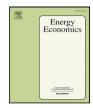
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The effect of temperature on energy related CO_2 emissions and economic performance in German industry.

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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 plants' energy-related CO_2 emissions and 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. Based on fixed effects panel regression models, 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 average plant-level emissions by $\approx 0.16\%$ or 4.2t CO_2 relative to a day with mean temperatures between 15 °C and 18 °C. Evidence for increased emissions from electricity consumption due to cooling needs is less consistent. Our findings indicate that, on average, plants in the German manufacturing sector experienced a 4–7.5% reduction in their annual CO_2 emissions from using fossil fuels in recent years (2004–2017 vs 2018–2022) due to warmer temperatures. 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 output, growth, and labor productivity, results for hot days are mixed. Finally, we interpret our estimates against the backdrop of climate projections.

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: fewer days with low temperatures require less energy for heating, while more days with high temperatures or heat waves increase cooling needs (Graff Zivin and Kahn, 2016). Additionally, outside conditions may also influence the energy required for industrial processes. 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 temperatures on energy use and related ${\rm CO}_2$ emissions in the German manufacturing sector. 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.¹

Our paper makes two main contributions. First, we extend the literature on the effects of temperature on manufacturing plants by examining how plants' energy related CO₂ emissions respond to temperature (and implicitly their energy use). Despite its relevance for economic development and its contribution to climate change, empirical evidence of temperature's effect on emissions in the manufacturing sector is lacking. Previous studies examining the temperature-energy

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

use relationship have predominantly focused on household-level energy consumption (Deschênes and Greenstone, 2011; Auffhammer and Aroonruengsawat, 2011) and some older studies have explored fuel choices in response to climate conditions using discrete choice models and cross-sectional survey data for households and firms combined (Vaage, 2000; Mansur et al., 2008). Hence, there remains a gap in understanding the direct impact of temperature on energy consumption at the firm-/plant-level. This need for further research has been highlighted by Auffhammer and Mansur (2014). Germany, as Europe's industrial powerhouse, provides an ideal setting to study this question. For instance, Germany's industrial sector accounts for roughly 20% of emissions from industry covered by the EU's Emissions Trading System (ETS), the highest share of any single country (European Environmental Agency, 2023). Compared to other sectors in Germany, the industrial sector is responsible for almost a quarter of Germany's total greenhouse gas emissions (Umweltbundesamt, 2024). If indirect emissions from purchased electricity are also attributed to the industrial sector, this share is significantly higher.

Second, by looking at the effect of temperature on output and 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 (cf. Jones and Olken (2010), Dell et al. (2012), Hsiang et al. (2015), Kalkuhl and Wenz (2020), Miller et al. (2021)). While older studies have primarily investigated how temperature affects production at the regional or country level, more recent research has increasingly employed micro-level data. For example, Zhang et al. (2018) and Chen and Yang (2019) use plant-level data from China to study the impact of temperature on productivity and factor reallocation. Similarly, Somanathan et al. (2021) study the effects of temperature on manufacturing plants in India, Addoum et al. (2020) focus on the United States, and Kabore and Rivers (2023) conduct such an analysis for Canada. Overall, evidence is still limited, and especially for advanced economies, inconclusive. For instance, Addoum et al. (2020) document a flat relationship between sales and temperature for the US while Kabore and Rivers (2023) find adverse temperature effects at the tails of the temperature distribution for Canadian firms. We add to this literature by studying the case of Germany, where the manufacturing sector is particularly significant for the overall economy.2 In our analysis, we account for lagged temperatures and examine their impact on both output levels and output growth. By adopting this approach, we contribute to the ongoing "level-vs.-growth" debate (cf. Dell et al. (2012), Hsiang et al. (2015), Kalkuhl and Wenz (2020)), offering insights from a microdata perspective. If temperature shocks induce long-term growth declines within exposed regions, such effects should manifest at the micro-level. Previous studies leveraging microdata have primarily focused on assessing plants' output without considering growth rates, and with the exception of Chen and Yang (2019), did not investigate permanent effects by including temperature lags.

For our econometric analysis, based on fixed effects panel regression models, we draw on comprehensive census data, which covers the universe of German manufacturing plants with more than 20 employees (\approx 40,000 plants annually), spans almost one-and-a-half decades from 2004 to 2017, and specifies such factors as plant-specific fuel use. Detailed reporting of fuel use by fuel type (more than 20 categories) allows us to precisely 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)). Finally, 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 ${\rm CO}_2$ emissions in response to more days with low temperatures. Specifically, our findings reveal that for each additional day with a mean temperature below -6 °C, plants experience a 0.16% increase in their annual total ${\rm CO}_2$ emissions on average and a 0.48% increase in their direct emissions, compared to days with mean temperatures between 15 °C and 18 °C.³ 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. Regarding economic performance, we find small but significant and robust adverse effects from low temperatures on output, output per worker and respective growth rates. Results for hot days are mixed.

To interpret the effect size and implied magnitudes, we use our estimates to calculate the temperature effect on CO_2 emissions in recent years. On average, plants in the German manufacturing sector experienced a 4–7.5% reduction in annual direct CO_2 emissions between 2018 and 2022 compared to a counterfactual where daily temperatures were distributed as they were between 2004 and 2017. Further, we interpret our estimates against the backdrop of climate projections, e.g., under a high climate change scenario and based on c.p. assumptions, direct emissions from fuel combustion will, on average, decrease by approximately 14%–16% until the end of the century, while electricity-related emissions will not change.

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 $^{\circ}\text{C}$ above the longterm 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

² 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 (cf. Statistisches Bundesamt (2020)). Against this background, studying the effect of temperature on the economic performance of plants in the manufacturing sector is of particular relevance.

 $^{^3}$ Total emissions refers to the sum of "direct emissions" from fuel combustion at the plants and "indirect emissions" embodied in the electricity procured from the grid.

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 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 plants, 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 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

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 –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%. Combining these 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 "AFiD Modul Industriebetriebe" (industrial plants module) with "AFiD Modul Energieverbrauch" (energy use module). In principle, the data covers more than two decades, from 1995 to 2017 but due to a major change in the reporting of energy variables between 2002 and 2003 we restrict ourselves to data from 2004 onward.

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. To calculate indirect emissions from electricity purchased from the grid we apply the average carbon content, which we also obtain from the "Umweltbundesamt" (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 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 location at the municipality level.

Table 1 provides summary statistics from our estimation sample. Panel A of Table 1 shows summary statistics for economic performance indicators. On average, plants in the sample have approximately 118 employees, a turnover of 25 million euros per year, which grows by 2.5%, an export share of 21%, paying an average annual wage per worker of \approx 32 thousand euros and invest roughly 833 thousand in

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.

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)).

 $^{^6\,}$ AFiD-Modul Industrie betriebe: 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.

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. Our results are, however, also robust to the longer period from 2003 onwards. For a detailed description of the dataset as well as the change in the reporting requirements see Petrick et al. (2011).

 $^{^8}$ To calculate plant-level CO $_2$ emissions, we draw upon the conversion factors provided by the Umweltbundesamt (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.

 $^{^9}$ The estimation sample has been cleaned from outliers: we dropped the bottom 0.5 percentile and the top 99.5 percentile regarding output, output per worker, growth, energy use, and CO_2 intensity. Moreover, we dropped plants with extreme spikes in either (direct) CO_2 intensity, output or CO_2 emissions. We define a plant as a "spike-plant" if the within-plant standard deviation of a variable is 50 larger than the plant's median of the variable.

Table 1
Economic performance indicators and CO₂ Emissions by Fuel (2004–2017)

Variable	Mean	Std. Dev	p10	p50 (Median)	p90	N
A. Economic Performance Indicators						
Number of Employees (L)	118	208.34	25	56	254	518 680
Output (Y) (in 1000€)	24 971.28	56 020.63	1917.85	7520.44	58 158.54	518 680
Output Growth (in %)	2.52	20.82	-19.66	2.72	24.21	500 372
Export Share (in %)	21	26	0	10	62	518 680
Average Wage (in 1000€)	32.49	12.28	17.65	31.48	48.24	518680
Investment (in 1000€)	833.56	3948.02	0	117.92	1734.71	518680
B. CO ₂ Emissions/Energy Use						
Total Energy (in MWh)	7952.77	31 981.77	193.80	1036.58	14 205.72	518 680
Total CO ₂ Emissions (in t)	2670.94	9709.31	68.82	404.67	5309.00	518 680
CO ₂ Emissions - Coal (in t)	84.00	2439.62	0	0	0	518 680
CO ₂ Emissions - Gas (in t)	732.78	4101.87	0	31.46	974.65	518 680
CO ₂ Emissions - Oil (in t)	118.79	1213.66	0	0	185.78	518 680
CO ₂ Emissions - Electricity (in t)	1632.56	5758.43	37.38	274.78	3493.76	518 680
CO ₂ Emission Intensity (kg/1000€)	107.16	174.09	12.79	57.82	221.78	518 680
Direct CO ₂ Emission Intensity (kg/1000€)	39.36	110.97	1.64	11.85	75.04 518 680	

Notes: Part A. of the table shows descriptive statistics for plant-level indicators of economic performance. 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 $1000 \in$ of 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.

buildings or machinery. A comparison between means and medians reveals mostly right-skewed distributions. Panel B of Table 1 contains summary statistics on energy use, CO2 emissions and emissions by fuel type. The average annual energy consumption is almost 8000 MWh, associated with more than 2670 tons of CO2 emissions. These emissions are the sum of direct and indirect emissions, i.e., emissions from fuel combustion at the plants plus emissions embodied in the electricity purchased from the grid. 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 can be seen that the average plant causes indirect emissions of ≈ 1630 tons per year, which is more than half of total emissions. Gas is the most critical direct energy source, causing approximately 25% of total emissions. Coal and oil are equally important and jointly account for $\approx 10\%$ of total emissions.¹⁰ Coal use appears most concentrated as consumption at the 90th percentile is zero, reflecting 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 output as shown in the last two rows of Table 1. Approximately 107 kg CO₂ are emitted in order to produce output worth 1000 euros and the average direct emission intensity amounts to $\approx 40 \text{ kg CO}_2$ per thousand euros 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". We downloaded gridded daily mean temperatures to calculate the mean temperature for all 11,000 German municipalities. 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 Fig. 1 summarizes the temperature distribution by Federal State for the period 2004 to 2017. The bins in Fig. 1 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 ("Flächenlander") 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.

Fig. 2 shows within Federal State variation by plotting the average number of days below 0 °C (Fig. 2(a)) and above 18 °C (Fig. 2(b)) 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.

3.3. Climate projections

To project the effect of climate change on ${\rm CO_2}$ emissions, energy consumption, and economic performance in the manufacturing sector, we use end-of-century climate projections for Germany. These

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 19 km 2 . Municipalities are nested within districts (401), which are nested in Federal States (16).

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

 $^{^{14}}$ There are 16 Federal States in Germany, which vary significantly in size. For example, the smallest state, Bremen, covers just 420 $\rm km^2$ and has 685,000 inhabitants, whereas North Rhine-Westphalia is the largest in terms of population, with 18,139,000 inhabitants, and Bavaria is the largest in geographic size, with 70,542 $\rm km^2$.

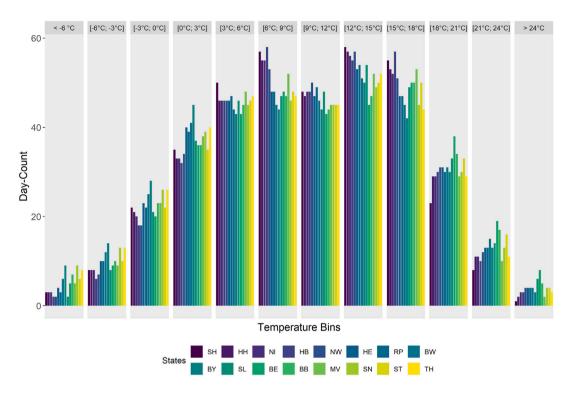


Fig. 1. Temperature bins by federal state.

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.

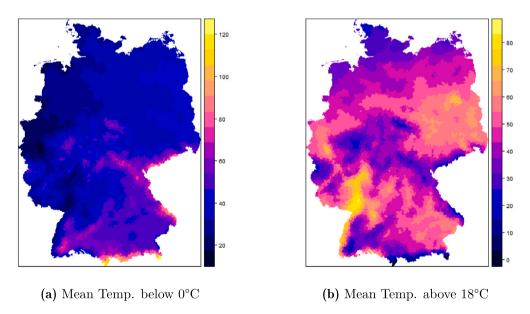


Fig. 2. Average number of cold and hot days per year.

Notes: Fig. 2(a) plots the average number of days with mean temperatures below 0 °C for the period 2004 to 2017. Fig. 2(b) 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.

projections can be downloaded from the World Climate Research Program (WCRP) and were produced in the framework of the ReKiEs-De Project. We use projections from two different climate models and for two representative concentration pathways (RCP). The first projection is based on the 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 scenario" (RCP2.6) and the "high climate change" scenario (RCP8.5). 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), Barreca et al. (2016) or Zhang et al. (2018). Specifically, we estimate the following fixed effects panel regression model using OLS:

$$y_{imsdt} = \sum_{j \neq z} \theta^j T_{mt}^j + \beta W_{mt} + v_{dt} + \lambda_s \times t + \lambda_s \times t^2 + \tau_i + \varepsilon_{imsdt}$$
 (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 include additional weather controls collected in the vector W_{mt} . Annual shocks common to subsectors are absorbed by the year-by-sector fixed effects v_{dt} . Federal State specific linear and quadratic time trends ($\lambda_s \times t, \lambda_s \times t^2$) 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. As a robustness check, we also estimate more demanding specifications. For example, we include year-by-output decile dummies to control for shocks occurring along the firm-size distribution, and year-exporter fixed effects to absorb shocks differentially affecting exporters.

The variables of interest are the measures of temperature. In Eq. (1), T_{mt}^{j} 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. ¹⁸ All days with a mean temperature below -6 °C are

collected in T_{mt}^1 . T_{mt}^{12} is the number of days with mean temperatures above 24 °C (cf. Fig. 1). The coefficients of interest are collected in the vector 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. In our application, the temperature bin 15–18 °C is excluded. Therefore, the coefficient θ^j indicates the change in the outcome resulting from an additional day with a mean temperature in bin j instead of within the interval 15–18 °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 first section describes our main 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' CO₂ emissions

Fig. 3(a) shows the effect of temperature on the log of total $\rm CO_2$ emissions estimated based on equation (1); a rather parsimonious specification, which only includes sector-year fixed effects to purge sector-specific shocks, linear and quadratic time trends by Federal State, and additional weather variables, e.g., average annual rainfall. The solid line connects the point estimates, i.e., the semi-elasticities, and the two dashed lines correspond to the 95th 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 15 °C and 18 °C. Because the weather data 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. ¹⁹ For reasons of conservatism we also cluster at the four-digit economic sector level.

From Fig. 3(a) one can see that more cold days cause an increase in CO $_2$ emissions. Specifically, one more day with a mean temperature below $-6~^{\circ}\mathrm{C}$ leads to an average rise in plants' annual CO $_2$ emissions by approximately 0.16% relative to a day with mean temperatures between 15 $^{\circ}\mathrm{C}$ and 18 $^{\circ}\mathrm{C}$. The point estimates that measure the effects of temperature between $-6~^{\circ}\mathrm{C}$ and $-3~^{\circ}\mathrm{C}$, $-3~^{\circ}\mathrm{C}$ and 0 $^{\circ}\mathrm{C}$ and 3 $^{\circ}\mathrm{C}$ are similar to each other, indicating a relative increase of emissions by slightly more than 0.1%. The effect then starts to flatten out, becomes insignificant for the [6 $^{\circ}\mathrm{C}$ – 9 $^{\circ}\mathrm{C}$] bin and remains small and statistically indistinguishable from zero for temperatures above 9 $^{\circ}\mathrm{C}$.

The effect of temperature on total emissions in Fig. 3(a) is a combination of the effects on emissions from different energy sources. We thus undertake a separate investigation of the response of direct emissions (emissions resulting from the combustion of fossil fuels at the plants themselves) and indirect emissions (emissions contained in the electricity purchased by plants) to temperature. The findings are shown in Fig. 3(b) and Fig. 3(c), 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 average increase of direct emissions by

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).

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).

 $^{^{17}}$ The weather controls include annual mean rainfall, the number of days with snow cover and a drought index.

 $^{^{18}\,}$ 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.

¹⁹ There exist 402 districts compared to more than 11,000 municipalities.

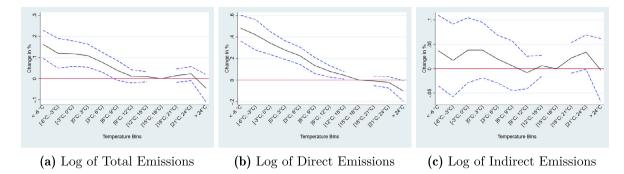


Fig. 3. Estimated effects of temperature on log annual CO_2 emissions.

Notes: The effects are estimated based on an unbalanced panel covering the period 2004 to 2017. The regressions include year by two-digit industry fixed effects, linear and quadratic time trends by Federal State and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 518,457 (Fig. a) and 493,135 (Fig. b) and 515,646 (Fig. c). Dashed lines show the 95th 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.

more than 0.48% relative to one day with mean temperatures between 15 °C and 18 °C. The effect declines almost linearly in the direction of the bin omitted but remains statistically significant for all point estimates. The estimates capturing the effects of additional days with mean temperatures above those in the omitted bin are insignificant except for the outermost coefficient which indicates a drop in direct emissions by approximately 0.1%. By contrast, the baseline specification shows that electricity consumption is entirely unaffected by temperatures, as can be seen from Fig. 3(c). All estimates are quantitatively but also qualitatively insignificant (notice the different *y*-axis scales between Figs. 3(b) and 3(c)).²⁰

The results presented so far indicate that direct CO₂ emissions rise when temperatures are low while indirect emissions do not respond to temperatures. Since energy is a highly flexible input, 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 CO2 emissions with output. The estimated effects of temperature on the log of total emission per unit of output (CO₂ emission intensity) as well as direct and indirect CO2 intensities are shown in Fig. 4. From Figs. 4(a) and 4(b) one can see that the effect of low temperatures on the logs of total and direct emission intensity measures is approximately 30% larger as compared to the effects on log emissions (Figs. 3(a) and 3(b)). Temperatures above the reference bin neither affect total nor direct emission intensity, contrasting with the negative effect of temperatures above 24 °C on direct emissions (Fig. 3(b)). Finally, the effect of temperature on indirect emission intensity (Fig. 4(c)) 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 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).

We also estimate specifications with total and direct emission (intensities) in levels instead of logs (cf. Figure A4 in the appendix), which sheds light on the relevance of the effect for aggregate emissions. If the effect of temperature on emissions were concentrated only among plants with very low emissions, one would expect a much smaller effect size in the specification with emissions in levels. Interestingly, the results are qualitatively and quantitatively similar to the log specification. For example, an additional day with a mean temperature below $-6~^{\circ}\text{C}$ causes an increase in the average firm's emissions by ≈ 4.2

tons, corresponding to $\approx 0.16\%$ 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 1.5–3 tons corresponding to approximately 0.1% of total emissions (cf. Table 1). Similarly, direct emissions increase by ≈ 3.5 t CO_2 in response to an additional day with a mean temperature below -6 °C, which is $\approx 0.35\%$ of average direct emissions. Total emission intensity increases by ≈ 0.3 kg/1000 \in with an additional day in the outermost bin and direct emission intensity by ≈ 0.16 kg/1000 \in corresponding to approximately 0.3% and 0.4% of respective means.

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 as explanatory variables. 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.

Fig. 5 shows the effect of seasonal mean temperatures on the log of 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 95th confidence intervals. A negative coefficient indicates that higher seasonal mean temperatures cause lower ${\rm CO}_2$ 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 seasonal mean temperature leads to a decrease in direct emissions by \approx 2.5% in fall, \approx 2% in winter and \approx 1.3% in spring. The effect of average summer temperature is also negative but small and statistically insignificant.²¹ In terms of 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 drop by about 1%. The point estimates for indirect emissions from electricity use are indistinguishable from zero except for fall, when the point estimate is negative and marginally significant.22

 $^{^{20}}$ Table A1 in the appendix report the results for the effects on the logs of total, direct and indirect emissions from estimating a tighter specification, which includes additional fixed effects such as sales-decile-year fixed effects and exporter-year fixed effects. Overall, our results are very robust towards the choice of the specification.

 $^{^{21}}$ Average within region standard deviations of mean temperatures in spring, summer and fall are approximately 1 $^{\circ}\text{C}$ and roughly 1.7 $^{\circ}\text{C}$ for winter means

 $^{^{22}}$ Results for log emission intensities are presented in Figure A3 in the appendix. The figure shows that higher mean temperatures in winter and spring have a slightly larger effect on direct emission intensity compared to

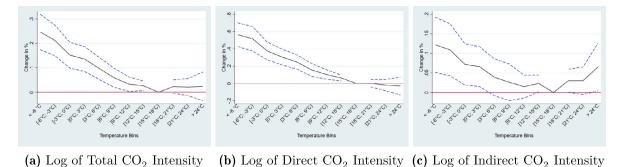


Fig. 4. Estimated effects of temperature on log annual CO₂ emission intensities.

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, linear and quadratic time trends by Federal State and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 518,457 (left figure), 493,135 (middle figure) and 515,646 (right figure). Dashed lines show the 95th 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.

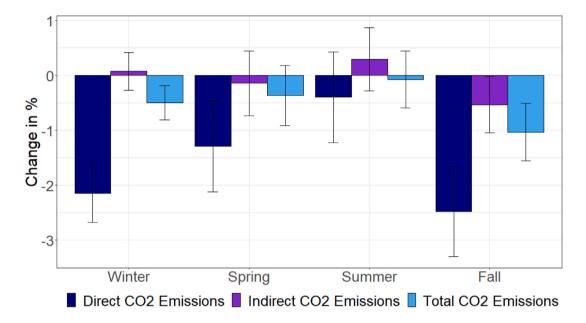


Fig. 5. Estimated effects of seasonal mean temperature on log annual CO₂ emission.

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, linear and quadratic time trends by Federal State and additional weather controls (rainfall, drought index and snowcover days). The number of observations is 493,135 for direct emissions, 482,717 for indirect emissions and 518,457 for total emissions. Thin lines show the 95th 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.

Split by factor intensities First, we divide the sample by factor intensity, *i.e.*, we split (1) between plants operating in sectors considered as energy intensive and other sectors, (2) between plants with an above/below median labor intensity in all years and likewise for (3) capital intensity.²³ The subsample results for direct and indirect

the effects on direct emissions. Conversely, mean temperatures in fall have a slightly attenuated effect on the log of direct emission intensities. Note that we find a significant increase in indirect emission intensity for higher mean temperatures in summer by about 0.5%, which could indicate cooling needs.

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

emissions are shown in Tables A2 and A3 in the appendix. Overall, heterogeneities are limited: we document a similar response of direct emissions between plants in energy-intensive sectors and those in other sectors, suggesting that the positive effects of cold days on log direct emissions are also relevant for aggregate direct emissions. We find direct emissions to be slightly more sensitive to cold days among plants with a below-median labor intensity, which is somewhat surprising given that 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 temperature and output in India's manufacturing industry. Therefore, if plants balance the marginal productivity gains from heating and cooling against the marginal costs, plants with relatively high labor intensity are expected to respond stronger to temperature. However, Somanathan et al. (2021) estimate labor

non-metallic mineral products and Manufacture of paper and paper products (cf. DESTATIS (2022)).

productivity's sensitivity to high temperatures, not low temperatures. In line with their findings, we provide some evidence for increasing indirect emissions in response to hot days among plants with high labor intensity. Specifically, the point estimate implies that labor-intensive plants' electricity use increases by 0.085% in response to one additional day with a mean temperature above 24 °C. Finally, we do not find that capital intensity alters the temperature-emissions relationship.

Split by geographic region Second, we divide the sample by geographic region, i.e., between plants in the north and those in the south, to assess adaptation.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 insulating their buildings, leading to a smaller increase in CO2 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. Indeed, our results indicate 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. Specifically, Table A4 shows that all point estimates from the subsample of firms located in the north are larger compared to the estimates from plants in the south. We do not find a systematic response of indirect emissions to temperature in either subsample (cf. A5).

Split by plant vintage Third, we evaluate whether older plants differ from more recently established ones regarding 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. Newly established plants are more likely to adopt these new technologies or adjust to changes in expectations since retrofitting older 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. Table A2). These estimates also suggest that energy savings potential exists from retrofitting. For example, taking the sum of the products of the differences in point estimates and the average number of days per bin implies that direct emissions from older plants due to low temperatures are approximately 20% higher than those from newer plants.26

Split by economic sectors Finally, we look at the effect of temperature on CO_2 emissions in different economic sectors. Since the number of observations within individual economic sectors can be small, we draw

upon the parsimonious seasonal means specification and aggregate some 2-digit sectors.²⁷ Results for direct and indirect emissions are shown in Figure A5 in the appendix. We find that the effect of the mean temperature in winter on direct emissions is relatively homogeneous across sectors, averaging at an increase of around 2%. The effects of mean temperatures in fall are similar in magnitude to those in winter, while the estimated effects of mean temperatures in spring and summer are mostly insignificant. The effects of temperature on indirect emissions are scattered around zero across economic sectors. In summer, they tend to be rather positive. For the "combined food industry", "printing and reproduction of recorded media", and the "combined machine building industry", we find positive and (marginally) significant effects of summer temperatures on indirect emissions, which, especially in the case of the food industry, is plausible. Besides these positive effects, seasonal mean temperatures' effects on indirect emissions are quantitatively and statistically mostly insignificant (cf. Figure A5b).

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 (Addoum et al., 2020; Somanathan et al., 2021; Kabore and Rivers, 2023), which is still inconclusive, especially for advanced economies. Like previous studies based on microdata, we first focus on the effect of temperature on output. We proceed by investigating the effects on plant-level output growth and shed light on possibly persistent temperature effects. In doing so, we contribute to a broader literature related to the unresolved "level vs. growth" controversy (cf. Dell et al. (2012), Hsiang et al. (2015), Kalkuhl and Wenz (2020)). Previous studies investigated possible dynamic effects of temperature on economic development based on more aggregate-level data using, for example, long-difference regressions. If persistent effects of temperature do not operate through the entry and exit of firms, we expect them to also materialize at the micro level and hence be discernible in our data.

We draw upon the same baseline specifications as before and replace the dependent variable – \log of CO_2 emissions – with the \log of output. Fig. 6(a) shows that negative temperatures significantly depress output. For example, one more day with mean temperature below -3 $^{\circ}\text{C}$ degree reduces the average firm's output by \approx 0.1%. The point estimate measuring the effect of an additional day with temperatures between -3 °C and 0 °C suggests a negative effect of approximately 0.035%, albeit statistically insignificant. For higher temperature bins, the estimates are close to zero and insignificant, except for the coefficient capturing the effect of temperatures in the outermost bin. The respective estimate implies that daily mean temperatures exceeding 24 $^{\circ}\text{C}$ depress output by approximately 0.07%. Fig. 6(b) plots the response of plant-level growth - the year-to-year log difference in output - to temperature. The figure shows that temperatures below 3 °C have an adverse effect on growth, while high temperatures have only a small and insignificant effect.

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.

 $^{^{26}}$ Specifically we calculate the following: 4*0.00199+8*0.00188+16.99*0.00189+32.77*0.0011+42,41*0.00085+46,63*0.00055+40.60*0.00053+45.06*0.00029+29,26*0.00011+11*0,00077+3.46*0.00195=0.21 (cf. Figure A2 for the average number of days per bin).

²⁷ 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.

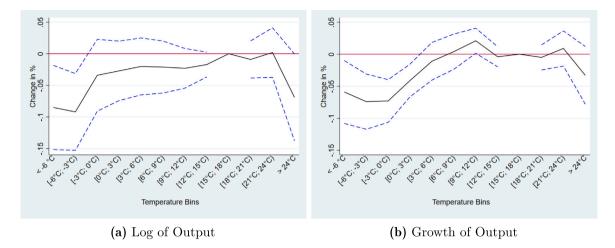


Fig. 6. Estimated effects of temperature on the log of output and output growth.

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, linear and quadratic time trends by Federal State 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 Subfigure (a) is 518,680 and 497,945 in Subfigure (b). 95th 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.

Whether the adverse effects of temperature on growth, as depicted in Fig. 6(b), are persistent or transitory is an empirical question subject to extensive debate in the literature. Ex-ante, the effects are unclear: damages to capital stocks or shifts in investment behavior could lead to a lasting reduction in growth. Conversely, growth rates might rebound following an adverse temperature shock. The resolution of these competing scenarios holds significant implications for the overall costs associated with temperature extremes.

To investigate persistence, we re-estimate the effect of temperature on growth and include lagged temperature bins. From Fig. 7(a), which reports the estimates from a specification with one lag, it is evident that lagged temperatures' effects are smaller in size and mostly insignificant but qualitatively still similar to the contemporaneous effects, hinting at some persistence in the short-run. This short-run persistence of temperature is fairly plausible; for instance, if production processes take some time, adverse temperature shocks in the last quarter of a year might affect output only at the beginning of the following year. To investigate persistence over the medium run, we add the second lag: contrary to the first lags, all second lag coefficients (Fig. 7(b)) are statistically insignificant and small while contemporaneous and lag-1 effects remain almost unchanged. Our results thus do not support the hypothesis that temperature shocks have a persistent negative effect on economic growth over the medium term. However, we do not observe any catch-up growth either, and therefore, our results also imply that adverse effects on output levels must show persistence. In line with this conjecture, Figure A6 in the appendix reports negative and significant effects of low temperatures and their lags on the log of output. The lagged coefficients are larger in absolute terms than the estimates of the contemporaneous effects, consistent with growth rate results that show some short-run persistence.

We further extend our analysis to include output per worker as a reduced form measure for labor productivity. The corresponding results, presented in Figure A7 in the appendix, closely mirror those of the previous analysis: Low temperatures depress labor productivity and its growth (Subfigures a and b), with persistent effects on levels but not on growth (Subfigures c–f). We find some indications of adverse effects from high temperatures, which are small and mostly insignificant.²⁸

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 Section 3.3. Furthermore, we contextualize our findings by considering recent temperature observations between 2018 to 2022, *i.e.*, we calculate the average change in plants' outcome relative to a counterfactual scenario in which the temperature distribution across bins mirrors the historical average observed 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 was the average percentage change in plants' emissions over the past five years compared to if temperatures during those years had matched the average temperatures 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 at the Federal State level and then aggregated to the country level using the Federal States' shares of CO2 emissions in the manufacturing sector (as observed in the AFiD data) as weights. Fig. 8(a) 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 the averages for 2004-2017 are then multiplied by the corresponding coefficients and aggregated across all bins. Fig. 8(b) illustrates the average annual percentage changes in (direct) emissions, output (growth), and output per worker. Our calculations suggest that in 2018, 2019, 2020, and 2022, direct emissions were 4-7.5% lower on average than they would have been with temperature distributions similar to those between 2004 and 2017. Total emissions showed a 1%-2% reduction, while output (growth) and output per worker increased

instance, the adverse growth effects are more pronounced among more laborintensive plants and those located in northern regions. However, this pattern is not consistently reflected in the results for temperatures' effects on output levels. Concerning the effects of high temperatures on output and growth, subsample results mostly confirm negative but small and insignificant effects.

²⁸ In Section C.1 of the appendix, we provide sample split results for output and the output growth rate. These subsample findings align with the main results, indicating adverse effects of low temperatures on the log of output and its growth rate for all subsamples, albeit with varying magnitudes. For

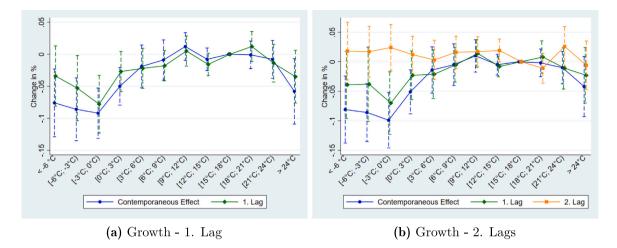


Fig. 7. Estimated effects of contemporaneous and lagged temperature on output growth.

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, linear and quadratic time trends by Federal State 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 Subfigure (a) is 495,276 and 440,489 in Subfigure (b). 95th 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.

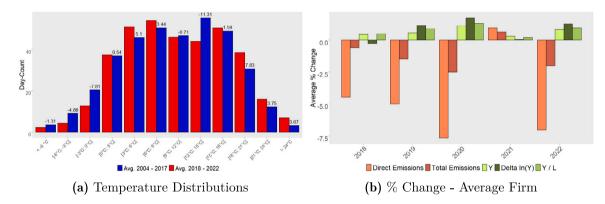


Fig. 8. Interpretation of the coefficients against the background of temperatures between 2018 and 2022.

Notes: Fig. 8(a) 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. Fig. 8(b) plots the average percentage change in 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: FOBS.

by 0.5%–1%. These changes are predominantly driven by fewer days below freezing. 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 on average. In contrast, 2021 exhibited a more typical temperature distribution, which is reflected in our calculations.

Climate Projections To combine the estimated relationships between temperature and plant-level outcomes with the climate projections, we first follow Deschênes and Greenstone (2011) and implement their "error-correction method" to correct for systematic errors in the projections.²⁹ We then bin the projected temperatures.³⁰ 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)

next to 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 high climate change (HCC) scenario and one emission-reduction scenario (RCP2.6) using the output from two climate models introduced in Section 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 HCC scenario indicates an average plant-level decrease in direct emissions by approximately 6% in the middle of the century and by 14%–16% by the end of the century, with fewer cold days driving these effects. These results align with the calculated effect of high temperatures in recent years described above (cf. Fig. 8(b)). The

²⁹ 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.

 $^{^{30}}$ Again we bin separately by Federal State and aggregate to the country level using the Federal States' share of $\rm CO_2$ emissions in the manufacturing sector as weights.

Projections Based on the Estimated Temperature-Emission(-Output) Relationship.

Outcome	Time	EC Earth (HCC)	EC Earth (RCP2.6)	ESM-LR (HCC)	ESM-LR (RCP2.6)
CO2 Total	Mid Century	-1.71	-1.17	-1.93	-1.85
CO2 Total	End Century	-4.85	-0.74	-4.53	-1.99
CO2 Direct	Mid Century	-6.28	-3.45	-6.70	-5.56
CO2 Direct	End Century	-16.06	-2.64	-14.23	-5.63
CO2 Elec.	Mid Century	-0.04	-0.29	-0.11	-0.40
CO2 Elec.	End Century	-0.49	-0.08	-0.63	-0.53
Y	Mid Century	0.60	0.36	0.57	0.60
Y	End Century	1.06	0.59	0.62	0.57
Y/L	Mid Century	0.80	0.45	0.83	0.78
Y/L	End Century	1.75	0.52	1.49	0.88
∆ln(Y)	Mid Century	0.76	0.60	0.86	1.00
∆ln(Y)	End Century	2.07	0.41	1.91	1.19

Notes: The table shows the change in CO₂ emissions (total, direct, indirect), output (growth) and output per worker that results from combining the regression estimates from the baseline model, which includes year by two-digit industry fixed effects, linear and quadratic time trends by Federal State 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 CO₂ emission scenarios (HCC 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.

decline in direct emissions translates into a decline in total emissions, amounting to roughly one-third of the reduction in direct emissions. The respective changes under the emission-reduction scenario are much smaller, particularly towards the end of the century. We also link our estimates of the effect of temperature on economic performance to the climate projections. The results yield an increase in output (growth) due to the rightward shift in temperature distribution. For the HCC scenario, this leads to an approximately 0.5% increase in output by the middle of the century and a 0.6%–1% increase by the end of the century. The changes are slightly larger for labor productivity and output growth (cf. Table 2). While fewer cold days drive the overall effects, their positive impacts are partly offset by the negative impacts of more hot days.³¹

6. Conclusion and discussion

This paper estimates the effect of temperature on energy related 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 0.16% relative to a day with a mean temperature between 15 °C and 18 °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 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 emissions are 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 $-6~\mathrm{C}$ and $-12~\mathrm{C}$, they estimate an increase in energy demand by 0.19% and for days with mean temperature below $-12~\mathrm{C}$, they find that energy demand increases by 0.32%. They find no effect of days with mean temperatures between $21~\mathrm{C}$ and $26~\mathrm{C}$ on energy consumption, but temperatures in the categories $26~\mathrm{C}$ to $32~\mathrm{C}$ and above $32~\mathrm{C}$ increase energy consumption by 0.17% and 0.37% respectively.

We have extended our analysis to include the effect of temperature on measures of economic performance, i.e. output, output per worker and respective growth rates. We find evidence for negative effects of low temperatures (below zero °C) on both. 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. For example, they estimate that an additional day with a mean temperature between -6 °C and -18 °C depresses firms' output by approximately 0.1%, and an additional day with a mean temperature below -18 °C depresses output by approximately 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. Chen and Yang (2019), Somanathan et al. (2021)) but is consistent with estimates for the US by Addoum et al. (2020). We extended the analysis by analyzing the effect of temperature on the growth rates of the performance measures and by looking at the possibly persistent effects of temperature. In line with the estimates of temperature's effects on output (per worker), we find adverse effects of low temperatures on corresponding growth rates. We further document short-lived persistence of those adverse effects:

 $^{^{31}}$ For example, the increase in the number of days with more than 24 °C lowers output by ${\approx}1\%$ at the end of the century under the HCC scenario, but this effect is more than offset by fewer days below the freezing point.

the first lags are still negative albeit insignificant, but the second lags are close to zero. Hence, growth rates are not depressed permanently, but the absence of catch-up growth after a temperature shock suggests that output levels are permanently depressed, which we find reflected in corresponding estimates. These persistent effects on output levels are similar to Chen and Yang (2019), who also document that lagged temperatures are related to contemporaneous output levels. However, they do not investigate the effects on growth rates and instead hypothesize that persistent effects could operate through inventories or damages of the capital stock. Instead, our view is that if temperature affects growth rates and no catch-up happens, plants are set to lower output levels when subject to temperature shocks.

Our analysis suggests that warmer temperatures will make it somewhat easier for Germany to reduce its CO2 emissions in the manufacturing sector. For instance, our estimates imply that high temperatures in recent years reduced plant-level direct emissions by 4-7.5% on average. 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 plants' direct emissions of approximately 14%-16% on average under a HCC 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 CO2 emissions, as described in Section 3, the overall emissions reduction in the manufacturing sector will likely be smaller than the average plant-level percentage change. 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.

CRediT authorship contribution statement

Jakob Lehr: Writing – review & editing, Writing – original draft, Software, Investigation, Formal analysis. **Katrin Rehdanz:** Writing – review & editing, Supervision, Funding acquisition.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107818.

References

- Addoum, Jawad M., Ng, David T., Ortiz-Bobea, Ariel, 2020. Temperature shocks and establishment sales. Rev. Financ. Stud. 33 (3), 1331–1366. http://dx.doi.org/10.1093/rfs/hhz126, arXiv:https://academic.oup.com/rfs/article-pdf/33/3/1331/32449227/hhz126.pdf.
- Aragón, Fernando M., Oteiza, Francisco, Rud, Juan Pablo, 2021. Climate change and agriculture: Subsistence farmers' response to extreme heat. Am. Econ. J.: Econ. Policy 13 (1), 1–35. http://dx.doi.org/10.1257/pol.20190316.
- Auffhammer, Maximilian, Aroonruengsawat, Anin, 2011. Simulating the impacts of climate change, prices and population on California's residential electricity consumption. Clim. Change 109 (1), 191–210.
- Auffhammer, Maximilian, Mansur, Erin T., 2014. Measuring climatic impacts on energy consumption: A review of the empirical literature. Energy Econ. 46, 522–530. http://dx.doi.org/10.1016/j.eneco.2014.04.017.
- Barreca, Alan, Clay, Karen, Deschenes, Olivier, Greenstone, Michael, Shapiro, Joseph S., 2016. Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. J. Polit. Econ. 124 (1), 105–159. http://dx.doi.org/10.1086/684582.
- Burke, Marshall, Emerick, Kyle, 2016. Adaptation to climate change: Evidence from US agriculture. Am. Econ. J.: Econ. Policy 8 (3), 106–140. http://dx.doi.org/10.1257/pol.20130025.
- Chen, Xiaoguang, Yang, Lu, 2019. Temperature and industrial output: Firm-level evidence from China. J. Environ. Econ. Manag. 95, 257–274. http://dx.doi.org/10.1016/j.jeem.2017.07.009.
- Dell, Melissa, Jones, Benjamin F., Olken, Benjamin A., 2012. Temperature shocks and economic growth: Evidence from the last half century. Am. Econ. J.: Macroecon. 4 (3), 66–95. http://dx.doi.org/10.1257/mac.4.3.66.
- Dell, Melissa, Jones, Benjamin F., Olken, Benjamin A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740-798.
- Deschênes, Olivier, Greenstone, Michael, 2007. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. Amer. Econ. Rev. 97 (1), 354–385. http://dx.doi.org/10.1257/aer.97.1.354.
- Deschênes, Olivier, Greenstone, Michael, 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. Am. Econ. J.: Appl. Econ. 3 (4), 152–185. http://dx.doi.org/10.1257/app.3.4.152.
- DESTATIS, 2022. Bedeutung der energieintensiven Industriezweige in Deutschland. https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Industrie-Verarbeitendes-Gewerbe/produktionsindex-energieintensive-branchen.html, (Accessed 08 May 2023).
- Elliott, Robert J.R., Liu, Yi, Strobl, Eric, Tong, Meng, 2019. Estimating the direct and indirect impact of typhoons on plant performance: Evidence from Chinese manufacturers. J. Environ. Econ. Manag. 98, 102252. http://dx.doi.org/10.1016/j. jeem.2019.102252.
- European Environmental Agency, 2023. European union emissions trading system (EU ETS) data from EUTL. (Accessed 15 May 2024).
- Graff Zivin, Joshua, Kahn, Matthew E., 2016. Industrial productivity in a hotter world:

 The aggregate implications of heterogeneous firm investment in air conditioning.

 In: Working Paper Series 22962, National Bureau of Economic Research, http://dx.doi.org/10.3386/w22962.
- Heal, Geoffrey, Park, Jisung, 2016. Reflections—Temperature stress and the direct impact of climate change: A review of an emerging literature. Rev. Environ. Econ. Policy 10 (2), 347–362. http://dx.doi.org/10.1093/reep/rew007.
- Hsiang, Solomon M., 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. Proc. Natl. Acad. Sci. 107 (35), 15367–15372. http://dx.doi.org/10.1073/pnas.1009510107, arXiv:https://www.pnas.org/content/107/35/15367.full.pdf.
- Hsiang, Solomon M., Burke, Marshall, Miguel, Edward, 2015. Global non-linear effect of temperature on economic production. Proc. Natl. Acad. Sci. 527, 1476–4687. http://dx.doi.org/10.1038/nature15725.
- Hübener, Heike, Spekat, Arne, Bülow, Katharina, Früh, Barbara, Keuler, Klaus, Menz, Christop, Radtke, Kai, Ramthun, Hans, Rathmann, Torsten, Steger, Christian, Toussaint, Frank, Warrach-Sagi, Kirsten, 2017. Reklies-de nutzerhandbuch. http://dx.doi.org/10.2312/WDCC/ReKliEsDe Nutzerhandbuch.
- Imbery, F., Friedrich, K., Fleckenstein, R., Plückhahn, B., Brömser, A., Bissolli, P., Daßler, J., Haeseler, S., Rustemeier, E., Ziese, M., Breidenbach, J.-N., Fränkling, S., Trentmann, J., Kaspar, F., 2023. Klimatologischer rückblick auf 2022: Das sonnenscheinreichste und eines der beiden wärmsten jahre in deutschland. Deutscher Wetterdienst Stand: 19.01.2023.
- Jia, Ruixue, Ma, Xiao, Xie, Victoria Wenxin, 2022. Expecting Floods: Firm Entry, Employment, and Aggregate Implications. MPRA Paper 112367, University Library of Munich. Germany.
- Jones, Benjamin F., Olken, Benjamin A., 2010. Climate shocks and exports. Amer. Econ. Rev. 100 (2), 454–459. http://dx.doi.org/10.1257/aer.100.2.454.
- Kabore, Philippe, Rivers, Nicholas, 2023. Manufacturing output and extreme temperature: Evidence from Canada. Can. J. Econ. 56 (1), 191–224. http://dx.doi.org/10.1111/caje.12633, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/caje.12633.

- Kalkuhl, Matthias, Wenz, Leonie, 2020. The impact of climate conditions on economic production. Evidence from a global panel of regions. J. Environ. Econ. Manag. 103, 102360. http://dx.doi.org/10.1016/j.jeem.2020.102360.
- Lin, Yatang, McDermott, Thomas K.J., Michaels, Guy, 2021. Cities and the Sea Level. CEP Discussion Papers dp1758. Centre for Economic Performance, LSE.
- Mansur, Erin T., Mendelsohn, Robert, Morrison, Wendy, 2008. Climate change adaptation: A study of fuel choice and consumption in the US energy sector. J. Environ. Econ. Manag. 55 (2), 175–193. http://dx.doi.org/10.1016/j.jeem.2007.10.001.
- Mendelsohn, Robert, Nordhaus, William D., Shaw, Daigee, 1994. The impact of global warming on agriculture: A Ricardian analysis. Am. Econ. Rev. 84 (4), 753–771.
- Miller, Steve, Chua, Kenn, Coggins, Jay, Mohtadi, Hamid, 2021. Heat waves, climate change, and economic output. J. Eur. Econom. Assoc. http://dx.doi.org/10.1093/jeea/jvab009, jvab009. arXiv:https://academic.oup.com/jeea/advance-article-pdf/doi/10.1093/jeea/jvab009/37988092/jvab009_miller_etal_replication_files.pdf.
- Petrick, Sebastian, Rehdanz, Katrin, Wagner, Ulrich J., 2011. Energy use patterns in german industry: Evidence from plant-level data. Jahrbücher für Nationalökonomie und Statistik 231 (3), 379–414. http://dx.doi.org/10.1515/jbnst-2011-0306.
- Schlenker, Wolfram, Roberts, Michael J., 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proc. Natl. Acad. Sci. 106 (37), 15594–15598. http://dx.doi.org/10.1073/pnas.0906865106, arXiv:https://www.pnas.org/doi/pdf/10.1073/pnas.0906865106.

- Somanathan, E., Somanathan, Rohini, Sudarshan, Anant, Tewari, Meenu, 2021. The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. J. Polit. Econ. 129 (6), 1797–1827. http://dx.doi.org/10.1086/ 713733.
- Statistisches Bundesamt, 2020. Bruttoinlandsproduktfür deutschland 2020.
- Umweltbundesamt, 2018. Entwicklung der spezifischen Kohlendioxid-Emissionen des deutschen Strommix in den Jahren 1990 – 2017. Umweltbundesamt, Wörlitzer Platz 1, 06844 Dessau-Roßlau, Germany, ISSN 1862-4359.
- Umweltbundesamt, 2024. Emission of greenhouse gases covered by the UN Framework Convention on Climate. German Environment Agency, National Greenhouse Gas Inventory 1990 to 2022 (as of 01/2024, EU Submission) and Early Estimate for 2023 (UBA Press release No. 11/2024).
- Vaage, Kjell, 2000. Heating technology and energy use: a discrete/continuous choice approach to Norwegian household energy demand. Energy Econ. 22 (6), 649–666. http://dx.doi.org/10.1016/S0140-9883(00)00053-0.
- Zhang, Peng, Deschenes, Olivier, Meng, Kyle, Zhang, Junjie, 2018. Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. J. Environ. Econ. Manag. 88, 1–17. http://dx.doi.org/10. 1016/j.jeem.2017.11.001.
- Zivin, Joshua Graff, Neidell, Matthew, 2014. Temperature and the allocation of time: Implications for climate change. J. Labor Econ. 32 (1), 1–26.