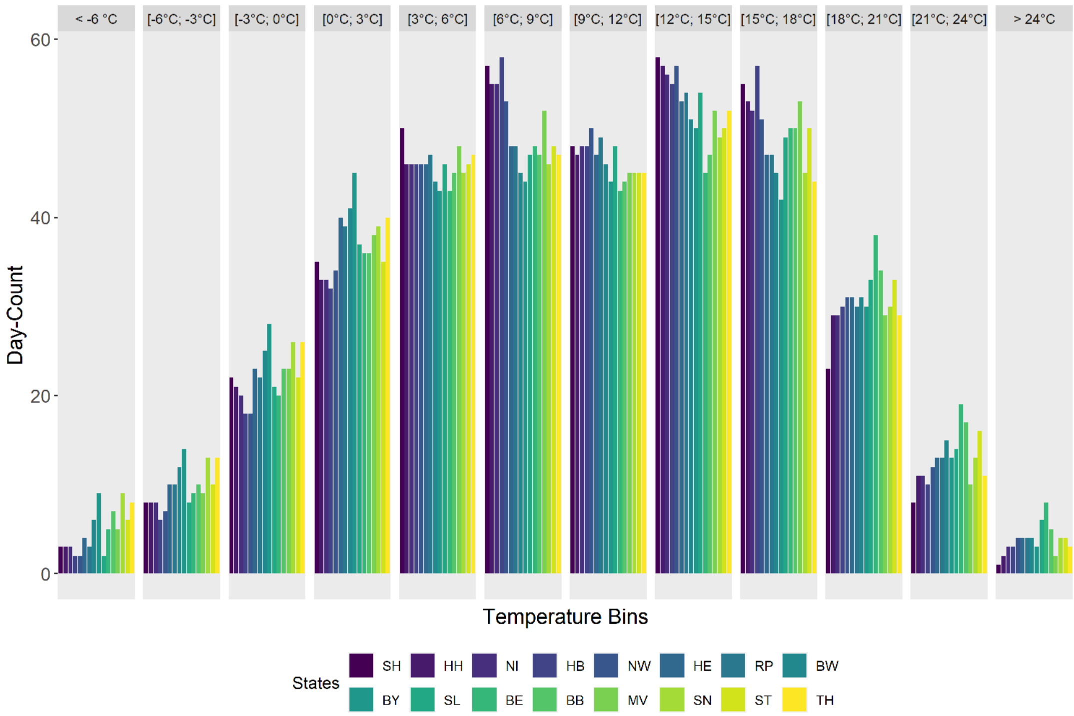
Notes: Part A. of the table shows descriptive statistics for plant level indicators of economic performance. Gross output, the average wage, and investment are expressed in 1000s of Euros per year. Part B. of the table shows descriptive statistics for annual energy use in MWh, CO_2 emissions in t, and emission intensities in kg per 1000€ of gross output. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Kostenstrukturerhebung und Energieverwendung, 2004-2017, own calculations.

are the unweighted averages across municipalities and years for each federal state. On average, about three-quarters of the days in a year have a mean temperature between 0°C and 21°C. The histogram is indicative of some spatial variation in the distribution of temperature. For example, the average municipalities in Bavaria (BY) and Saxonie (SN) experienced ten days with mean temperatures below -6°C compared to just three days in the average municipality in Schleswig-Holstein (SH); the most northern federal state located between the Baltic and the Northern Sea.

Towards the upper end of the temperature distribution, Berlin (BE) experienced on average eight days with temperatures above 24°C compared to just one day in Schleswig Holstein (SH). Because Berlin is geographically small compared to other federal states, aggregation at the level of federal states masks out only little within state variation in the case of Berlin. For so-called territorial lands ("Flächenlïider") there exists substantial within state variation, e.g. regions along the Rhine in the South West of Germany experienced significantly more hot days than Berlin.

Figure 2 shows within federal state variation by plotting the average number of days below 0°C (Figure 2a) and above 18°C (Figure 2b) at the municipality level. One can see that days with mean temperatures below 0°C rarely occur in regions with a maritime climate in the North and along the Rhine in the (south) west of Germany. They are generally more frequent further east and most frequent in regions with higher elevation, which tend to be in the south and along the borders. Hot days occur most often along the Rhine, especially in the metropolitan area around Frankfurt. Figure A1 in the appendix shows the annual mean temperature in municipalities for the period 2004 to 2017.

Figure 1: Temperature Bins by Federal State



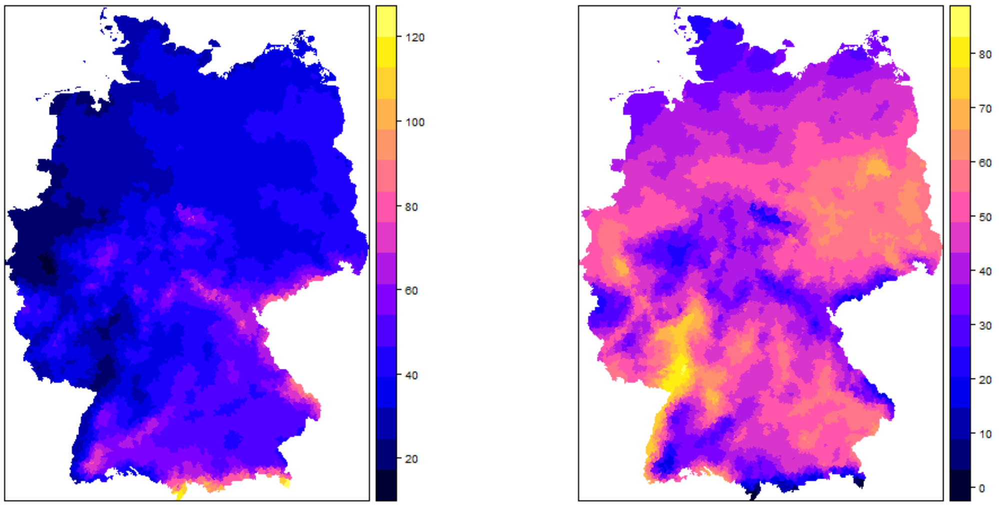
Notes: The figure shows the average number of days per bin between 2004 and 2017 for each federal state. The abbreviations in the legend stand for the federal states in Germany: SH = Schleswig-Holstein, HH = Hamburg, NI = Lower Saxony (Niedersachsen), HB = Bremen, HE = Hesse (Hessen), RP = Rhineland-Palatinate (Rheinland-Pfalz), BW = Baden-Württemberg, BY = Bavaria (Bayern), SL = Saarland, BE = Berlin, BB = Brandenburg, MV = Mecklenburg-Western Pomerania (Mecklenburg-Vorpommern), SN = Saxony (Sachsen), ST = Saxony-Anhalt (Sachsen-Anhalt), TH = Thuringia (Thüringen). Source: E-OBS dataset from the EU-FP6 project UERRA (https://www.uerra.eu) and the Copernicus Climate Change Service, own calculations.

3.3 Climate Projections

To project the effect of climate change on CO_2 emissions, energy consumption, and economic performance 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 in the framework of the ReKiEs-De Project.[14] We use projections from two different climate models and for two representative concentration pathways (RCP). The first projection is based on the MPI-ESM-LR global climate model and the CCLM regional downscaling model. The second projection is based on the EC-Earth global model and the same downscaling model, i.e. CCLM. Both models provide projections for the ”climate-protection

[14]We 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. In particular, we thank ReKliEs-De (Regionale Klimaprojektionen Ensemble für Deutschland) 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).

Figure 2: Average Number of Cold and Hot Days per Year



(a) Mean Temp. below 0°C **(b)** Mean Temp. above 18°C

Notes: Subfigure 2a plots the average number of days with mean temperatures below 0°C for the period 2004 to 2017. Subfigure 2b shows the average number of days with mean temperatures above 20°C for the period 2003 to 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

scenario" (RCP2.6) and the "business-as-usual" scenario (RCP8.5).[15] The projections begin in 2006 and extend to 2100. Using the same temperature bins we used for historical temperature information, Figure A2 in the appendix shows the projected mean temperatures (red bars) distribution under the RCP8.5 scenario alongside the historical distribution (blue bars) across temperature bins. It is readily apparent that the distribution of projected temperatures is shifted to the right.

4 Empirical Approach

We are interested in the effect of temperatures on plant-level outcomes. To align the frequencies between the annually observed plant-level outcomes and the daily temperature data, we use temperature bins and seasonal means to summarize the annual distribution of mean daily temperatures. The temperature bin approach is widely used in the literature, for example, by Deschênes and Greenstone (2011), Zhang et al. (2018) or Barreca et al. (2016). Specifically, we estimate variants of the following equation:

$$y_{imsdt} = \sum_{j \neq z} \theta^j T^j_{mt} + \beta W_{mt} + \nu_{dt} + \lambda_s \times t + \tau_i + \varepsilon_{imsdt} \tag{1}$$

where y_{imsdt} can be any outcome of plant i located in municipality m, federal state s and industry d in year t. As common in this literature we also control for additional weather controls collected

[15] ReKiEs-De stands for Regionale Klimaprojektionen Ensemble für Deutschland. Background information on the various climate projections, their underlying global and regional models, and general information on the ReKiEs Project can be found in Hübener et al. (2017).

in the vector W_{mt}.[16] Annual shocks common to subsectors are absorbed by the year-by-sector fixed effects ν_{dt}. Federal state specific time trends $\lambda_s \times t$ control for differential trends in economic development between the federal states, e.g. the catch-up of regions that formerly belonged to the German-Democratic-Republic (GDR). Finally, time-invariant plant characteristics are controlled for by the plant fixed effect τ_i and ε_{imsdt} is a random disturbance term.

The variables of interest are the measures of temperature. In equation 1, T^j_{mt} is the number of days in municipality m and year t with a mean temperature in bin j. In total, we define twelve bins, each inner bin having a width of 3°C.[17] All days with a mean temperature below -6°C are collected in T^1_{mt}. T^{12}_{mt} is the number of days with mean temperatures above 24°C (cf. Figure 1). 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 that day being in the leave-out bin z. Our application excludes the temperature bin 12-15°C, which is the mode (cf. Figure A2). The coefficient θ^j thus indicates the change in the outcome resulting from an additional day with a mean temperature falling in bin j instead of a temperature in the interval 12-15°C. 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. Therefore, the approach can capture non-linear effects of temperature on plants' outcomes which is an advantage compared to potential alternative temperature measures like averages or heating and cooling degree days. The coefficient θ^j is estimated consistently if the year-to-year temperature variation experienced by plant i is exogenous, which is arguably true of temperature.

5 Results

This section describes our findings on the relationship between temperature and CO_2 emissions (5.1). Subsequently, we examine the effect of alternative measures of temperature (5.2) and heterogeneities in terms of factor intensities, plant age, plant location, and plants' economic activity (5.3). We then analyze the temperature-output relationship (5.4) and finally interpret our results against the backdrop of temperatures in recent years and climate projections (5.5).

5.1 Main Results: Temperature and Plants' CO_2 Emissions

Figure 3 shows the effect of temperature on the log of total CO_2 emissions based on equation 1. The solid line connects the point estimates, i.e. the semi-elasticities, and the two dashed lines correspond to the 95^{th} confidence intervals. The figure shows the estimated effect of an additional day in bin j relative to the bin omitted, i.e. relative to a day with a mean temperature between 12°C and 15°C. This baseline regression includes sector-year fixed effects to purge sector-specific shocks, sales-decile-year fixed effects to control for shocks that occurred along the firm-size distribution, exporter-year fixed effects, and federal state-specific time trends. We also control for additional weather variables, e.g. average annual rainfall. Because the weather data

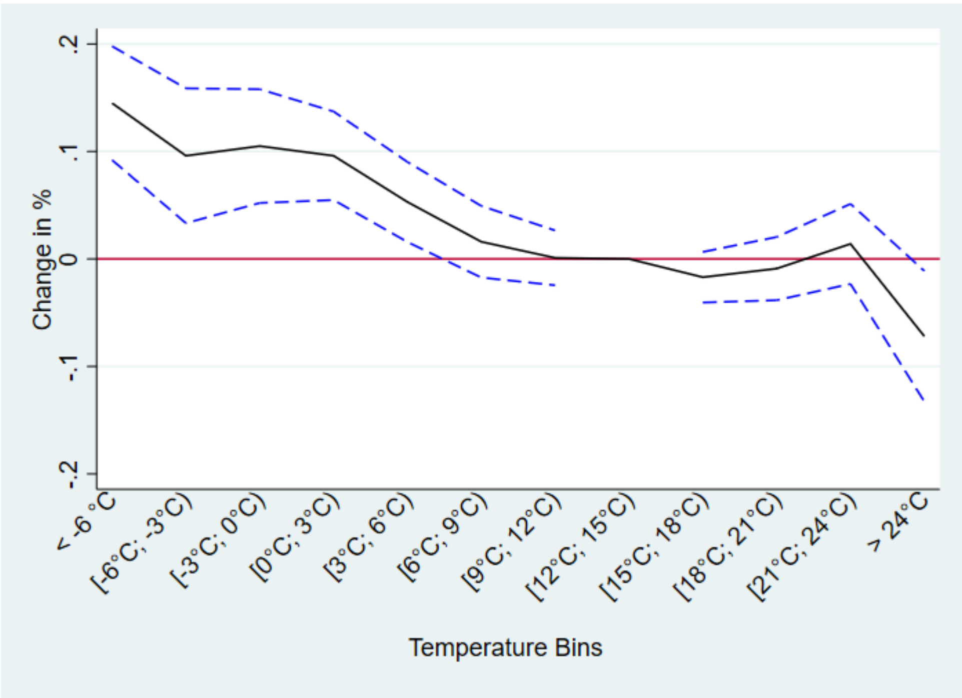
[16] The weather controls include annual mean rainfall, the number of days with snow cover and a drought index.

[17] We also tried other bin sizes, for example, considering bins with a width of 4°C. The results are qualitatively the same and can be made available on request.

is reanalyzed from station data and the network of stations does not cover all municipalities, we cluster standard errors at the district level, a much higher level of regional aggregation.[18] For reasons of conservatism we also cluster at the four-digit economic sector level.

From Figure 3 one can see that more cold days cause an increase in CO_2 emissions. Specifically, one more day with a mean temperature below -6°C leads to a increase in annual CO_2 emissions by approximately 0.15% relative to a day with mean temperatures between 12°C and 15°C. The point estimates that measure the effects of temperature between -6°C and -3°C, -3°C and 0°C and 0°C and 3°C are similar to each other, indicating a relative increase of emissions by approximately 0.1%. The effect then starts to flatten out and becomes insignificant for the [6°C - 9°C] bin. The point estimates that capture the effect of additional days with mean temperatures above those in the omitted bin are insignificant except for the one measuring the effect of days with mean temperature above 24°C. This outermost coefficient indicates a drop in total emissions by approximately 0.7%. The effect is significant at the 5% percent level but estimated with comparably low precision.

Figure 3: Estimated Effects of Temperature on Log Annual CO_2 Emissions



Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. The regression includes year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 485,295. Dashed lines show the 95^{th} confidence interval. Standard errors are clustered at the district level and at the four-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A1 in the appendix reports the results from estimating alternative specifications using different sets of controls and fixed effects. The most parsimonious specification includes only

[18]There exist 402 districts compared to more than 11,000 municipalities

sector-year fixed effects along the weather controls (column 1). Column 2 adds time trends by federal states; column 3 additionally controls for sales-decile-year fixed effects; column 4 adds exporter-year fixed effects and column 5 lagged temperature bins. Overall, our results are very robust across specifications.

Estimating the baseline specification with total emissions in levels yields an additional perspective on the magnitude of the effect. Interestingly, the results are qualitatively and quantitatively similar to the log specification (Figure A4a in the appendix). For example, an additional day with a mean temperature below -6°C causes an increase in the average firm's emissions by ≈ 6 tons corresponding to more than 0.2% of the average firm's CO_2 emissions. Temperatures in the bins -6°C to -3°C, -3°C to 0°C and 0°C to 3°C increase emissions by ≈ 3 tons corresponding to approximately 0.1% of total emissions (cf. Table 1). If the effect of temperature on emissions was concentrated only among plants with very low emissions, one would expect a much smaller effect size in the specification with emissions in levels. Thus, a similar magnitude of the effect in levels compared to the estimates in logs speaks to the relevance of the impact of temperature on emissions for aggregate emissions.

The effect of temperature on total emissions is a combination of the effect of temperature on emissions from different energy sources. In the next step, we thus undertake a separate investigation of the response of indirect emissions (i.e. emissions contained in the electricity purchased by plants) and direct emissions (i.e. emissions resulting from the combustion of fossil fuels at the plants themselves). The findings are shown in Figure 4a and Figure 4b, respectively.

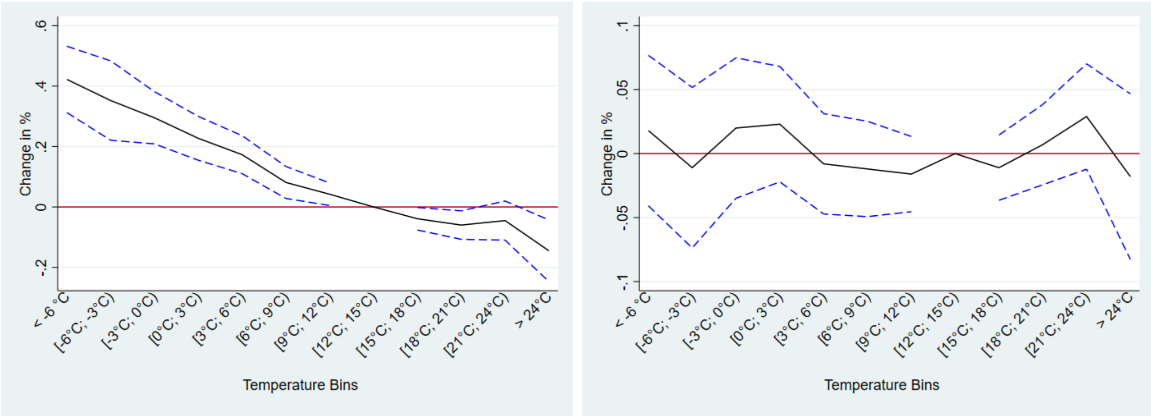
One can see that direct emissions drive the effect of low temperatures on total emissions. The point estimate capturing the effect of one additional day in the lowest temperature bin implies an increase of direct emissions by more than 0.4% relative to one day with mean temperatures between 12°C and 15°C. The effect declines almost linearly in the direction of the bin omitted but remains statistically significant for all point estimates. Direct emissions decrease further at the right end of the temperature distribution as temperatures rise. However, except for the outermost bin, the effect seems to flatten out.[19] By contrast, the baseline specification shows that electricity consumption is entirely unaffected by temperatures, as can be seen from Subfigure 4b. All estimates are quantitatively but also qualitatively insignificant (notice the different y-axis scales between Subfigures 4a and 4b).[20]

The results presented so far indicate that direct CO_2 emissions rise when temperatures are low while indirect emissions do not respond to temperatures. Since energy is a highly flexible input,

[19]Table A2 in the appendix reports estimates from the alternative specifications, yielding qualitatively similar results. In light of the results on the effect of temperature on total emissions, it is worth noting that the most parsimonious specification without federal state specific time trends (column 1 of Table A2) indicates even larger negative effects of hot days on direct emissions.

[20]Results from further regression specifications are in the appendix (Table A3). As anticipated from the discussions above, a positive effect of high temperatures on indirect emissions exists if we do not control for time trends by federal state (cf. column 1 of Table A3). These results could be indicative of cooling needs. However, they could also reflect differential trends in economic activity, leading to differences in energy demand, a point to which we will return in subsection 5.4. The results from alternative specifications as reported in columns 2 to 5 of Table A3 are similar to each other.

Figure 4: Estimated Effects of Temperature on Log Annual CO_2 Emissions by Type of Emissions



(a) Log of Direct Emissions **(b)** Log of Indirect Emissions

Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. The regressions include year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 453,919 (left figure) and 482,717 (right figure). Dashed lines show the 95^{th} confidence interval. Standard errors are clustered at the district and the four-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

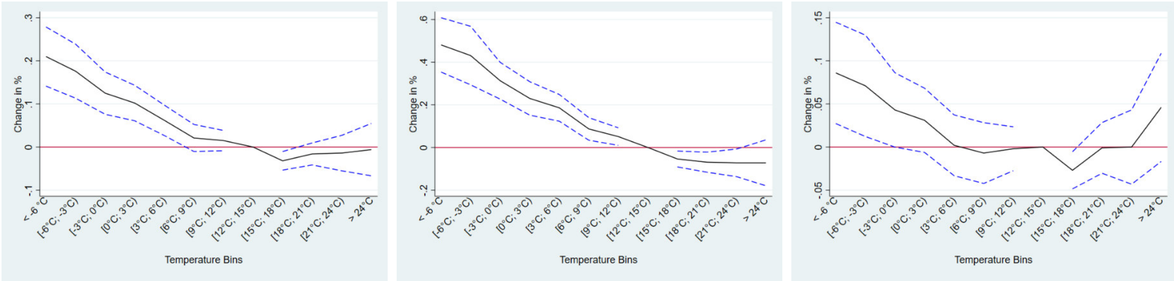
one would expect a high correlation between energy use and a plant's economic activity. In order to isolate changes in emission intensity of production, we scale annual CO_2 emissions with gross output. The estimated effects of temperature on total emission per unit of gross output (CO_2 emission intensity) plus direct and indirect CO_2 intensities are shown in Figure 5.

Figure 5a shows that the effect of low temperatures on total emission intensity is similar to the effect of temperature on total emissions. The point estimates are slightly larger than those in Figure 3. Temperatures above the reference bin do not affect total emission intensity, contrasting with the negative effect of temperatures above 24°C on total emissions. Figure 5b reports results for the effect of temperature on direct emission intensity. As for total emission intensity, the point estimates are larger than those for direct emissions and the relationship between higher temperatures and direct emission intensities is flat. Finally, the effect of temperature on indirect emission intensity (Figure 5c) looks u-shaped. This result contrasts the flat and insignificant relationship between temperature and indirect emissions. The increase in intensities at the tails of the distributions (the effect for high temperatures is insignificant) could be explained by electricity use for heating and cooling but also with an imperfect adjustment of electricity consumption to changes in output (the denominator of emission intensity).[21]

Overall, the estimates presented thus far show clear evidence for increased heating needs during cold periods. By contrast, they do not provide compelling evidence of cooling needs during hot periods.

[21] In the appendix, we show baseline estimates with direct emissions and intensities in levels instead of logs in Figure A4. The effects are qualitatively and quantitatively similar to the estimates in the respective log specifications.

Figure 5: Estimated Effects of Temperature on Log Annual CO_2 Emission Intensities



(a) Log of Total CO_2 Intensity **(b)** Log of Direct CO_2 Intensity **(c)** Log of Indirect CO_2 Intensity

Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. The regressions include year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 485,295 (left figure), 453,919 (middle figure) and 482,717 (right figure). Dashed lines show the 95^{th} confidence interval. Standard errors are clustered at the district and the four-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

5.2 Alternative Measures of Temperature

In order to test the robustness of our findings and gain deeper insights into the relationship between temperature and CO_2 emissions, we extend our analysis by estimating this relationship using seasonal mean temperatures. This alternative approach allows us to shed light on seasonally differentiated effects of temperature deviations from its average. An approach based on a simple annual average would be unable to differentiate these heterogeneous temperature effects.

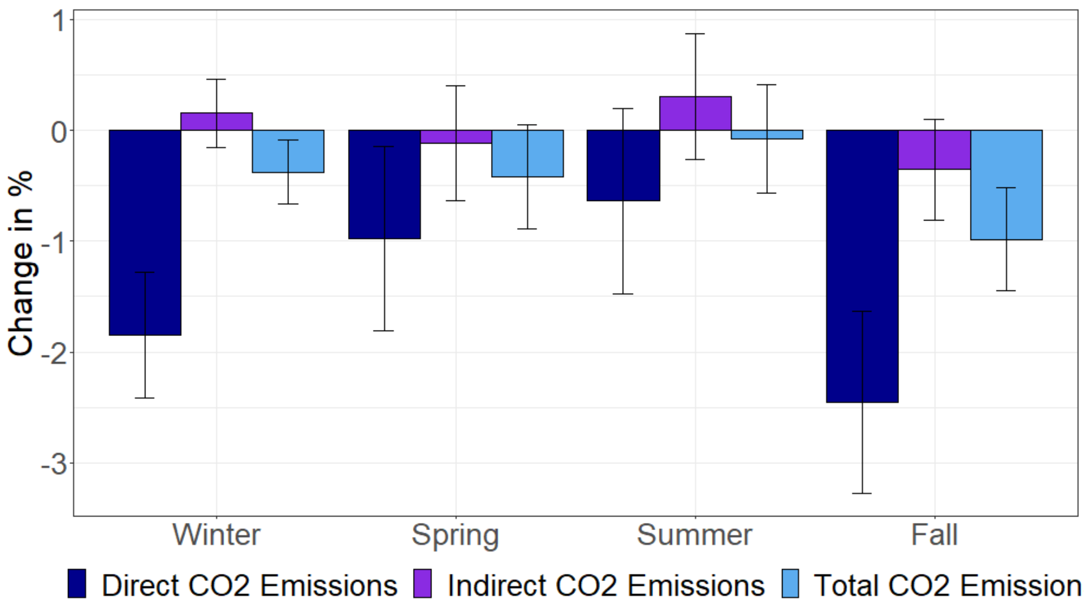
Figure 6 shows the effect of mean seasonal temperatures on total emissions, direct emissions, and indirect emissions obtained from our baseline specification. The height of the bars corresponds to the size of the point estimates, and the thin lines show the 95^{th} confidence intervals. A negative coefficient indicates that higher mean seasonal temperatures cause lower CO_2 emissions. As expected from our previous analysis, we find that higher temperatures have a strong negative effect on direct emissions. The negative relation between direct emissions and mean temperatures is significant for all seasons except summer. Quantitatively, the point estimates imply that a 1°C increase of the mean temperature in fall leads to a decrease in direct emissions by $\approx$ 2.5%, in winter a 1°C increase leads to a decrease in direct emissions by $\approx$ 2%, in spring to a decrease by $\approx$ 1% and in summer by $\approx$ 0.5%, which is statistically insignificant, however.[22] This effect carries over to total emissions: a 1°C higher mean temperature in winter and spring leads to a drop in overall emissions by about 0.5% and a 1°C higher mean temperature during fall causes total emissions to fall by about 1%. The point estimates for indirect emissions from electricity use are indistinguishable from zero for every season.

The effects on emission intensities are shown in the appendix in Figure A3. The effects of mean temperatures in spring and winter on direct emission intensity are slightly larger than the effect on direct emissions. In contrast, the effect of temperatures in fall on direct emissions is slightly attenuated. Note that we find a significant increase in the indirect emission intensity for higher

[22] Average within region standard deviations of mean temperatures in spring, summer and fall are approximately 1°C and roughly 1.7°C for winter means.

mean temperatures in summer by about 0.5%, which could indicate heating needs.

Figure 6: Estimated Effects of Seasonal Mean Temperature on Log Annual CO_2 Emission



Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. The regressions include year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 453,919 for direct emissions, 482,717 for indirect emissions and 485,295 for total emissions. Thin lines show the 95^{th} confidence interval. Standard errors are clustered at the district and the four-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

5.3 Effect Heterogeneity

To assess possible effect heterogeneities we continue by analyzing subsamples. The following paragraphs describe the sample splits and their rational and briefly summarize the results. A more detailed description of the results is contained in the appendix (cf. section B.1)

Split by factor intensities First, we divide by energy intensity to gauge the relevance of the effect of temperature on the average plants' emissions for aggregate emissions. Specifically, we divide between plants operating in sectors considered as energy intensive and those operating in other sectors.[23] We find the response of plants' emissions to temperature to be smaller in the energy-intensive sectors but still quantitatively meaningful. This suggests that the positive effects of cold days on the average plant's direct emissions are also relevant for direct emissions in the aggregate. We proceed by splitting between plants with an above/below median labor intensity in all years and likewise for capital intensity. Studies suggest that labor is a particularly temperature-sensitive production factor; for example, Somanathan et al. (2021) show that decreasing labor productivity can fully explain the negative relationship between

[23]The following five two-digit sectors are classified as energy-intensive: Manufacture of chemicals and chemical products, Manufacture of basic metals, Manufacture of coke and refined petroleum products, Manufacture of other non-metallic mineral products and Manufacture of paper and paper products (cf. DESTATIS, 2022).

temperature and output in India's manufacturing industry. Therefore, plants with a relatively high labor intensity might respond more strongly to temperature fluctuations if they balance the marginal productivity gains from heating and cooling against the marginal costs. Our results, however do not point to stark heterogeneities. The estimates only yield some suggestive evidence for a positive response of indirect emissions to high temperatures in the more labor-intensive subsample, indicative of energy consumption for cooling (cf. Tables A4 and A5).

Split by geographic region Second, we divide the sample by geographic region to assess adaptation. To divide by region, we split the sample into plants in the north and those in the south.[24] In the north of Germany, temperatures are moderate, i.e. winters are mild and summers relatively cool. Studies investigating the temperature-output relationship yield mixed evidence regarding adaptation. Chen and Yang (2019) find that higher summer temperatures have larger adverse effects on output in colder regions. In contrast, Kabore and Rivers (2023) find no evidence for a differential output response to extreme temperatures depending on plants' location. In the context of our study, adaptation implies that plants located in regions with relatively cold winters invest more in isolating their buildings, leading to a smaller increase in CO_2 emissions in response to cold days. In regions where hot periods occur more frequently, firms might invest in air conditioning; hence, higher temperatures are more likely to increase electricity demand. Our results provide some indication for adaptation to a more frequent occurrence of cold days, i.e. direct emissions from plants in the north increase stronger in response to cold days (cf. Table A6).

Split by plant vintage Thirdly, we are evaluating whether older plants differ from more recently established ones in terms of their emissions response to temperature. To achieve this, we classify the sample into plants observed as early as 1995 and those that became part of the sample after that year.[25] Insulating material has improved over time and is available at a lower cost. Expectations regarding future climate conditions have also changed, and therefore firms' calculations concerning investment profitability, e.g. in air conditioning, changed. Newly established plants are more likely to adopt these new technologies or adjust to changes in expectations since retrofitting old plants will likely be more expensive than installing them during construction. Therefore, their emissions might respond differently to temperature. Indeed, we find clear evidence that the response of direct emissions to cold days becomes attenuated over time, i.e. plants established more recently need less energy for heating (cf. Tables A4 and A8). These estimates also suggest that there exists energy savings potential from retrofitting. For example, the difference between the point estimates in the outermost bins is 0.00084 and 0.00143, which, given the average number of days in respective bins, implies that the average old firm's emissions would be $\approx 1.46\%$ lower if their direct emissions were as sensitive to temperatures in

[24] All plants in Schleswig-Holstein, Hamburg, Lower Saxony, Bremen, North Rhine-Westphalia, Berlin, Mecklenburg-West Pomerania, and Brandenburg are classified as located in the north. All other plants are classified as being located in the south.

[25] Note that we have no direct information concerning the plants' vintage. The fact that we did not observe some plants in 1995 does not necessarily imply that they did not exist then. For example, a plant with fewer than 20 employees is not included in the sample.

the outermost bins as the new firm's direct emissions.[26].

Split by economic sectors Finally, we look at the effect of temperature on CO_2 emissions in different economic sectors. We find a relatively homogenous effect of cold temperatures across sectors. We find positive and (marginally) significant effects of higher temperatures on indirect emissions in the "combined food industry" and in "printing and reproduction of recorded media" (cf. Figure A5b). It seems plausible that the cooling demand in the food industry is comparably high.

5.4 Temperature and Plants' Economic Performance

Our aim is also to contribute to the literature investigating the effect of temperature on the economic performance of firms and plants (Kabore and Rivers (2023); Somanathan et al. (2021); Addoum et al. (2020)). In pursuit of this aim, we estimate the effect of temperature on gross output and labor productivity measured as gross output per worker. For this, we draw upon the same baseline specifications that we used to estimate the effect of temperature on CO_2 emissions. Figure 7 shows the estimates from the temperature bin specification (upper part) and the effects from seasonal mean temperatures (lower part).

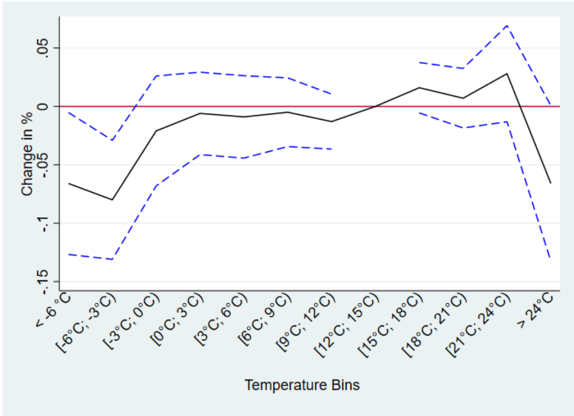
Subfigure 7a plots the estimated response of gross output to temperature, showing that negative temperatures significantly depress gross output. For example, one more day with mean temperature below -3°C degree depresses the average firm's output by 0.07%. For higher temperature bins the point estimates are very close to zero, implying that temperatures between 0°C and 24°C do not affect gross output. Temperatures at the right end of the distribution (above 24°C) are found to depress output, too. The estimate is relatively imprecise, however. These results are mostly robust to estimating the specification based on seasonal mean temperatures, as shown in Subfigure 7c. The results imply that a 1°C higher mean temperature in winter and spring increases the average firm's gross output by $\approx$ 0.4%. Albeit negative, the effect of mean summer temperatures is relatively small and statistically insignificant.

The adverse effects of cold temperatures are also evident when looking at labor productivity (cf. Subfigure 7b). Each day in which the mean temperature falls below -6°C reduces labor productivity by $\approx$ 0.06% compared to a day with a temperature between 12°C and 15°C. The effect becomes continuously smaller reaching zero for days with a mean temperature between 3°C and 6°C. In contrast, higher temperatures have no detrimental effect on sales per worker. The results from the seasonal means specification again mirror these findings: higher temperatures in winter and spring increase gross output, and the point estimates for mean temperatures in summer and fall are small and insignificant (cf. Subfigure 7d).

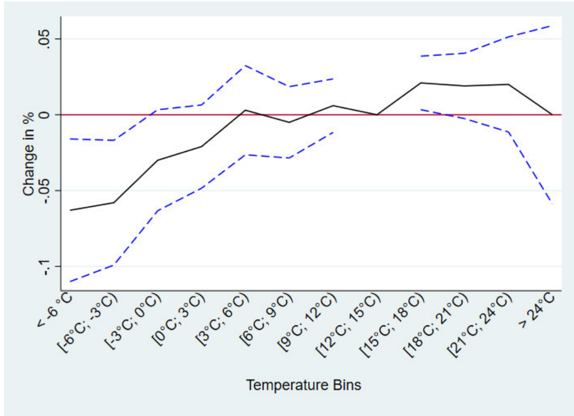
When applying the baseline specification using dependent variables in levels (see Figure A6 in the appendix), the results indicate that an extra cold day with a mean temperature below -3°C leads to an average reduction of approximately €20,000 in gross output for plants. This

[26] On average, the number of days in respective bins has been 4 and 8 (cf. Figure A2): 0.00084*4 + 0.00143 * 8 = 0.0146).

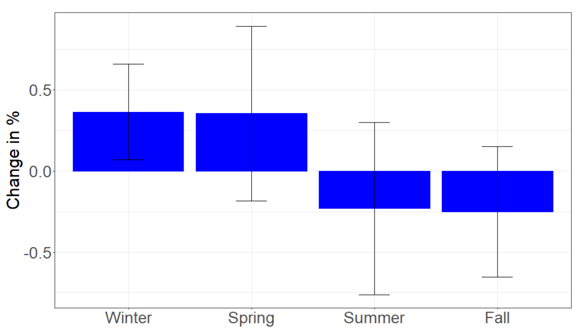
Figure 7: Estimated Effects of Temperature on the Log of Gross Output and Gross Output per Worker



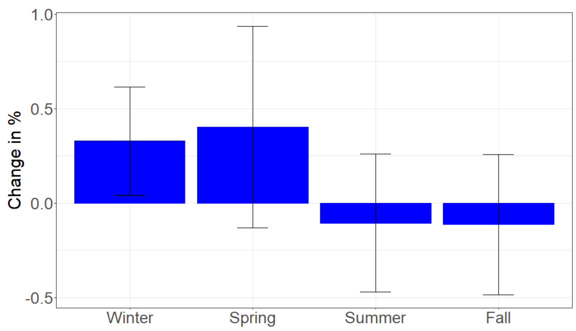
(a) Log of Gross Output



(b) Log of Gross Output per Worker



(c) Log of Gross Output



(d) Log of Gross Output per Worker

Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. All regressions include year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). Standard errors are clustered at the district and the four-digit sector level. The number of observations in all regressions is 485,619. 95^{th} confidence intervals are demarcated by the dashed lines in the upper part of Figure 7 and by thin lines in the lower part of Figure 7. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

reduction corresponds to around 0.08% of a plant's annual output. The estimate thus closely matches the result from the log specification concerning its magnitude. Towards the other end of the temperature distribution, we find that an extra hot day with a mean temperature above 24°C depresses output by ≈ 30,000 Euro. Positive, albeit insignificant, effects of seasonal mean temperatures in winter and spring reflect the negative impact of cold days on gross output. The negative coefficient of mean summer temperatures reflects the adverse effect of hot days on gross output. Specifically, a 1°C higher mean summer temperature causes a reduction of gross output by 200,000 Euro, which is almost 1% of the dependent variable's average (cf. Figure A6c), which is a substantially larger effect than the result from the log specification. Subfigures A6b and A6d show the results from the levels specifications for labor productivity. The results confirm the negative effect of cold days on labor productivity found in the log specifications. Using temperature bins (subfigure A6b), we do not find an adverse effect of high temperatures on labor productivity, whereas the seasonal mean specification is indicative of such an effect (cf. Subfigure A6d).

Tables A9 to A14 in the appendix report the results from alternative specifications including sample splits. The effect on sales and sales per worker is relatively stable across subsamples divided by factor intensities (cf. Tables A11 and A12). If anything, the effects of cold days are slightly stronger for plants with a lower labor intensity and for plants with a higher capital intensity. The response of gross output to temperature is quantitatively similar in the north and south (cf. Table A14). Since the effects for plants in the north are less precise, they mostly lack significance. We find a negative and marginally significant effect of high temperatures on labor productivity in the south. No consistent differences exit by plants vintage as shown in the right parts of Tables A13 and A14.

5.5 Effect Size, Climate Projections and Recent Temperatures

To interpret the size of the effects, we follow the literature (Deschênes and Greenstone, 2011; Chen and Yang, 2019; Kabore and Rivers, 2023) and combine the estimated relationships between temperature and plant-level outcomes with the climate projections introduced in subsection 3.3. Furthermore, we contextualize our findings by considering recent temperature observations between 2018 to 2022, i.e., we calculate the change in the average plant's outcome relative to a counterfactual scenario in which the temperature distribution across bins mirrors the historical average observed during the period from 2004 to 2017.

Recent Temperature Realizations In recent years, Germany has experienced some of its warmest temperatures on record (Imbery et al., 2023). To put the temperature-emission relationships that we estimate in perspective, we pose the following question: What percentage change has occurred in the average emissions of plants over the past five years, relative to a scenario in which temperatures averaged out between 2004 and 2017? To answer this question we first construct temperature bins for the years 2018 to 2022. Next, we calculate the average number of days in each bin during the reference period from 2004 to 2017. In each case the bins are constructed separately for each federal state and then aggregated to the country level using the federal states' share of CO_2 emissions in the manufacturing sector (as observed in the AFiD data) as weights. Figure A7a in the appendix displays the weighted average number of days per temperature bin during the 2018-2022 period, compared to the weighted averages from 2004-2017. This representation highlights a substantial increase in temperatures between these two periods. The differences between 2018-2022 and these averages are then multiplied by the corresponding coefficients and aggregated across all bins. Figure A7b illustrates the annual percentage changes in (direct) emissions, gross output, and gross output per worker for the average plant. Our calculations suggest that in 2018, 2019, 2020, and 2022, direct emissions for the average plant were 4-7% lower than they would have been with temperature distributions similar to those between 2004 and 2017. Total emissions showed a 1-2% reduction, while output (output per worker) increased by 0.5-1%. Taking the sample average for total emissions as shown in Table 1 these calculations correspond to an emission reduction in the order of 26-52t for the average plant. In contrast, 2021 exhibited a more typical temperature distribution, which is reflected in our calculations.

Climate Projections First, we follow Deschênes and Greenstone (2011) and implement their "error-correction method" to correct for systematic errors in the projections.[27] We then bin the projected temperatures.[28] Figure A2 in the appendix shows the result from this exercise, i.e. the weighted number of days per bin from the projected temperatures (red bar) at the end of the century (average day count between 2080 and 2099). The same Figure also shows the weighted average number of days per temperature bin for the historical temperature distribution (blue bars). To calculate the implied change in plants' outcomes, we multiply each regression coefficient with the corresponding difference in the number of days per bin, i.e. the difference in the height of the red and blue bars (the procedure is akin to the exercise above based on recent temperatures).

In Table 2, we report the projected emission change under a business-as-usual (BAU) scenario and one emission-reduction scenario (RCP2.6) using the output from two climate models introduced in subsection 3.3. For each model-scenario combination, we calculate the change in total emissions, direct emissions, and electricity-related indirect emissions (a) for the middle of the present century (average for years 2050 - 2069) and (b) for the end of the century (average for years 2080 - 2099).

As expected, linking our point estimates with climate-change projections results in a decrease in direct emissions that translates to total emissions but constant electricity-related indirect emissions. Combining baseline estimates for direct emissions with climate projections under a BAU scenario indicates a decrease in direct emissions by approximately 6% in the middle of the century and by 12-14% by the end of the century for the average plant. These findings align with the calculated effect of high temperatures in recent years described above (cf. Figure A7b). The respective changes under the emission-reduction scenario are much smaller, particularly towards the end of the century. These direct emission declines correspond to declines in total emissions, which are roughly one-third of the direct emission declines. We also link our estimates of the effect of temperature on economic performance to the climate projections. The results yield an increase in gross output due to the rightward shift in temperature distribution. For the BAU scenario, this increase amounts to an approximately 0.5% increase in gross output by the middle of the century and a 0.9% increase by the end of the century. The changes are slightly larger for labor productivity (cf. Table 2). Fewer cold days must drive the results in this exercise and the small magnitudes result from the small point estimates.

[27] We use the period from 2006 to 2018 to compare the simulated mean temperatures in each federal state with the actual temperature. We take the average differences between each day's projected mean and actual mean temperatures. These day-specific average projection errors are then added to the projected temperatures for each day.

[28] Again we bin separately by federal state and aggregate to the country level using the federal states' share of CO_2 emissions in the manufacturing sector as weights.

Table 2: Projections Based on the Estimated Temperature-Emission(-Output) Relationship

Outcome	Time	EC Earth (BAU)	EC Earth (RCP2.6)	ESM-LR (BAU)	ESM-LR (RCP2.6)
A. Δ Emissions					
CO2 Total	Mid Century	-1.57	-0.98	-1.78	-1.67
CO2 Total	End Century	-4.38	-0.57	-4.16	-1.84
CO2 Direct	Mid Century	-5.48	-2.96	-5.92	-4.95
CO2 Direct	End Century	-14.12	-2.22	-12.62	-5.10
CO2 Elec.	Mid Century	0.08	-0.11	0.00	-0.23
CO2 Elec.	End Century	-0.07	0.04	-0.29	-0.37
B. Δ Econ. Perf.					
GO	Mid Century	0.52	0.28	0.48	0.48
GO	End Century	0.89	0.49	0.51	0.43
GO / L	Mid Century	0.80	0.42	0.82	0.69
GO / L	End Century	1.74	0.46	1.45	0.73

Notes: The table shows the change in CO_2 emissions (total, direct, indirect), gross output and gross output per worker that results from combining the regression estimates from the baseline model, which includes year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days) with the projected change in temperatures from different scenarios for climate change. Mid century refers to the average of the period 2050-2069 and end century to the average of the period 2080-2099. The columns are different combinations of climate models and future CO_2 emission scenarios (BAU vs. emission reductions). Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017 and World Climate Research Program (WCRP)/ ReKiEs-De Project, own calculations.

6 Conclusion and Discussion

This paper estimates the effect of temperature on CO_2 emissions and economic performance in the German manufacturing sector. We use daily temperature information from 11,000 German municipalities 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 from 2004 to 2017.

We find large and significant effects of cold days on CO_2 emissions, presumably reflecting heating needs. For example, one additional day with a mean temperature below -6°C increases CO_2 emissions at the plant-level by about 0.15% relative to a day with a mean temperature between 12°C and 15°C. The response of direct CO_2 emissions, which is about three times as big as the effect on total emissions, drives the effect. In contrast to direct emissions, indirect CO_2 emissions from electricity use do not respond to temperatures. All point estimates pertaining to the effect of cold days tend to increase when we look at emission intensities, specified as emissions relative to gross output instead of emissions.

To investigate heterogeneities in the response of plants to temperature, we split the sample by plants' factor intensities (energy, labor and capital), between geographic regions and by age. Qualitatively, the response of emissions to temperature is similar for most subsamples. We find some indication that direct emission (intensity) is less sensitive to cold days among plants located in the south compared to direct emissions from plants located in the north. This difference could suggest that plants adapt since low temperatures are more frequent in the south. We also find that new plants' response to cold days is attenuated relative to the response by older plants. The availability of better materials, e.g. building insulation materials, may cause a dampened response to cold days in new plants. This heterogeneity provides us with an indication of the energy savings potential from retrofitting old plants. Finally, we find suggestive evidence that indirect emissions (intensity) increase with high temperatures among more labor-intensive plants.

We cannot compare our findings on the relationship between temperature and CO_2 emissions with those of other studies as this is, to our knowledge, the first study to investigate this relationship for the manufacturing sector. Validation or falsification of our results must therefore be left to future studies. We can say however, that our results accord well with estimates for residential energy consumption in the US (Deschênes and Greenstone, 2011). For days with mean temperature between -6°C and -12°C, they estimate an increase in energy demand by 0.19% and for days with mean temperature below -12°C, they find that energy demand increases by 0.32%. They find no effect of days with mean temperatures between 21° and 26° on energy consumption but temperatures in the categories 26° to 32° and above 32° increase energy consumption by 0.17% and 0.37%.

We have extended our analysis to include the effect of temperature on gross output and gross output per worker. We find evidence for a small negative effect of low temperatures (below zero °C) on both measures of economic performance. In terms of direction and size our results are in line with the existing literature for developing countries (cf. Chen and Yang, 2019) as well as for developed countries. In particular, the estimates from Kabore and Rivers (2023), who look at manufacturing firms in Canada, accord well with our results on both ends of the temperature distribution. They find that temperatures between 0°C and -12°C adversely affect firms' gross output. Their estimates increase disproportionately with lower temperatures finding that an additional day with a mean temperature below -18°C depresses output by $\approx 0.2\%$ relative to a day with a mean temperature between 12°C and 18°C. Their estimates of the effect of cold temperatures on output per worker are also of a similar size as ours. Interestingly, they find that high temperatures above 24°C negatively affect output while the coefficient capturing the effect on output per worker is insignificant and has a positive sign which matches our findings. This last result stands in some contrast to findings for developing countries (cf. Somanathan et al., 2021; Chen and Yang, 2019) but is consistent with estimates for the US by Addoum et al. (2020).

Our analysis suggests that warmer temperatures will make it somewhat easier for Germany to reduce its CO_2 emissions in the manufacturing sector. For instance, our estimates imply that high temperatures in recent years reduced the average plants' direct emissions by 4-7%. Similarly to the counterfactual calculations for recent years, we also link our estimates to climate projections to calculate how emissions would change under a c.p. assumption. These calculations yield a decrease of the average plants' direct emissions of approximately 12-14% under a BAU scenario by the end of the century. Since we do not estimate a positive effect of hot days on electricity demand, the right shift of the temperature distribution does not lead to higher indirect emissions in our calculations. Given the right-skewed distribution of CO_2 emissions, as described in Section 3, the overall emissions reduction in the manufacturing sector will likely be smaller than the reduction of the average plant. We want to emphasize that these calculations should not be seen as predictions but rather as an interpretation of the empirical results and the effect size against the backdrop of projected climate change. The calculations are based on c.p. assumptions, i.e., firms do not adapt to climate change through relocation or investment strategies. Since the projected changes in temperature distribution imply far more extreme temperatures at the distribution's right tail, i.e. hot periods will occur with unexampled frequency (Figure A2), it appears likely that firms will adapt, e.g. by installing air conditioning. This adaptation behavior would increase electricity demand when temperatures are high. For example, Deschênes and Greenstone (2011) project an increase in households' energy demand in the US due to climate change because the increased demand for cooling dominates the decreased energy demand for heating. Yet, our estimates show that in the case of manufacturing plants in Germany, this is not the case based on the current relationship between temperature and energy use.

Besides a general shift in the temperature distribution, climate change will lead to more extreme and catastrophic events occurring more frequently. An aspect that we have not considered in this paper. Therefore, complementary empirical work could investigate the effect of such extreme events, to the extent that they have happened in the past, like heat waves, floods or extreme storms on German manufacturing plants.

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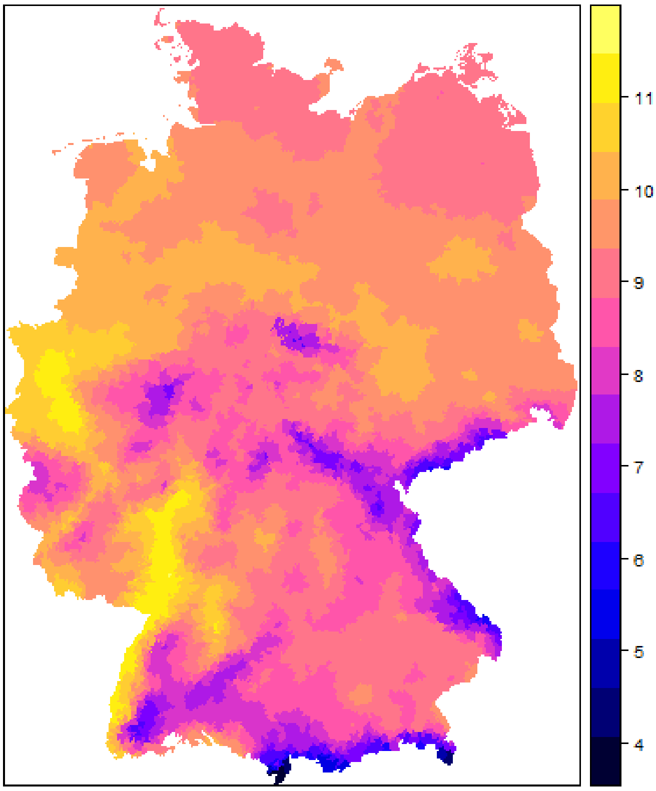
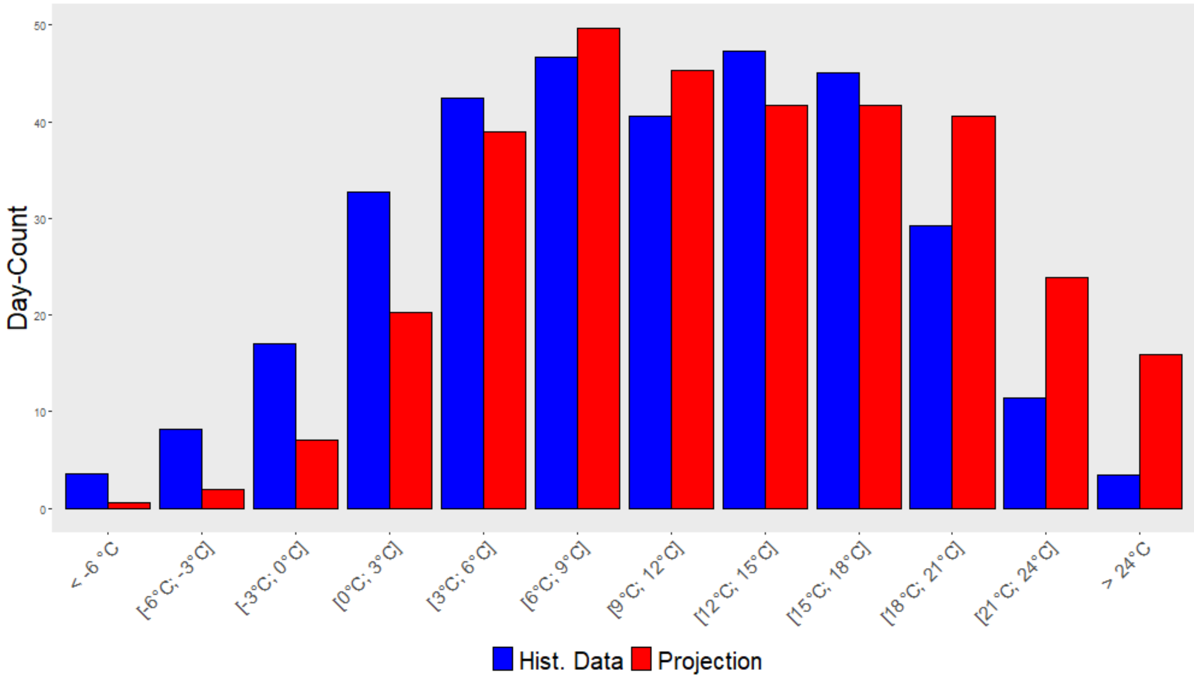
Appendix A Additional Material

Figure A1: Mean Temperature by Municipality



Notes: The temperature is the average of the annual means from 2004 to 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 A2: Historical and Projected Number of Days per Temperature-Bin



Notes: The height of the bars indicates the average number of days per temperature bin. The average is a weighted average across federal states, the weights corresponding to a federal state's share in total CO_2 emissions for the manufacturing industry. The blue bars are historical temperatures, 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. Projection from the Copernicus Climate Change Service. The projections result from the business-as-usual scenario (RCP8.5).

Appendix B Additional Results

Table A1: Effect of Temperature on Total CO_2 Emissions

	Log of Total CO_2 Emissions				
	(1)	(2)	(3)	(4)	(5)
[Temp $< -6°$]	0.00158***	0.00151***	0.00151***	0.00145***	0.00151***
	(0.00034)	(0.00028)	(0.00027)	(0.00027)	(0.00030)
[$-6° <$ Temp $\leq -3°$]	0.00085**	0.00098***	0.00102***	0.00096***	0.00108***
	(0.00039)	(0.00032)	(0.00032)	(0.00032)	(0.00030)
[$-3° <$ Temp $\leq 0°$]	0.00113***	0.00107***	0.00108***	0.00105***	0.00109***
	(0.00031)	(0.00027)	(0.00027)	(0.00027)	(0.00025)
[$0° <$ Temp $\leq 3°$]	0.00092***	0.00099***	0.00098***	0.00096***	0.00096***
	(0.00026)	(0.00021)	(0.00021)	(0.00021)	(0.00025)
[$3° <$ Temp $\leq 6°$]	0.00023	0.00053***	0.00054***	0.00053***	0.00056***
	(0.00019)	(0.00019)	(0.00019)	(0.00019)	(0.00021)
[$6° <$ Temp $\leq 9°$]	-0.00005	0.00017	0.00017	0.00016	0.00023
	(0.00017)	(0.00017)	(0.00017)	(0.00017)	(0.00019)
[$9° <$ Temp $\leq 12°$]	-0.00024	0.00000	0.00001	0.00001	0.00003
	(0.00016)	(0.00013)	(0.00014)	(0.00013)	(0.00013)
[$15° <$ Temp $\leq 18°$]	-0.00010	-0.00016	-0.00017	-0.00017	-0.00013
	(0.00012)	(0.00011)	(0.00011)	(0.00012)	(0.00013)
[$18° <$ Temp $\leq 21°$]	0.00017	-0.00011	-0.00010	-0.00009	-0.00009
	(0.00016)	(0.00015)	(0.00015)	(0.00015)	(0.00015)
[$21° <$ Temp $\leq 24°$]	0.00057***	0.00012	0.00013	0.00014	0.00019
	(0.00021)	(0.00019)	(0.00019)	(0.00019)	(0.00022)
[$24° <$ Temp]	-0.00014	-0.00078**	-0.00071**	-0.00072**	-0.00079**
	(0.00038)	(0.00031)	(0.00031)	(0.00031)	(0.00035)
Number of Observations	485,295	485,295	485,295	485,295	479,838
Adjusted R-Squared	0.976	0.976	0.976	0.976	0.977
Weather-Controls	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes
Trends by State		Yes	Yes	Yes	Yes
Sales-Decile-Year-FE			Yes	Yes	Yes
Exporter-Year-FE				Yes	Yes
Lagged Temperature					Yes

Notes: This table shows the estimated effects of temperature on the log of total CO_2 emissions at the plant level. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover.Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A2: Effect of Temperature on Direct CO_2 Emissions

	Log of Direct CO_2 Emissions				
	(1)	(2)	(3)	(4)	(5)
[Temp $< -6°$]	0.00526***	0.00431***	0.00427***	0.00422***	0.00350***
	(0.00061)	(0.00056)	(0.00056)	(0.00056)	(0.00059)
[$-6° <$ Temp $\leq -3°$]	0.00468***	0.00360***	0.00357***	0.00352***	0.00303***
	(0.00077)	(0.00067)	(0.00068)	(0.00067)	(0.00063)
[$-3° <$ Temp $\leq 0°$]	0.00342***	0.00300***	0.00298***	0.00295***	0.00257***
	(0.00049)	(0.00045)	(0.00044)	(0.00044)	(0.00038)
[$0° <$ Temp $\leq 3°$]	0.00223***	0.00230***	0.00227***	0.00227***	0.00174***
	(0.00041)	(0.00037)	(0.00037)	(0.00037)	(0.00041)
[$3° <$ Temp $\leq 6°$]	0.00124***	0.00175***	0.00174***	0.00173***	0.00129***
	(0.00035)	(0.00032)	(0.00032)	(0.00032)	(0.00033)
[$6° <$ Temp $\leq 9°$]	0.00064**	0.00083***	0.00082***	0.00081***	0.00057**
	(0.00027)	(0.00027)	(0.00027)	(0.00027)	(0.00028)
[$9° <$ Temp $\leq 12°$]	-0.00025	0.00042**	0.00041**	0.00042**	0.00029
	(0.00021)	(0.00018)	(0.00019)	(0.00019)	(0.00020)
[$15° <$ Temp $\leq 18°$]	-0.00009	-0.00040**	-0.00040**	-0.00039**	-0.00012
	(0.00018)	(0.00018)	(0.00018)	(0.00019)	(0.00019)
[$18° <$ Temp $\leq 21°$]	-0.00063***	-0.00062**	-0.00060**	-0.00060**	-0.00044
	(0.00023)	(0.00024)	(0.00024)	(0.00024)	(0.00028)
[$21° <$ Temp $\leq 24°$]	-0.00069**	-0.00050	-0.00045	-0.00045	-0.00010
	(0.00031)	(0.00033)	(0.00033)	(0.00033)	(0.00038)
[$24° <$ Temp]	-0.00255***	-0.00149***	-0.00142***	-0.00145***	-0.00123**
	(0.00067)	(0.00051)	(0.00053)	(0.00052)	(0.00058)
Number of Observations	453,919	453,919	453,919	453,919	449,299
Adjusted R-Squared	0.942	0.942	0.942	0.942	0.943
Weather-Controls	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes
Trends by State		Yes	Yes	Yes	Yes
Sales-Decile-Year-FE			Yes	Yes	Yes
Exporter-Year-FE				Yes	Yes
Lagged Temperature					Yes

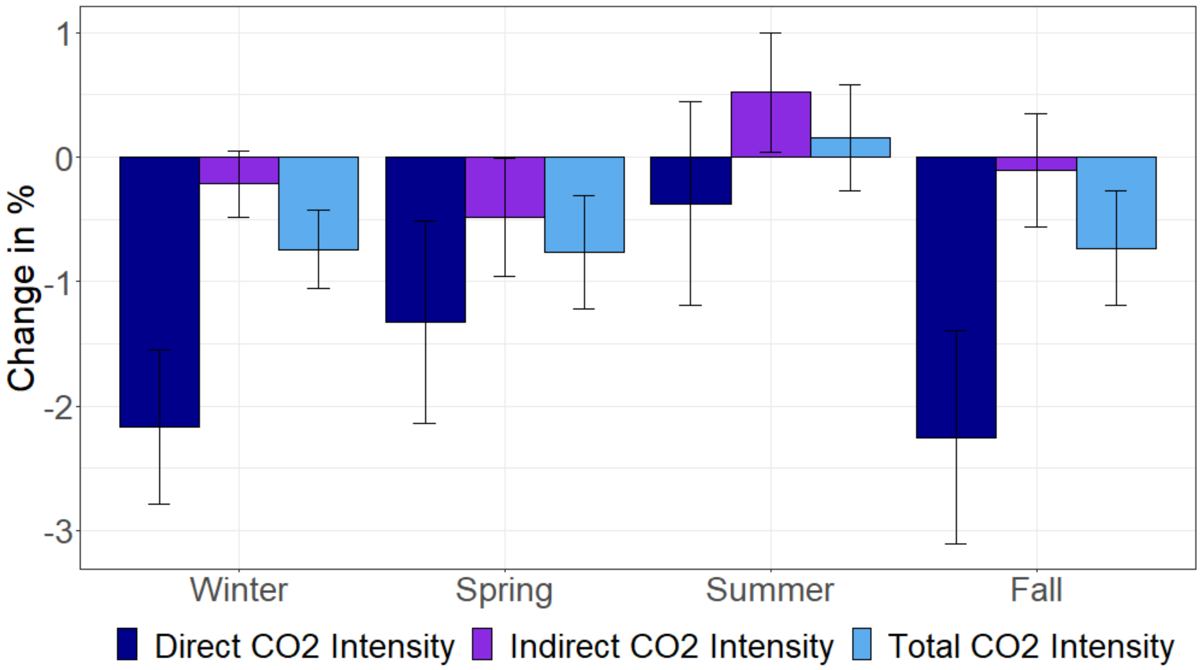
Notes: This table shows the estimated effects of temperature on the log of direct CO_2 emissions at the plant level. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A3: Effect of Temperature on Indirect CO_2 Emissions

	Log of Indirect CO_2 Emissions				
	(1)	(2)	(3)	(4)	(5)
[Temp $< -6°$]	0.00006	0.00021	0.00025	0.00018	0.00038
	(0.00036)	(0.00030)	(0.00031)	(0.00030)	(0.00034)
[$-6° <$ Temp $\leq -3°$]	-0.00058	-0.00010	-0.00004	-0.00011	0.00012
	(0.00036)	(0.00033)	(0.00032)	(0.00032)	(0.00032)
[$-3° <$ Temp $\leq 0°$]	0.00020	0.00022	0.00025	0.00020	0.00033
	(0.00031)	(0.00028)	(0.00028)	(0.00028)	(0.00026)
[$0° <$ Temp $\leq 3°$]	0.00020	0.00028	0.00026	0.00023	0.00032
	(0.00026)	(0.00023)	(0.00023)	(0.00023)	(0.00027)
[$3° <$ Temp $\leq 6°$]	-0.00028	-0.00006	-0.00005	-0.00008	0.00004
	(0.00020)	(0.00020)	(0.00020)	(0.00020)	(0.00023)
[$6° <$ Temp $\leq 9°$]	-0.00031	-0.00011	-0.00011	-0.00012	-0.00005
	(0.00020)	(0.00019)	(0.00019)	(0.00019)	(0.00021)
[$9° <$ Temp $\leq 12°$]	-0.00025	-0.00017	-0.00015	-0.00016	-0.00014
	(0.00018)	(0.00015)	(0.00015)	(0.00015)	(0.00016)
[$15° <$ Temp $\leq 18°$]	-0.00016	-0.00011	-0.00012	-0.00011	-0.00015
	(0.00013)	(0.00013)	(0.00012)	(0.00013)	(0.00013)
[$18° <$ Temp $\leq 21°$]	0.00037**	0.00005	0.00006	0.00007	0.00001
	(0.00017)	(0.00016)	(0.00016)	(0.00016)	(0.00017)
[$21° <$ Temp $\leq 24°$]	0.00095***	0.00028	0.00028	0.00029	0.00024
	(0.00024)	(0.00021)	(0.00021)	(0.00021)	(0.00024)
[$24° <$ Temp]	0.00091**	-0.00023	-0.00018	-0.00018	-0.00044
	(0.00038)	(0.00033)	(0.00033)	(0.00033)	(0.00037)
Number of Observations	482,717	482,717	482,717	482,717	477,303
Adjusted R-Squared	0.972	0.972	0.972	0.972	0.973
Weather-Controls	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes
Trends by State		Yes	Yes	Yes	Yes
Sales-Decile-Year-FE			Yes	Yes	Yes
Exporter-Year-FE				Yes	Yes
Lagged Temperature					Yes

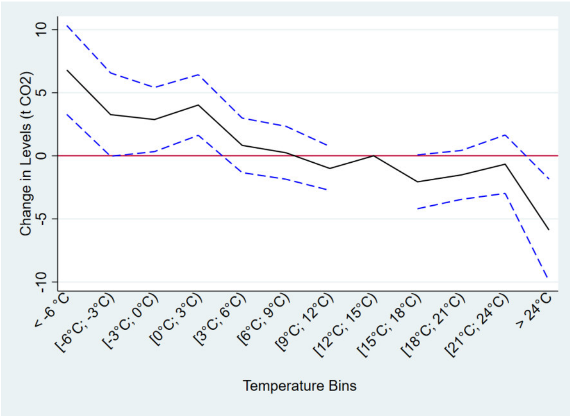
Notes: This table shows the estimated effects of temperature on the log of indirect CO_2 emissions (i.e. electricity use) at the plant level. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Figure A3: Estimated Effects of Seasonal Mean Temperatures on Emission Intensities

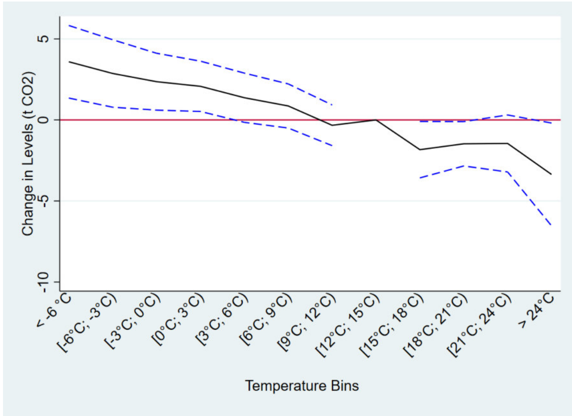


Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. The regressions include year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 453.919 for direct emission intensity, 482,717 for indirect emission intensity and 485.295 for total emission intensity. Thin lines show the 95^{th} confidence interval. Standard errors are clustered at the district and the four-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

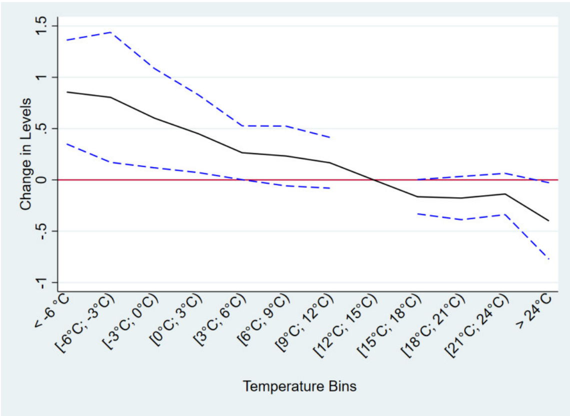
Figure A4: Estimated Effects of Temperature on (Direct) Emission (Intensities) in Levels



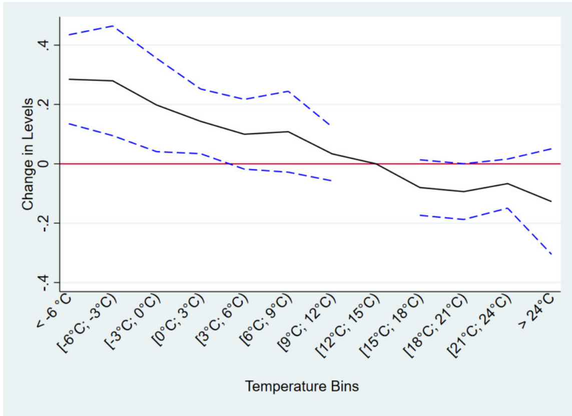
(a) Total Emissions



(b) Direct Emissions



(c) Total Emission Intensity (kg/1000 Euro)



(d) Direct Emission Intensity (kg/1000 Euro)

Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. All regressions include year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). Standard errors are clustered at the district and the four-digit sector level. The number of observations in all regressions is 481,642. 95^{th} confidence intervals are demarcated by the dashed lines. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

B.1 Sample Splits

Factor Intensities: From Table A4, one can see that the response of direct emissions to cold temperatures is stronger among plants with a low energy intensity which is plausible since the share of energy used for heating is arguably higher. Nonetheless, the estimated effects of days with mean temperatures in the five bins at the low end of the temperature distribution are quantitatively and statistically significant for plants operating in the energy-intensive sectors. For example, the point estimate of the lowest bin implies that an additional day with a mean temperature below -6°C increases direct emissions by 0.35% compared to 0.43% among plants in the non-energy-intensive sectors. This split suggests that the positive effects of cold days on the average plant's direct emissions are also relevant for direct emissions in the aggregate. We do not find evidence for a differential response of indirect emissions to temperature depending on the sector's energy intensity (cf. Table A5).

We then split based on plants' labor intensity. Table A4 yields no support for the hypothesis that more labor-intensive plants respond stronger to low temperatures. Indeed the point estimates in both subsamples are very similar. Table A5 yields suggestive evidence for an increase in indirect emissions among plants with a high labor intensity and a decrease among plants with low labor intensity. Specifically, the point estimates imply that labor-intensive plants' electricity use increases by 0.086% in response to one additional day with a mean temperature above 24°C. In contrast, the point estimate is negative for plants with low labor intensity. These results look qualitatively similar when focusing on indirect emission intensities (not reported in the paper). Still, none- of the effects is statistically significant at conventional levels. We also split by capital intensity, which does not indicate relevant effect heterogeneities for direct or indirect emissions on either end of the temperature distribution (cf. Tables A4 and A5).

Table A4: Sample Splits: Effect of Temperature on Direct CO_2 Emissions

	Log of Direct CO_2 Emissions					
	Energy Intensity		Labor Intensity		Capital Intensity	
	(Low)	(High)	(Low)	(High)	(Low)	(High)
[Temp $< -6°$]	0.00431***	0.00361***	0.00391***	0.00346***	0.00378***	0.00424***
	(0.00061)	(0.00115)	(0.00097)	(0.00101)	(0.00080)	(0.00078)
[$-6° <$ Temp $\leq -3°$]	0.00354***	0.00322***	0.00281***	0.00270**	0.00306***	0.00368***
	(0.00074)	(0.00094)	(0.00087)	(0.00117)	(0.00083)	(0.00092)
[$-3° <$ Temp $\leq 0°$]	0.00305***	0.00225***	0.00231***	0.00223***	0. 00283***	0.00250***
	(0.00048)	(0.00082)	(0.00073)	(0.00074)	(0.00067)	(0.00061)
[$0° <$ Temp $\leq 3°$]	0.00233***	0.00183**	0.00166***	0.00170***	0.0 0214***	0.00207***
	(0.00040)	(0.00074)	(0.00058)	(0.00062)	(0.00056)	(0.00050)
[$3° <$ Temp $\leq 6°$]	0.00172***	0.00170**	0.00118**	0.00126**	0.0 0181***	0.00160***
	(0.00034)	(0.00064)	(0.00054)	(0.00051)	(0.00049)	(0.00046)
[$6° <$ Temp $\leq 9°$]	0.00081***	0.00075	0.00002	0.00071*	0.0 0085**	0.00104***
	(0.00029)	(0.00059)	(0.00043)	(0.00038)	(0.00042)	(0.00039)
[$9° <$ Temp $\leq 12°$]	0.00044**	0.00018	0.00037	0.00046	0. 00035	0.00029
	(0.00019)	(0.00052)	(0.00033)	(0.00030)	(0.00034)	(0.00029)
[$15° <$ Temp $\leq 18°$]	-0.00033*	-0.00075	-0.00061	-0.00012	-0 .00019	-0.00055*
	(0.00019)	(0.00067)	(0.00037)	(0.00033)	(0.00030)	(0.00028)
[$18° <$ Temp $\leq 21°$]	-0.00055**	-0.00088	-0.00095**	-0.00048	-0 .00051	-0.00084**
	(0.00025)	(0.00068)	(0.00042)	(0.00038)	(0.00037)	(0.00038)
[$21° <$ Temp $\leq 24°$]	-0.00032	-0.00116	-0.00062	-0.00071	0 .00032	-0.00100**
	(0.00035)	(0.00090)	(0.00057)	(0.00047)	(0.00051)	(0.00047)
[$24° <$ Temp]	-0.00133**	-0.00208*	-0.00147*	-0.00149*	-0.00164**	-0.00084
	(0.00056)	(0.00123)	(0.00086)	(0.00087)	(0.00082)	(0.00097)
Number of Observations	388,714	65,082	136,913	140,267	147,544	162,183
Adjusted R-Squared	0.933	0.956	0.946	0.916	0.936	0.947
Weather-Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of direct emissions at the plant level for various subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Plants operating in the economic sectors "manufacture of chemicals and chemical products", "manufacture of basic metals", "manufacture of coke and refined petroleum products", "manufacture of other non-metallic mineral products" and "manufacture of paper and paper products" are classified as energy intensive. All other plants have a low energy intensity. We require a plant to be below or above the median labor/capital intensity every year to be classified as low/high labor/capital intensive. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A5: Sample Splits: Effect of Temperature on Indirect CO_2 Emissions

	Log of Indirect CO_2 Emissions					
	Energy Intensity		Labor Intensity		Capital Intensity	
	(Low)	(High)	(Low)	(High)	(Low)	(High)
[Temp $< -6°$]	0.00019	0.00008	0.00027	0.00009	0.00058	0.00005
	(0.00035)	(0.00062)	(0.00052)	(0.00043)	(0.00047)	(0.00041)
[$-6° <$ Temp $\leq -3°$]	-0.00008	-0.00047	-0.00025	-0.00033	- 0.00005	-0.00001
	(0.00035)	(0.00078)	(0.00050)	(0.00047)	(0.00051)	(0.00045)
[$-3° <$ Temp $\leq 0°$]	0.00029	-0.00056	-0.00002	-0.00009	0. 00006	0.00006
	(0.00030)	(0.00057)	(0.00043)	(0.00040)	(0.00039)	(0.00036)
[$0° <$ Temp $\leq 3°$]	0.00028	-0.00015	0.00018	-0.00010	0.0 0004	0.00023
	(0.00026)	(0.00050)	(0.00029)	(0.00030)	(0.00037)	(0.00030)
[$3° <$ Temp $\leq 6°$]	-0.00007	-0.00031	-0.00016	-0.00027	-0.0 0015	-0.00016
	(0.00022)	(0.00045)	(0.00031)	(0.00033)	(0.00032)	(0.00032)
[$6° <$ Temp $\leq 9°$]	-0.00017	0.00003	-0.00053*	-0.00013	-0.0 0016	-0.00023
	(0.00021)	(0.00037)	(0.00031)	(0.00029)	(0.00029)	(0.00028)
[$9° <$ Temp $\leq 12°$]	-0.00013	-0.00042	-0.00044**	-0.00002	-0. 00027	-0.00016
	(0.00016)	(0.00028)	(0.00021)	(0.00022)	(0.00020)	(0.00024)
[$15° <$ Temp $\leq 18°$]	-0.00013	-0.00004	-0.00010	-0.00003	0 .00003	-0.00018
	(0.00013)	(0.00029)	(0.00021)	(0.00018)	(0.00020)	(0.00020)
[$18° <$ Temp $\leq 21°$]	0.00008	-0.00013	-0.00023	0.00025	0 .00009	0.00000
	(0.00019)	(0.00036)	(0.00024)	(0.00027)	(0.00026)	(0.00024)
[$21° <$ Temp $\leq 24°$]	0.00026	0.00046	0.00026	0.00041	0 .00039	0.00032
	(0.00022)	(0.00056)	(0.00037)	(0.00034)	(0.00034)	(0.00030)
[$24° <$ Temp]	-0.00031	0.00047	-0.00060	0.00086	0.00042	-0.00019
	(0.00038)	(0.00076)	(0.00054)	(0.00054)	(0.00057)	(0.00058)
Number of Observations	415,830	66,759	143,577	151,575	159,340	171,090
Adjusted R-Squared	0.970	0.976	0.973	0.959	0.972	0.970
Weather-Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of indirect emissions at the plant level for various subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Plants operating in the economic sectors "manufacture of chemicals and chemical products", "manufacture of basic metals", "manufacture of coke and refined petroleum products", "manufacture of other non-metallic mineral products" and "manufacture of paper and paper products" are classified as energy intensive. All other plants have a low energy intensity. We require a plant to be below or above the median labor/capital intensity every year to be classified as low/high labor/capital intensive. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Regions: Table A6 shows the results from the baseline specification for direct emissions and Table A7 for indirect emissions estimated separately for plants in the north and those in the south. Overall the estimates in Table A6 indicate that direct emissions from plants in the north increase stronger in response to cold days. All point estimates except the one at the outermost bin are larger in the subsample of firms located in the north. Notice that the coefficient for the −6°C bin is estimated imprecisely (cf. Figure 1, which shows that days with mean temperature below −6°C occur much less often in the north). This result, consistent with the hypothesis that firms in the south adjusted to more frequent cold temperatures, also holds when looking at direct emission intensity (not reported in the paper). We do not find a systematic response of indirect emissions to temperature in either subsample (cf. A7)

Age: Table A4 shows that the response of direct emissions to cold days is stronger among old plants. The point estimates are approximately one-third larger than those from the subsample of new plants. To put this into perspective: the difference between the point estimates in the outermost bins is 0.00084 and 0.00143. On average, the number of days in respective bins has been 4 and 8 (cf. Figure A2); thus the average old firm's emissions would be $\approx 1.46\%$ lower if their direct emissions were as sensitive to temperature as the new firm's direct emissions (0.00084*4 + 0.00143 * 8). The difference between old and new plants is even more pronounced when looking at direct emission intensities (not reported in the paper). For indirect emissions, there exist no consistent differences between old and new plants (cf. Table A5). These direct emission (intensities) results suggest a relevant energy savings potential from retrofitting, for example, installing better insulation. To further investigate changes in the response of emissions to cold days over time, we interact each temperature bin with a linear time-trend. A negative interaction implies that the response of energy use to temperature becomes attenuated over time. Table A8 reports the estimates for total, direct and indirect emissions and respective intensities. Focussing on direct emissions in the middle of the table, one can see that the main effects for the five outermost bins are larger compared to the baseline results in Table A2. All interactions (i.e. the time trends) are negative. For instance, the interaction for the −6°C bin is 0.00017, which means that every ten years the response of direct emissions to another day with mean temperatures below −6°C is attenuated by 0.17%. In line with the results from the sample split, Table A8 yields no indication of a time trend in the response of indirect emissions to temperature.

Table A6: Sample Splits: Effect of Temperature on Direct CO_2 Emissions

	Log of Direct CO_2 Emissions			
	South vs. North		New vs. Old	
	(South)	(North)	(New)	(Old)
[Temp $< -6^{\circ}$]	0.00353***	0.00329**	0.00368***	0.00452***
	(0.00069)	(0.00128)	(0.00084)	(0.00062)
[$-6^{\circ} <$ Temp $\leq -3^{\circ}$]	0.00269***	0.00376***	0.00260***	0.00403***
	(0.00080)	(0.00105)	(0.00091)	(0.00067)
[$-3^{\circ} <$ Temp $\leq 0^{\circ}$]	0.00215***	0.00333***	0.00230***	0.00321***
	(0.00050)	(0.00076)	(0.00058)	(0.00051)
[$0^{\circ} <$ Temp $\leq 3^{\circ}$]	0.00180***	0.00225***	0.00217***	0.00227***
	(0.00047)	(0.00075)	(0.00052)	(0.00044)
[$3^{\circ} <$ Temp $\leq 6^{\circ}$]	0.00124***	0.00197***	0.00157***	0.00175***
	(0.00042)	(0.00061)	(0.00048)	(0.00042)
[$6^{\circ} <$ Temp $\leq 9^{\circ}$]	0.00044	0.00137***	0.00100***	0.00055*
	(0.00034)	(0.00049)	(0.00036)	(0.00033)
[$9^{\circ} <$ Temp $\leq 12^{\circ}$]	0.00032	0.00064	0.00041	0.00032
	(0.00022)	(0.00039)	(0.00030)	(0.00026)
[$15^{\circ} <$ Temp $\leq 18^{\circ}$]	0.00000	-0.00052	-0.00024	-0.00048**
	(0.00023)	(0.00044)	(0.00028)	(0.00024)
[$18^{\circ} <$ Temp $\leq 21^{\circ}$]	-0.00034	-0.00085	-0.00063*	-0.00062*
	(0.00030)	(0.00057)	(0.00036)	(0.00032)
[$21^{\circ} <$ Temp $\leq 24^{\circ}$]	-0.00015	-0.00053	-0.00075	-0.00025
	(0.00043)	(0.00055)	(0.00051)	(0.00037)
[$24^{\circ} <$ Temp]	-0.00038	-0.00345**	-0.00106	-0.00182***
	(0.00070)	(0.00133)	(0.00083)	(0.00066)
Number of Observations	274,398	179,521	189,674	264,245
Adjusted R-Squared	0.944	0.940	0.927	0.942
Weather-Controls	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of direct emissions at the plant level in subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. To split between north and south we classify all plants in Schleswig-Holstein, Hamburg, Lower Saxony, Bremen, North Rhine-Westphalia, Berlin, Mecklenburg-West Pomerania, and Brandenburg as located in the north. The rest is considered south. We treat all plants we observed in 1995 as old plants and those entering the sample later as new plants. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A7: Sample Splits: Effect of Temperature on Indirect CO_2 Emissions

	Log of Indirect CO_2 Emissions			
	South vs. North		New vs. Old	
	(South)	(North)	(New)	(Old)
[Temp $< -6^\circ$]	-0.00002	-0.00016	0.00103*	-0.00037
	(0.00037)	(0.00075)	(0.00055)	(0.00037)
[$-6^\circ <$ Temp $\leq -3^\circ$]	-0.00043	-0.00050	0.00078	-0.00073**
	(0.00039)	(0.00065)	(0.00053)	(0.00037)
[$-3^\circ <$ Temp $\leq 0^\circ$]	-0.00020	0.00020	0.00052	-0.00008
	(0.00032)	(0.00047)	(0.00041)	(0.00032)
[$0^\circ <$ Temp $\leq 3^\circ$]	0.00003	0.00006	0.00057	0.00001
	(0.00029)	(0.00038)	(0.00036)	(0.00025)
[$3^\circ <$ Temp $\leq 6^\circ$]	-0.00049*	0.00025	0.00015	-0.00025
	(0.00027)	(0.00033)	(0.00031)	(0.00023)
[$6^\circ <$ Temp $\leq 9^\circ$]	-0.00042*	0.00018	0.00001	-0.00029
	(0.00023)	(0.00035)	(0.00029)	(0.00023)
[$9^\circ <$ Temp $\leq 12^\circ$]	-0.00025	-0.00014	-0.00011	-0.00025*
	(0.00017)	(0.00029)	(0.00025)	(0.00015)
[$15^\circ <$ Temp $\leq 18^\circ$]	0.00008	-0.00004	-0.00011	-0.00008
	(0.00017)	(0.00027)	(0.00019)	(0.00015)
[$18^\circ <$ Temp $\leq 21^\circ$]	0.00024	-0.00014	-0.00009	0.00015
	(0.00027)	(0.00029)	(0.00024)	(0.00019)
[$21^\circ <$ Temp $\leq 24^\circ$]	0.00028	0.00072*	-0.00006	0.00044*
	(0.00034)	(0.00040)	(0.00034)	(0.00024)
[$24^\circ <$ Temp]	0.00007	-0.00055	-0.00017	-0.00029
	(0.00058)	(0.00075)	(0.00051)	(0.00043)
Number of Observations	291,596	191,121	207,575	275,142
Adjusted R-Squared	0.971	0.973	0.966	0.973
Weather-Controls	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of indirect emissions at the plant level in subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. To split between north and south we classify all plants in Schleswig-Holstein, Hamburg, Lower Saxony, Bremen, North Rhine-Westphalia, Berlin, Mecklenburg-West Pomerania, and Brandenburg as located in the north. The rest is considered south. We treat all plants we observed in 1995 as old plants and those entering the sample later as new plants. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A8: Adaptation: Time Trends

	Total Emissions		Direct Emissions		Indirect Emissions	
	(log(Lv.))	(log(Int.))	(log(Lv.))	(log(Int.))	(log(Lv.))	(log(Int.))
[Temp $< -6^{\circ}$]	0.00237**	0.00253***	0.00690***	0.00688***	0.00031	0.00054
	(0.00096)	(0.00088)	(0.00149)	(0.00168)	(0.00114)	(0.00111)
$[-6^{\circ} <$ Temp $\leq -3^{\circ}]$	0.00272***	0.00342***	0.00785***	0.00829***	0.00150	0.00223**
	(0.00099)	(0.00094)	(0.00173)	(0.00175)	(0.00109)	(0.00101)
$[-3^{\circ} <$ Temp $\leq 0^{\circ}]$	0.00150**	0.00259***	0.00431***	0.00515***	0.00025	0.00134**
	(0.00066)	(0.00063)	(0.00119)	(0.00118)	(0.00068)	(0.00061)
$[0^{\circ} <$ Temp $\leq 3^{\circ}]$	0.00134**	0.00225***	0.00339***	0.00407***	0.00077	0.00173***
	(0.00062)	(0.00056)	(0.00127)	(0.00126)	(0.00063)	(0.00059)
$[3^{\circ} <$ Temp $\leq 6^{\circ}]$	0.00185**	0.00136*	0.00421***	0.00346**	0.00127	0.00082
	(0.00085)	(0.00078)	(0.00142)	(0.00138)	(0.00086)	(0.00076)
$[6^{\circ} <$ Temp $\leq 9^{\circ}]$	-0.00084	0.00045	-0.00116	-0.00011	-0.00027	0.00104
	(0.00080)	(0.00065)	(0.00126)	(0.00123)	(0.00084)	(0.00066)
$[9^{\circ} <$ Temp $\leq 12^{\circ}]$	-0.00021	-0.00029	-0.00028	-0.00055	-0.00018	-0.00024
	(0.00054)	(0.00048)	(0.00071)	(0.00082)	(0.00054)	(0.00043)
$[15^{\circ} <$ Temp $\leq 18^{\circ}]$	-0.00037	-0.00005	-0.00000	0.00026	-0.00008	0.00021
	(0.00047)	(0.00049)	(0.00067)	(0.00066)	(0.00050)	(0.00047)
$[18^{\circ} <$ Temp $\leq 21^{\circ}]$	0.00099	0.00022	-0.00012	-0.00108	0.00092	0.00017
	(0.00062)	(0.00060)	(0.00099)	(0.00098)	(0.00063)	(0.00058)
$[21^{\circ} <$ Temp $\leq 24^{\circ}]$	0.00328***	-0.00002	0.00288**	-0.00061	0.00317***	-0.00013
	(0.00091)	(0.00096)	(0.00133)	(0.00135)	(0.00097)	(0.00100)
$[24^{\circ} <$ Temp]	0.00296**	0.00144	0.00140	-0.00039	0.00380**	0.00225*
	(0.00144)	(0.00097)	(0.00214)	(0.00212)	(0.00161)	(0.00117)
Trend-Bin 1	-0.00004	-0.00004	-0.00017*	-0.00017*	0.00002	0.00001
	(0.00006)	(0.00006)	(0.00009)	(0.00010)	(0.00007)	(0.00007)
Trend-Bin 2	-0.00009	-0.00013**	-0.00028***	-0.00031***	-0.00007	-0.00012*
	(0.00006)	(0.00006)	(0.00009)	(0.00010)	(0.00007)	(0.00006)
Trend-Bin 3	-0.00001	-0.00010**	-0.00009	-0.00016**	0.00002	-0.00007*
	(0.00004)	(0.00004)	(0.00007)	(0.00007)	(0.00004)	(0.00004)
Trend-Bin 4	-0.00003	-0.00009**	-0.00009	-0.00013*	-0.00004	-0.00009**
	(0.00004)	(0.00004)	(0.00008)	(0.00008)	(0.00004)	(0.00004)
Trend-Bin 5	-0.00008	-0.00006	-0.00018**	-0.00014*	-0.00008	-0.00006
	(0.00005)	(0.00005)	(0.00008)	(0.00008)	(0.00005)	(0.00005)
Trend-Bin 6	0.00007	-0.00003	0.00010	0.00002	0.00002	-0.00007**
	(0.00005)	(0.00004)	(0.00007)	(0.00007)	(0.00005)	(0.00004)
Trend-Bin 7	0.00002	0.00002	0.00004	0.00005	0.00001	0.00001
	(0.00003)	(0.00003)	(0.00004)	(0.00005)	(0.00003)	(0.00003)
Trend-Bin 9	0.00001	-0.00001	-0.00003	-0.00004	-0.00001	-0.00003
	(0.00003)	(0.00003)	(0.00004)	(0.00004)	(0.00003)	(0.00003)
Trend-Bin 10	-0.00008*	-0.00003	-0.00004	0.00003	-0.00006	-0.00002
	(0.00004)	(0.00004)	(0.00006)	(0.00006)	(0.00004)	(0.00004)
Trend-Bin 11	-0.00019***	-0.00001	-0.00020**	-0.00000	-0.00018***	0.00001
	(0.00005)	(0.00006)	(0.00008)	(0.00009)	(0.00006)	(0.00006)
Trend-Bin 12	-0.00022**	-0.00010*	-0.00019	-0.00005	-0.00023**	-0.00012*
	(0.00009)	(0.00006)	(0.00013)	(0.00013)	(0.00009)	(0.00007)
Number of Observations	485,295	485,295	453,919	453,919	482,717	482,717
Adjusted R-Squared	0.976	0.939	0.942	0.892	0.972	0.935
Weather-Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of total emissions, direct emissions, indirect emissions and respective intensities. The table also shows the interactions between the bin count and a linear time trend. All effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

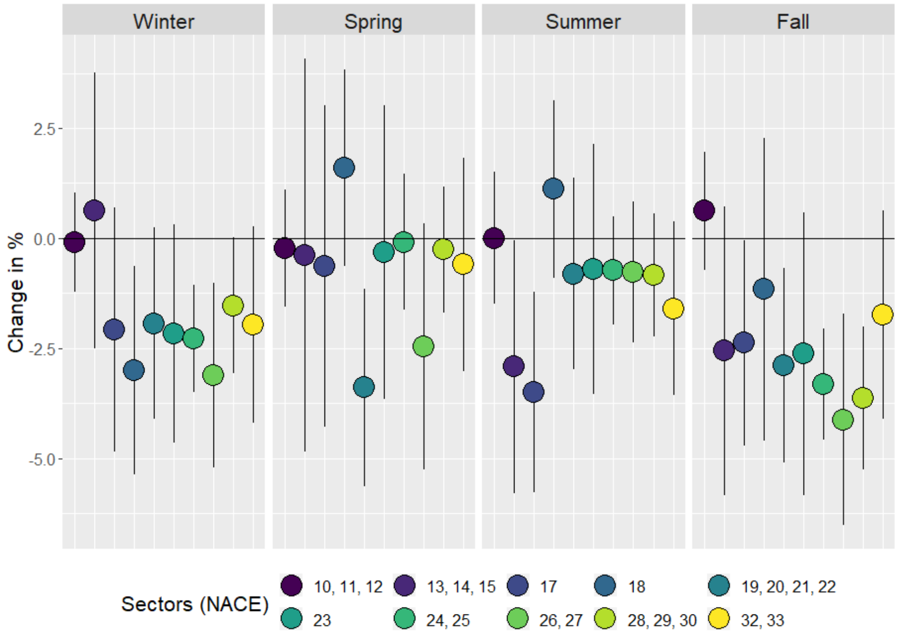
Economic Sectors: Since the number of observations within individual economic sectors can be fairly small, we draw upon the parsimonious seasonal means specification to estimate the sectorial effect of temperature on CO_2 emissions. For the same reason we also aggregate some 2-digit sectors.[29] Results for direct and indirect emissions are shown in Figure A5.

We find that the effect of the mean temperature in winter on direct emissions is relatively homogenous across sectors averaging at around 2.5%. This estimate is similar to the main effect shown in Figure 6. We estimate coefficients close to and indistinguishable from zero for the combined sectors 10-12 (combined food production) and 13-15 (combined textile production) only. The effects for the energy-intensive sectors 20 to 22 (combined chemical industry), 23 (which includes glass and cement) and 24-25 (combined metal) are of similar magnitude as the main effect and at least marginally significant. Together, those sectors account for more than 80% of direct emissions in the German industry. The estimated effects of mean temperatures in spring and summer are mostly insignificant. Effects of mean temperatures in fall look similar to those in winter but slightly more scattered with the ”combined food industry” again being an outlier in that direct emissions do not fall with higher temperatures.

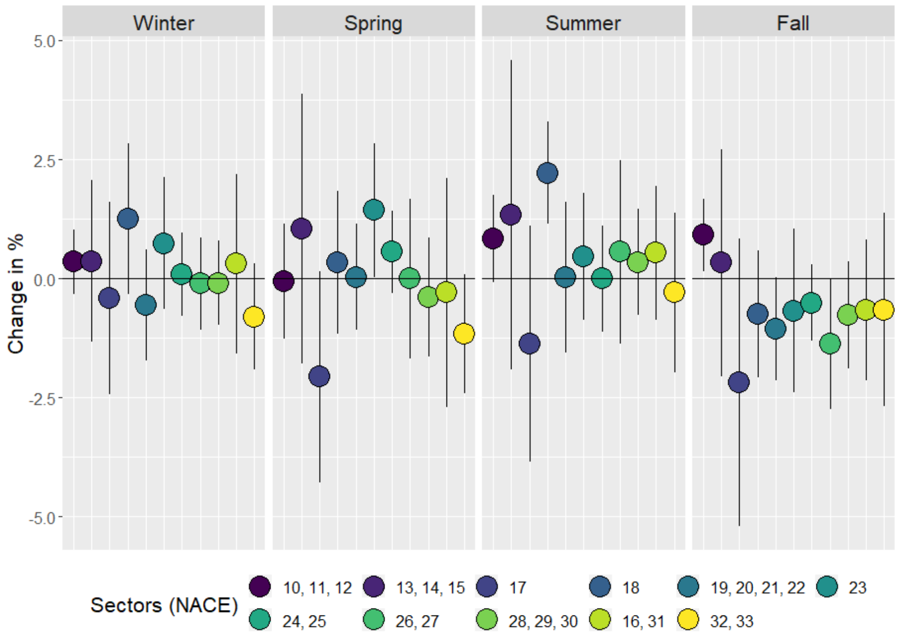
We find positive and (marginally) significant effects of mean summer and fall temperatures on indirect emissions in the ”combined food industry” and of mean summer temperatures in ”printing and reproduction of recorded media.” It seems plausible that the cooling demand in the food industry is comparably high. Besides these positive effects, seasonal mean temperatures' effects on indirect emissions are quantitatively and statistically mostly insignificant (cf. Figure A5b).

[29] The combinations were as follows: (1) manufacturing of food products with manufacturing of beverages and manufacture of tobacco; (2) manufacture of textiles, manufacture of wearing apparel and manufacture of leather and related products; (3) manufacture of coke and refined petroleum products, manufacture of chemicals and chemical products, manufacture of basic pharmaceutical products and pharmaceutical preparations and manufacture of rubber and plastic products; (4) manufacture of basic metals with manufacture of fabricated metal products, except machinery and equipment; (5) manufacture of computer, electronic and optical products with manufacture of electrical equipment; (6) manufacture of machinery and equipment n.e.c. with manufacture of motor vehicles, trailers and semi-trailers and manufacture of other transport equipment; (7) manufacture of furniture with manufacture of wood and products of wood and cork except furniture; (8) manufacture of articles of straw and plaiting materials and other manufacturing with repair and installation of machinery and equipment. Sectors not mentioned here were treated individually.

Figure A5: Sector-wise Effects of Seasonal Mean Temperatures on Direct (a) and Indirect Emissions (b)



(a) Log Direct Emissions



(b) Log Indirect Emissions

Notes: Subfigure A5a shows sectoral effects of seasonal mean temperatures on the log of direct CO_2 emissions. Subfigure A5b shows the effect for indirect emissions. The effects are the sum of the main effect and the interactions of seasonal mean temperatures with the respective sector dummy. NACE sectors were partly aggregated (see legend). The effects are estimated based on an unbalanced panel covering 2004 to 2017. The total number of observations in Subfigure (a) is 453919 and 482717 in (b). We controlled for year-exporter fixed effects, federal state-specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). Standard errors are clustered at the district and the four-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

B.2 Economic Performance

Table A9: Effect of Temperature on Sales

	Log of Sales				
	(1)	(2)	(3)	(4)	(5)
[Temp $< -6^{\circ}$]	-0.00013	-0.00057*	-0.00055*	-0.00066**	-0.00034
	(0.00035)	(0.00031)	(0.00031)	(0.00031)	(0.00032)
[$-6^{\circ} <$ Temp $\leq -3^{\circ}$]	-0.00090***	-0.00068**	-0.00067**	-0.00080***	-0.00055**
	(0.00034)	(0.00027)	(0.00027)	(0.00026)	(0.00026)
[$-3^{\circ} <$ Temp $\leq 0^{\circ}$]	0.00017	-0.00012	-0.00012	-0.00021	-0.00003
	(0.00030)	(0.00024)	(0.00024)	(0.00024)	(0.00024)
[$0^{\circ} <$ Temp $\leq 3^{\circ}$]	0.00009	-0.00000	-0.00003	-0.00006	0.00012
	(0.00023)	(0.00018)	(0.00018)	(0.00018)	(0.00022)
[$3^{\circ} <$ Temp $\leq 6^{\circ}$]	-0.00031	-0.00005	-0.00006	-0.00009	0.00008
	(0.00022)	(0.00018)	(0.00018)	(0.00018)	(0.00021)
[$6^{\circ} <$ Temp $\leq 9^{\circ}$]	-0.00027	0.00000	-0.00003	-0.00005	0.00011
	(0.00018)	(0.00015)	(0.00015)	(0.00015)	(0.00017)
[$9^{\circ} <$ Temp $\leq 12^{\circ}$]	-0.00013	-0.00012	-0.00013	-0.00013	-0.00005
	(0.00016)	(0.00011)	(0.00012)	(0.00012)	(0.00012)
[$15^{\circ} <$ Temp $\leq 18^{\circ}$]	0.00001	0.00015	0.00015	0.00016	0.00005
	(0.00011)	(0.00011)	(0.00011)	(0.00011)	(0.00012)
[$18^{\circ} <$ Temp $\leq 21^{\circ}$]	0.00038***	0.00003	0.00005	0.00007	-0.00006
	(0.00014)	(0.00013)	(0.00013)	(0.00013)	(0.00014)
[$21^{\circ} <$ Temp $\leq 24^{\circ}$]	0.00122***	0.00026	0.00026	0.00028	0.00015
	(0.00022)	(0.00021)	(0.00021)	(0.00021)	(0.00024)
[$24^{\circ} <$ Temp]	0.00093**	-0.00070**	-0.00064*	-0.00066*	-0.00083**
	(0.00038)	(0.00034)	(0.00034)	(0.00034)	(0.00038)
Number of Observations	485,619	485,619	485,619	485,619	480,155
Adjusted R-Squared	0.965	0.965	0.966	0.966	0.967
Weather-Controls	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes
Trends by State		Yes	Yes	Yes	Yes
Sales-Decile-Year-FE			Yes	Yes	Yes
Exporter-Year-FE				Yes	Yes
Lagged Temperature					Yes

Notes: This table shows the estimated effects of temperature on the log of gross output at the plant level. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A10: Effect of Temperature on Sales per Worker

	Log of Sales per Worker				
	(1)	(2)	(3)	(4)	(5)
[Temp $< -6^{\circ}$]	-0.00016	-0.00060**	-0.00059**	-0.00063***	-0.00052**
	(0.00027)	(0.00024)	(0.00024)	(0.00024)	(0.00026)
[$-6^{\circ} <$ Temp $\leq -3^{\circ}$]	-0.00046*	-0.00049**	-0.00052**	-0.00058***	-0.00048**
	(0.00026)	(0.00022)	(0.00022)	(0.00021)	(0.00022)
[$-3^{\circ} <$ Temp $\leq 0^{\circ}$]	0.00001	-0.00023	-0.00025	-0.00030*	-0.00025
	(0.00019)	(0.00018)	(0.00018)	(0.00017)	(0.00019)
[$0^{\circ} <$ Temp $\leq 3^{\circ}$]	-0.00006	-0.00019	-0.00019	-0.00021	-0.00013
	(0.00017)	(0.00015)	(0.00015)	(0.00014)	(0.00018)
[$3^{\circ} <$ Temp $\leq 6^{\circ}$]	0.00003	0.00005	0.00005	0.00003	0.00010
	(0.00018)	(0.00015)	(0.00015)	(0.00015)	(0.00018)
[$6^{\circ} <$ Temp $\leq 9^{\circ}$]	-0.00003	-0.00001	-0.00004	-0.00005	0.00002
	(0.00013)	(0.00011)	(0.00012)	(0.00012)	(0.00014)
[$9^{\circ} <$ Temp $\leq 12^{\circ}$]	0.00016	0.00009	0.00006	0.00006	0.00011
	(0.00011)	(0.00008)	(0.00009)	(0.00009)	(0.00009)
[$15^{\circ} <$ Temp $\leq 18^{\circ}$]	0.00004	0.00020**	0.00021**	0.00021**	0.00014
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00010)
[$18^{\circ} <$ Temp $\leq 21^{\circ}$]	0.00017*	0.00016	0.00018	0.00019*	0.00011
	(0.00010)	(0.00011)	(0.00011)	(0.00011)	(0.00014)
[$21^{\circ} <$ Temp $\leq 24^{\circ}$]	0.00063***	0.00017	0.00019	0.00020	0.00002
	(0.00016)	(0.00016)	(0.00016)	(0.00016)	(0.00018)
[$24^{\circ} <$ Temp]	0.00081***	0.00000	0.00001	0.00000	-0.00014
	(0.00027)	(0.00030)	(0.00030)	(0.00030)	(0.00033)
Number of Observations	485,619	485,619	485,619	485,619	480,155
Adjusted R-Squared	0.918	0.918	0.919	0.919	0.920
Weather-Controls	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes
Trends by State		Yes	Yes	Yes	Yes
Sales-Decile-Year-FE			Yes	Yes	Yes
Exporter-Year-FE				Yes	Yes
Lagged Temperature					Yes

Notes: This table shows the estimated effects of temperature on the log of gross output per worker at the plant level. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A11: Sample Splits: Effect of Temperature on Sales

	Log of Sales					
	Energy Intensity		Labor Intensity		Capital Intensity	
	(Low)	(High)	(Low)	(High)	(Low)	(High)
[Temp $< -6^{\circ}$]	-0.00065*	-0.00072	-0.00063	-0.00043	-0.00074*	-0.00076*
	(0.00034)	(0.00063)	(0.00044)	(0.00041)	(0.00043)	(0.00039)
[$-6^{\circ} <$ Temp $\leq -3^{\circ}$]	-0.00072**	-0.00138**	-0.00108***	-0.00042	- 0.00037	-0.00103***
	(0.00028)	(0.00060)	(0.00038)	(0.00041)	(0.00042)	(0.00034)
[$-3^{\circ} <$ Temp $\leq 0^{\circ}$]	-0.00009	-0.00110**	-0.00059*	0.00004	-0. 00021	-0.00046
	(0.00025)	(0.00054)	(0.00030)	(0.00033)	(0.00035)	(0.00031)
[$0^{\circ} <$ Temp $\leq 3^{\circ}$]	0.00001	-0.00059	-0.00011	-0.00009	-0.0 0014	-0.00019
	(0.00019)	(0.00045)	(0.00024)	(0.00028)	(0.00027)	(0.00023)
[$3^{\circ} <$ Temp $\leq 6^{\circ}$]	0.00001	-0.00077*	-0.00019	-0.00001	0.0 0004	-0.00027
	(0.00020)	(0.00042)	(0.00025)	(0.00028)	(0.00027)	(0.00025)
[$6^{\circ} <$ Temp $\leq 9^{\circ}$]	0.00000	-0.00046	-0.00035	0.00017	0.0 0000	-0.00020
	(0.00016)	(0.00029)	(0.00025)	(0.00022)	(0.00025)	(0.00020)
[$9^{\circ} <$ Temp $\leq 12^{\circ}$]	-0.00005	-0.00068***	-0.00011	-0.00018	0. 00003	-0.00027*
	(0.00012)	(0.00023)	(0.00017)	(0.00017)	(0.00015)	(0.00015)
[$15^{\circ} <$ Temp $\leq 18^{\circ}$]	0.00012	0.00039	0.00026	0.00006	0 .00021*	0.00001
	(0.00011)	(0.00026)	(0.00017)	(0.00014)	(0.00013)	(0.00013)
[$18^{\circ} <$ Temp $\leq 21^{\circ}$]	0.00009	-0.00010	0.00020	0.00011	0 .00011	0.00010
	(0.00013)	(0.00029)	(0.00020)	(0.00018)	(0.00015)	(0.00020)
[$21^{\circ} <$ Temp $\leq 24^{\circ}$]	0.00020	0.00079**	0.00045	0.00031	0 .00019	0.00035
	(0.00022)	(0.00039)	(0.00031)	(0.00025)	(0.00027)	(0.00028)
[$24^{\circ} <$ Temp]	-0.00074**	-0.00020	-0.00038	0.00004	0.00010	-0.00051
	(0.00037)	(0.00075)	(0.00046)	(0.00038)	(0.00042)	(0.00045)
Number of Observations	418,279	67,211	144,646	152,490	160,131	172,299
Adjusted R-Squared	0.966	0.964	0.963	0.944	0.977	0.968
Weather-Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of plants' gross output for various subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Plants operating in the economic sectors "manufacture of chemicals and chemical products", "manufacture of basic metals", "manufacture of coke and refined petroleum products", "manufacture of other non-metallic mineral products" and "manufacture of paper and paper products" are classified as energy intensive. All other plants have a low energy intensity. We require a plant to be below or above the median labor/capital intensity every year to be classified as low/high labor/capital intensive. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A12: Sample Splits: Effect of Temperature on Sales per Worker

	Log of Sales per Worker					
	Energy Intensity		Labor Intensity		Capital Intensity	
	(Low)	(High)	(Low)	(High)	(Low)	(High)
[Temp $< -6^{\circ}$]	-0.00067**	-0.00043	-0.00042	-0.00051*	-0.00073*	-0.00056*
	(0.00026)	(0.00055)	(0.00037)	(0.00027)	(0.00039)	(0.00031)
[$-6^{\circ} <$ Temp $\leq -3^{\circ}$]	-0.00058**	-0.00064	-0.00073**	-0.00051*	- 0.00048	-0.00055**
	(0.00023)	(0.00051)	(0.00031)	(0.00028)	(0.00040)	(0.00028)
[$-3^{\circ} <$ Temp $\leq 0^{\circ}$]	-0.00028	-0.00050	-0.00050*	-0.00016	-0. 00032	-0.00025
	(0.00019)	(0.00043)	(0.00026)	(0.00020)	(0.00034)	(0.00023)
[$0^{\circ} <$ Temp $\leq 3^{\circ}$]	-0.00016	-0.00054	-0.00038*	-0.00009	-0.0 0028	-0.00012
	(0.00015)	(0.00033)	(0.00022)	(0.00018)	(0.00024)	(0.00020)
[$3^{\circ} <$ Temp $\leq 6^{\circ}$]	0.00008	-0.00026	-0.00012	0.00004	0.0 0005	0.00006
	(0.00016)	(0.00035)	(0.00021)	(0.00019)	(0.00024)	(0.00018)
[$6^{\circ} <$ Temp $\leq 9^{\circ}$]	-0.00006	-0.00003	-0.00018	-0.00001	-0.0 0005	-0.00009
	(0.00013)	(0.00026)	(0.00018)	(0.00017)	(0.00021)	(0.00015)
[$9^{\circ} <$ Temp $\leq 12^{\circ}$]	0.00007	-0.00001	0.00004	-0.00002	0. 00012	0.00006
	(0.00009)	(0.00018)	(0.00013)	(0.00012)	(0.00015)	(0.00013)
[$15^{\circ} <$ Temp $\leq 18^{\circ}$]	0.00018**	0.00039	0.00019	0.00012	0 .00022*	0.00004
	(0.00009)	(0.00025)	(0.00012)	(0.00011)	(0.00012)	(0.00012)
[$18^{\circ} <$ Temp $\leq 21^{\circ}$]	0.00022*	-0.00005	0.00019	0.00028**	0 .00010	0.00024
	(0.00012)	(0.00021)	(0.00016)	(0.00014)	(0.00016)	(0.00016)
[$21^{\circ} <$ Temp $\leq 24^{\circ}$]	0.00019	0.00024	0.00025	0.00023	0 .00020	0.00001
	(0.00017)	(0.00033)	(0.00021)	(0.00023)	(0.00021)	(0.00022)
[$24^{\circ} <$ Temp]	-0.00001	0.00021	0.00031	0.00034	0.00032	-0.00024
	(0.00033)	(0.00054)	(0.00031)	(0.00042)	(0.00036)	(0.00033)
Number of Observations	418,279	67,211	144,646	152,490	160,131	172,299
Adjusted R-Squared	0.915	0.919	0.886	0.852	0.945	0.911
Weather-Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of plants' gross output per worker for various subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. Plants operating in the economic sectors ”manufacture of chemicals and chemical products”, ”manufacture of basic metals”, ”manufacture of coke and refined petroleum products”, ”manufacture of other non-metallic mineral products” and ”manufacture of paper and paper products” are classified as energy intensive. All other plants have a low energy intensity. We require a plant to be below or above the median labor/capital intensity every year to be classified as low/high labor/capital intensive. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A13: Sample Splits: Effect of Temperature on Sales

	Log of Sales			
	South vs. North		New vs. Old	
	(South)	(North)	(New)	(Old)
[Temp $< -6^{\circ}$]	-0.00072*	-0.00105	-0.00026	-0.00091***
	(0.00039)	(0.00070)	(0.00042)	(0.00033)
[$-6^{\circ} <$ Temp $\leq -3^{\circ}$]	-0.00101***	-0.00089*	-0.00044	-0.00110***
	(0.00038)	(0.00050)	(0.00040)	(0.00032)
[$-3^{\circ} <$ Temp $\leq 0^{\circ}$]	-0.00052	-0.00007	-0.00000	-0.00043
	(0.00032)	(0.00041)	(0.00033)	(0.00026)
[$0^{\circ} <$ Temp $\leq 3^{\circ}$]	-0.00010	-0.00019	0.00012	-0.00019
	(0.00029)	(0.00032)	(0.00027)	(0.00020)
[$3^{\circ} <$ Temp $\leq 6^{\circ}$]	-0.00030	-0.00005	-0.00001	-0.00019
	(0.00026)	(0.00038)	(0.00026)	(0.00021)
[$6^{\circ} <$ Temp $\leq 9^{\circ}$]	-0.00016	-0.00003	0.00002	-0.00017
	(0.00020)	(0.00033)	(0.00021)	(0.00017)
[$9^{\circ} <$ Temp $\leq 12^{\circ}$]	-0.00016	-0.00046**	-0.00018	-0.00014
	(0.00014)	(0.00021)	(0.00017)	(0.00014)
[$15^{\circ} <$ Temp $\leq 18^{\circ}$]	0.00026**	0.00007	-0.00004	0.00035***
	(0.00012)	(0.00025)	(0.00015)	(0.00011)
[$18^{\circ} <$ Temp $\leq 21^{\circ}$]	0.00013	-0.00002	-0.00022	0.00025
	(0.00021)	(0.00032)	(0.00021)	(0.00017)
[$21^{\circ} <$ Temp $\leq 24^{\circ}$]	0.00026	0.00042	-0.00014	0.00047*
	(0.00030)	(0.00038)	(0.00032)	(0.00026)
[$24^{\circ} <$ Temp]	-0.00100**	-0.00117	-0.00097**	-0.00050
	(0.00049)	(0.00084)	(0.00049)	(0.00041)
Number of Observations	293,602	192,017	209,139	276,480
Adjusted R-Squared	0.966	0.966	0.960	0.966
Weather-Controls	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes

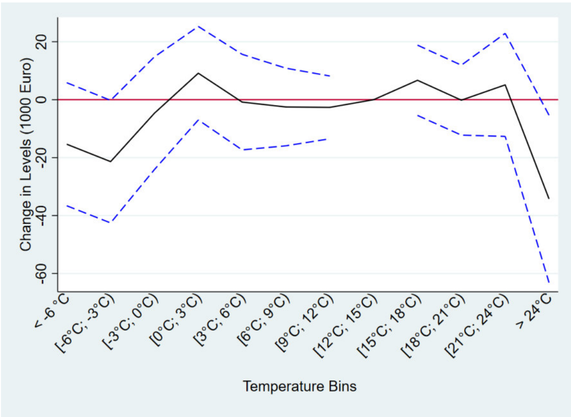
Notes: This table shows the estimated effects of temperature on the log of plants' gross output in subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. To split between north and south we classify all plants in Schleswig-Holstein, Hamburg, Lower Saxony, Bremen, North Rhine-Westphalia, Berlin, Mecklenburg-West Pomerania, and Brandenburg as located in the north. The rest is considered south. We treat all plants we observed in 1995 as old plants and those entering the sample later as new plants. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

Table A14: Sample Splits: Effect of Temperature on Sales per Worker

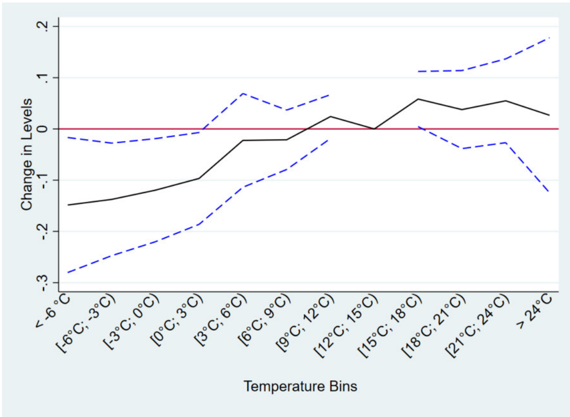
	Log of Sales per Worker			
	South vs. North		New vs. Old	
	(South)	(North)	(New)	(Old)
[Temp $< -6^{\circ}$]	-0.00068**	-0.00089	-0.00074**	-0.00061**
	(0.00029)	(0.00055)	(0.00030)	(0.00029)
[$-6^{\circ} <$ Temp $\leq -3^{\circ}$]	-0.00082***	-0.00039	-0.00059*	-0.00059**
	(0.00030)	(0.00036)	(0.00032)	(0.00026)
[$-3^{\circ} <$ Temp $\leq 0^{\circ}$]	-0.00048**	-0.00026	-0.00034	-0.00029
	(0.00023)	(0.00033)	(0.00025)	(0.00021)
[$0^{\circ} <$ Temp $\leq 3^{\circ}$]	-0.00027	-0.00036	-0.00025	-0.00021
	(0.00020)	(0.00026)	(0.00021)	(0.00016)
[$3^{\circ} <$ Temp $\leq 6^{\circ}$]	-0.00005	-0.00016	-0.00012	0.00013
	(0.00019)	(0.00031)	(0.00023)	(0.00018)
[$6^{\circ} <$ Temp $\leq 9^{\circ}$]	-0.00006	-0.00028	-0.00016	0.00003
	(0.00014)	(0.00025)	(0.00019)	(0.00013)
[$9^{\circ} <$ Temp $\leq 12^{\circ}$]	0.00002	-0.00018	-0.00005	0.00014
	(0.00011)	(0.00014)	(0.00014)	(0.00010)
[$15^{\circ} <$ Temp $\leq 18^{\circ}$]	0.00012	0.00032*	0.00015	0.00027***
	(0.00011)	(0.00016)	(0.00013)	(0.00010)
[$18^{\circ} <$ Temp $\leq 21^{\circ}$]	0.00009	0.00035	0.00014	0.00024*
	(0.00014)	(0.00027)	(0.00017)	(0.00015)
[$21^{\circ} <$ Temp $\leq 24^{\circ}$]	0.00007	0.00045	0.00012	0.00027
	(0.00020)	(0.00036)	(0.00027)	(0.00018)
[$24^{\circ} <$ Temp]	-0.00056*	0.00032	-0.00016	0.00017
Number of Observations	293,602	192,017	209,139	276,480
Adjusted R-Squared	0.918	0.918	0.925	0.910
Weather-Controls	Yes	Yes	Yes	Yes
Sector-Year-FE	Yes	Yes	Yes	Yes
Trends by State	Yes	Yes	Yes	Yes
Sales-Decile-Year-FE	Yes	Yes	Yes	Yes
Exporter-Year-FE	Yes	Yes	Yes	Yes

Notes: This table shows the estimated effects of temperature on the log of plants' gross output per worker in subsamples. The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. Standard errors, shown in parenthesis, are clustered at the district and four-digit sector levels. Controls and fixed effects are indicated at the bottom of the table. Weather controls include annual rainfall, a drought index and the number of days with snowcover. To split between north and south we classify all plants in Schleswig-Holstein, Hamburg, Lower Saxony, Bremen, North Rhine-Westphalia, Berlin, Mecklenburg-West Pomerania, and Brandenburg as located in the north. The rest is considered south. We treat all plants we observed in 1995 as old plants and those entering the sample later as new plants. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

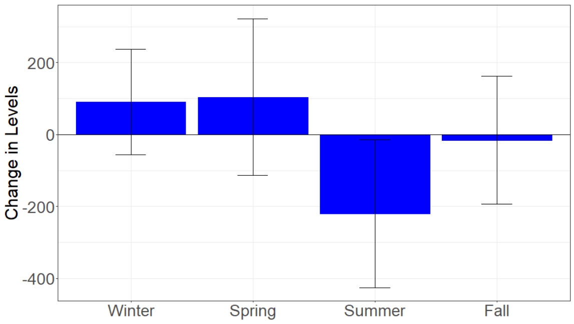
Figure A6: Estimated Effects of Temperature on Gross Output and Gross Output per Worker in Levels



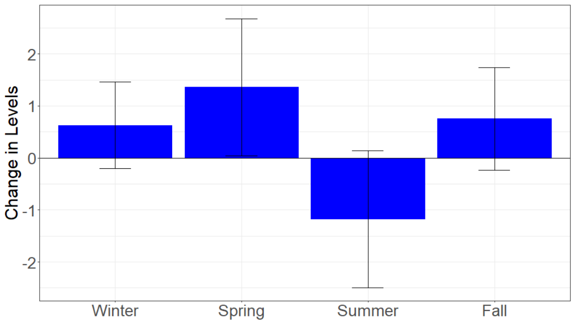
(a) Gross Output



(b) Gross Output per Worker



(c) Gross Output

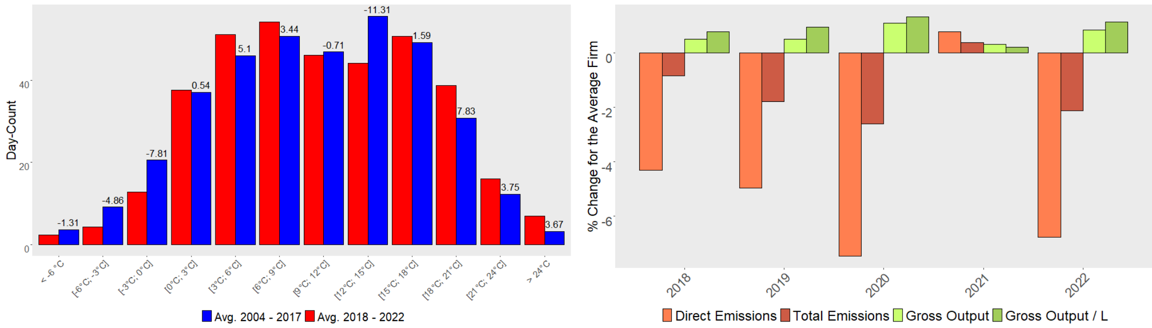


(d) Gross Output per Worker

Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. All regressions include year by two-digit industry fixed effects, year-exporter fixed effects, federal state specific time trends, gross output decile-year fixed effects and additional weather controls (rainfall, drought index and snowcover days). Standard errors are clustered at the district and the four-digit sector level. The number of observations in all regressions is 481,642. 95^{th} confidence intervals are demarcated by the dashed lines in the upper part of Figure 7 and by thin lines in the lower part of Figure 7. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe, 2004-2017, own calculations.

B.3 Counterfactual Calculation

Figure A7: Interpretation of the Coefficients Against the Background of Temperatures between 2018 and 2022



(a) Temperature Distributions

(b) % Change - Average Firm

Notes: Subfigure A7a plots the average day count per temperature bin for 2004 - 2017 and the average day count for 2018 - 2022. Small numbers on top of the bars indicate the difference in their height. Subfigure A7b plots the change in the average plant's outcomes for the years 2028, 2019, 2020, 2021 and 2022 - based on our estimates - relative to a counterfactual in which temperatures were distributed between 2004 and 2017. Own calculations. Source: EOBS