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Temperature and Exports: Evidence from the United States

Jimmy Karlsson[1]

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Abstract
This paper estimates the effect of exogenous short-term temperature changes on the economy of the United States, using high-resolution data on monthly exports which has not been previously exploited in the literature. The detailed disaggregation of U.S. export data into sectors enables a top-down estimation of the net effect of temperature, while also identifying potential mechanisms at the micro level. Using an econometric specification which allows high parametric flexibility, I find significantly negative effects of both high and low temperatures. The magnitude of the effects corresponds to an average reduction of annual U.S. exports by 0.20%, following a uniform 2 °C temperature increase. Industry heterogeneity in the temperature effect suggests disparate mechanisms behind hot and cold days, which are important to take into account when estimating the future economic damages of climate change in the United States.

Keywords Climate change · Exports · Manufacturing · Temperature · United States

1 Introduction

The recent surge in economics studying socioeconomic impacts of weather changes has resulted in a continuously growing understanding of the linkages between climate and society. Reviewing the emerging weather-economy literature, Carleton and Hsiang (2016) and Dell et al. (2014) conclude that weather fluctuations are responsible for variations in agricultural and industrial output, labor productivity, health, conflict and political instability. Park et al. (2020) also find a negative correlation between heat and learning in a study using 10 million American students. This paper extends the existing literature, by investigating the effect of temperature on monthly exports in U.S. states. The detailed sectoral disaggregation of U.S. export statistics enables a macroeconomic perspective on the net effect of temperature on the U.S. economy, which at the same time provides suggestions for plausible channels of the temperature effect. The temporal resolution of the outcome

A previous version of this paper, which was my master thesis, is published at the University of Gothenburg's repository for student theses, and can be found at https://gupea.ub.gu.se/bitstream/2077/60833/1/gupea_2077_60833_1.pdf. Substantial changes have been made since.

Jimmy Karlsson
jimmy.karlsson@economics.gu.se

[1] Department of Economics, University of Gothenburg, Box 640, 405 30 Gothenburg, Sweden

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variable facilitates the identification of possibly nonlinear effects of short-term weather changes that are less likely to appear when aggregated to annual measures, and ensures that the studied population does not change substantially during treatment, which reduces the likelihood of biases from time-varying confounding factors (Hsiang and Burke 2013).

Previous literature has demonstrated microeconomic impacts from temperature fluctuations in a broad range of economies (Cachon et al. 2012; Cai et al. 2018; Zhang et al. 2018; Somanathan et al. 2015; Adhvaryu et al. 2019). Studies showing significant effects on aggregated economic outcomes in developed countries are seemingly scarcer. Dell et al. (2012) find significant, negative effects of higher average annual temperature on growth in GDP, but only for poor countries. Likewise, Jones and Olken (2010) estimate similar impacts on growth in poor countries' annual exports. More novel research does, however, indicate substantial impacts of higher temperatures on the U.S. economy as well. At subnational level, Colacito et al. (2018) find that annual growth rates in U.S. states are negatively affected by increases in average summer temperature. Deryugina and Hsiang (2017) also estimate a significantly negative relationship between increases in temperature and income in U.S. counties, using an estimation approach which accounts for the nonlinearity established in earlier research (Burke et al. 2015). Burke and Tanutama (2019) too observe adverse effects of rising temperatures on a global sample of subnational economies, where e.g. the United States is estimated to have lost US$5 trillion in output during 2000–2015 due to warming.

Consistent with this novel strand of the literature, I estimate a nonlinear temperature-economy relationship, where both hot and cold days have significantly adverse effects. I find that one additional day with average temperature above 25 °C is associated with a decrease in exports by 0.22%, compared to days in the 5–10 °C interval. As for cold temperatures, an extra day below −5 °C reduces monthly exports by 0.21%, compared to baseline temperature. Isolating the effect for each industry separately, I estimate hot days to have a significantly negative impact on livestock and capital-intensive industries mainly related to the transformation of raw materials into final products. Cold days are, in addition to agriculture and non-metallic mineral products, instead found to reduce exports in the labor-intensive industries of apparel and textiles. In the Oil and Gas industry, I find that an extra day above 25 °C leads to a reduction in exports by as much as 5.5% compared to baseline temperature. However, by estimating the same temperature effect on electricity consumption and production, I find suggestive evidence attributing this negative impact to a rise in domestic demand for natural gas.

The results of this paper have two main implications. The industry estimates of the temperature effect indicate which economic sectors that are in need of defensive investments in order to effectively mitigate the negative effects of outdoor weather. Further, the results contribute to a more detailed understanding of the economic damages caused by future warming in the United States. The estimated impacts highlight the importance of incorporating the heterogeneity in weather vulnerability across sectors, and in climates across states, into the design of future U.S. climate policies.

The remainder of this paper is organized as follows. Section 2 provides a theoretical framework of the results. Section 3 describes the data and discusses potential limitations. Section 4 describes the empirical framework of the estimations. Section 5 presents the results. Section 6 explores the robustness of the results. Section 7 provides a discussion and concluding remarks.

2 Theoretical Framework

This section presents a simple reduced-form model of the effect of temperature on exports, based on the wealth of previous micro-level studies of the temperature impact on productivity and input levels. For simplicity, productivity impacts are modeled using production instead of exports, implicitly assuming that domestic temperature only affects exports through supply, and is uncorrelated with temperatures in importing countries, to rule out potentially confounding demand effects.

High temperatures have been shown to reduce the number of hours worked in occupations exposed to outdoor weather (Graff Zivin and Neidell 2014), as well as reducing productivity among office workers (Seppänen et al. 2006), garment workers (Adhvaryu et al. 2019) and agricultural workers (Stevens 2018). Extreme temperatures are also known to negatively impact cognitive output and performance (Cook and Heyes 2020; Heyes and Saberian 2019; Park et al. 2020; Graff Zivin et al. 2018). At the firm-level, high temperature has been found to reduce productivity in both capital-intensive and labor-intensive establishments (Cachon et al. 2012; Zhang et al. 2018; Somanathan et al. 2015; Li et al. 2021).

As in Zhang et al. (2018), firm output Q takes the form of a Cobb–Douglas production function with two inputs, labor L and capital K:

$$Q = (\lambda_L(T)L)^{\sigma_L}(\lambda_K(T)K)^{\sigma_K} \tag{1}$$

where λ_L and λ_K are labor and capital productivity, and σ_L and σ_K are the respective output elasticities. As suggested by micro-level research, input productivity is a function of temperature T. By setting $\sigma_L + \sigma_K = 1$, firms are assumed to produce at constant returns to scale.

Taking the natural logarithm and rearranging terms, the following equation is obtained:

$$\ln Q = \sigma_L \ln[\lambda_L(T)L] + \sigma_K \ln[\lambda_K(T)K] \tag{2}$$

Finally, the marginal effect of temperature on output is found by differentiating with respect to T:

$$\underbrace{\frac{\partial \ln Q}{\partial T}}_{\substack{\text{Relative change}\\ \text{in output}}} = \underbrace{\sigma_L \frac{\frac{\partial \lambda_L(T)}{\partial T}}{\lambda_L(T)} + \sigma_K \frac{\frac{\partial \lambda_K(T)}{\partial T}}{\lambda_K(T)}}_{\substack{\text{Average relative change}\\ \text{in productivity}}} \tag{3}$$

The resulting equation shows that the relative change in output from a small change in temperature is equal to the average relative change in input productivity from the same temperature change, weighted by the inputs' respective output elasticity. Constant returns to scale ensures that the sum of weights equals one. Intuitively, the effect of temperature is larger with a higher output elasticity for the input most sensitive to temperature, which provides a rationale for sectoral heterogeneity in the effect of temperature on the economy.

3 Data

3.1 Exports

Merchandise export data for the United States is collected at state level with monthly frequency from the U.S. Import and Export Merchandise trade statistics database (United States Census Bureau 2018). The time range of the data covers January 2002–December 2018. For each state, the data is disaggregated according to the NAICS 3-digit classification, which enables trade flows of goods to be grouped into 28 product categories. As in Jones and Olken (2010), I remove product categories in states without a positive value of exports for all time periods.

I use the monthly CPI Research Series from the Bureau of Labor Statistics (2018) to convert nominal values into inflation-adjusted exports in 2002 $US. The CPI-All Urban Consumer series (Bureau of Labor Statistics 2019a) completes the inflation indices for the months of 2018 which the previous series at the time of download did not cover (adjusted to the same base period). The following analyses on exports are thereby based on real changes, if not otherwise specified.

3.2 Weather

The weather data comes from the Global Historical Climatology Network—Daily Summaries (Menne et al. 2012), which during the time of retrieval contained 46,663 available stations for the United States.[1] The variables collected from the weather stations include daily maximum and minimum temperature (°C), average temperature (°C), precipitation (mm), wind speed (m/s) and snow depth (mm). Average temperature is the main variable used for the 24-h daily average temperature measure. When missing, I use the mean value of the daily maximum and minimum temperature in order to have observations for all states and dates. To exclude outliers within these variables that are likely errors by the stations measuring equipment, I omit values that exceed the minimum and maximum historical daily record, which can be found in the Archive of Weather and Climate Extremes (Cerveny 2018).[2] An important feature of the 24-h daily average measure of temperature, is that night temperatures drive the average towards colder values. An average temperature in the data might therefore display a more negative value than what was actually experienced during the day.

To create representative averages of daily weather outcomes, I follow the methodology of Dell et al. (2012) and use population-weighted averages for each state. Population data is collected from the U.S. Census Grids (Center For International Earth Science Information Network-CIESIN-Columbia University 2017), which contains estimated population data assigned to grids over the U.S. area. The spatial resolution of the grids corresponds to approximately 1 square kilometer. The population counts are time-invariant and based on the year 2010, which means that the population counts before and after 2010 are likely to be different. Choosing a year in the middle of the time range (2002–2018) is thereby preferred, as this is likely to be the best approximation of within-state population distribution for the entire time period. A more detailed description of creating population-weighted measures is available in the "Appendix".

Table 1 presents descriptive statistics of the variables included in the estimations. As I exclude state-industry pairs without positive values for the entire time period, I present the export statistics with and without this condition. The minimum and maximum average temperature show that a large range of the temperature scale is captured in the data.

[1] The R package *RNOAA* by Chamberlain et al. (2019) was used to download the data.

[2] The records are 56.7 °C for highest temperature (North America), −63.0 °C for lowest temperature (North America), and 1.825 m for the global greatest rainfall (La Réunion). Snow depth and wind speed lack easily translated records, and are thereby not altered.

Table 1 Descriptive statistics

Variables	Mean	SD	Min	Max	Obs
Temperature (°C)	12.00	9.86	−18.19	32.09	306,000
# Days per Month:					
< −5 °C	1.89	4.99	0	31	306,000
−5 to 0 °C	2.38	4.29	0	28	306,000
20–25 °C	5.74	8.13	0	31	306,000
> 25 °C	3.04	7.18	0	31	306,000
Precipitation (mm)	2.78	1.88	0.00	17.16	306,000
Snow depth (mm)	17.41	56.10	0.00	855.16	306,000
Wind speed (m/s)	3.04	1.02	0.00	6.95	306,000
State exports	51.83	194.89	0.00	5337.07	306,000
State exports > 0	64.50	215.94	0.002	5337.07	244,800

All statistics are based on monthly frequency. Exports are presented in million 2002 $US. The last row reports statistics for exports for observations with non-zero values

4 Empirical Framework

As previous studies have used different econometric specifications with varying results, I apply two different specifications to estimate a nonlinear effect of temperature on U.S. exports. Focusing on flexibility in the functional form, I first estimate a Restricted Cubic Spline (RCS) regression. RCS are cubic estimations between different intervals of the regressor, which restrict the marginal effect to be constant at the extreme values (where observations are few and inference less certain), as well as continuously differentiable over intervals (Blanc and Schlenker 2017). The result is a flexible estimation of a nonlinear relationship of export and temperature. The intervals are determined by the distribution of the temperature variable, to increase the flexibility in the estimation where variation in the data is large (Harrell 2015). Consequently, the intervals correspond to equally spaced percentiles of temperature.

In comparison, an ordinary quadratic function would force a global structure to the data points, where the slope for individual regressor levels is fitted by minimizing the sum of squared residuals for all levels. If the export-maximizing temperature appears as a kink at a specific level, the smooth regression line will be a poor representation of the export–temperature relationship. If the slope after the kink is strongly negative, the marginal effect is likely to intersect the temperature axis at a lower level, to better fit the larger negative effect of high temperatures. The derived optimal temperature with respect to export might thereby not be the true value, but rather reflect a sharp decline where temperature becomes detrimental. The use of RCS partly alleviates this problem, by reducing the global structure of an ordinary polynomial function.

The RCS is estimated based on the following specification:

$$\ln Y_{i,s,t} = \alpha_0 + f(T_{s,t}) + \mathbf{X}_{s,t} + \gamma_s + \eta_{i,y} + \theta_m + \varepsilon_{i,s,t} \tag{4}$$

The dependent variable is the natural logarithm of exports of NAICS industry i in state s in time t. The variable of interest is a continuous function of monthly average temperature $T_{s,t}$. I control for additional weather outcomes $\mathbf{X}_{s,t}$ available in the data (precipitation, snow depth and wind speed), which are likely correlated with temperature, as well as state-level fixed effects γ_s (such as climate). I also include month-of-year fixed effects θ_m to account for cyclical effects during a year, which removes the potential bias in the effect of temperature on exports stemming from season-specific circumstances, such as growing season for crops. Industry-year fixed effects $\eta_{i,y}$ control for national economic shocks specific to each industry in a given year. $\varepsilon_{i,s,t}$ is the error term specific to each observation. The log-linear relationship of the dependent variable and the regressors takes into account the variation in size of the economy across states, and transforms the estimated coefficients into relative changes in exports due to temperature fluctuations.

Further, I estimate what is the main specification of this paper:

$$\ln Y_{i,s,t} = \alpha_0 + \sum_{k=1}^{m-1} [\beta_k Tbin_{k,s,t}] + \mathbf{X}_{s,t} + \gamma_s + \eta_{i,y} + \theta_m + \varepsilon_{i,s,t} \tag{5}$$

In this equation, the continuous temperature variables are replaced by $m-1$ temperature bins, following previous work in the literature (see e.g., Deryugina and Hsiang 2017; Zhang et al. 2018; Graff Zivin and Neidell 2014; Deschênes and Greenstone 2011; Chen and Yang 2019; Somanathan et al. 2015; Li et al. 2021). The temperature variables measure the number of days for a given month t the daily average temperature is realized within the respective bin. I divide the temperature scale into 8 bins ($m = 8$), of which 7 are included in the estimation to avoid perfect multicollinearity. The excluded bin captures temperature days within 5–10 °C, and is thereby the benchmark the other bins are compared to. This specification enables the highest flexibility in the estimation of a nonlinear effect of temperature, since the effect of different levels of temperature is estimated as separate variables, which removes the global structure inherent to polynomial equations. Measuring temperature in daily averages instead of monthly averages also increases the temporal resolution of the data.

Since the total number of days in a month varies from 28 to 31, the temperature variables will not be perfectly correlated, but rather *almost* perfectly correlated. This variation in the upper bound of monthly days leaves the interpretation of the coefficients as relative effects only to some extent, and thereby less comprehensible. To overcome this problem, I adjust the number of days to equal 31 for all months in the sample when estimating Eq. (5), by increasing the value of one temperature bin for the corresponding months. The temperature bin is chosen to match the average temperature of the specific month. For example, as the average monthly temperature in Alabama in April 2007 was 15.5 °C, I increase the variable representing days in the 15–20 °C interval for this state and time period. Another approach to this problem is for example to remove the last day of a month with 31 days, instead of adding days to months that are shorter. However, it is not likely that being in the final period of a month is uncorrelated with temperature, since days within months become on average warmer when approaching summer, and colder when approaching winter. Although the method used is to some extent arbitrarily applied, it is chosen with the intention make the needed adjustment of the temperature variables with as little systematic bias as possible. The impact of this procedure is evaluated in Table 4 in the "Appendix", and leads to qualitatively similar results as estimations based on the unadjusted sample.

The standard errors are clustered both at state-level and climate zone by month-of-sample, using the two-way clustering approach in Cameron et al. (2011), which allows error terms to be correlated within states across time periods, as well as across states within the same climate zone and time period. This takes into account the possible spatial correlation in other weather outcomes in the error term. For the definition of climate zones I follow Karl and Koss (1984), who divide the contiguous U.S. into 9 climatically consistent regions. Since this definition does not include the states of Alaska and Hawaii, I treat them as separate climate zones, leading to a total of 11 climate zones.

4.1 Limitations

A possible concern is that several weather outcomes are correlated with temperature. Since there is a limitation in the number of variables available from the weather stations, I cannot rule out possible biases in the estimated effect of temperature from other weather outcomes (Auffhammer et al. 2013). For example, variables not included in the regressions that are likely covariates to temperature are humidity and solar radiation, whose effect on exports is uncertain. As suggested by a reviewer, solar radiation is often high both during high and low temperature, and could thereby bias the effect of both temperature extremes. Hence, one should have in mind the potential confounding weather factors when interpreting the estimated effect of temperature on the economy, as it is likely to capture additional unobserved factors of the climate system that are distinct from, but related to temperature.

Since climate is not constant across the United States, the weather data exhibits a large variation that is not equally distributed across the country. Figure 3 in the "Appendix" displays the spatial distribution of four end-scale temperature variables used in the main estimation of this paper. Extreme daily averages (below −5 °C and above 25 °C) are rare occurrences, appearing only in very few states. Moderate intervals at the end of the temperature scale are more evenly distributed across states, although daily averages below 0 °C seem to characterize only northern states. Extrapolating the estimated effects to the United States as a country thus requires the assumption that states respond similarly to temperatures changes, even though some states have not experienced the temperature outcomes in question during the studied time period. Historically, states have had the time to integrate their long-run climate into the economy, and thereby into their individual response functions. This implies that states with an experience of the tails of the temperature distribution may have a different sensitivity to these outcomes, compared to other states. The nonlinear panel estimation approaches used in this paper will capture parts of this long-term adaptation, despite the short-term weather measures used, due to the cross-sectional differences in climate in the sample (Kolstad and Moore 2020). Nevertheless, this does not affect the causality nor the unbiasedness of the results, but rather the generalizability of the effect of temperature to a national average.

An additional limitation relates to the use of exports as the dependent variable of the analysis. Given that weather in the U.S. is potentially correlated with weather in some of its trading partners, there is a risk that the empirical design captures temperature-induced demand effects in importing countries, in addition to local temperature effects on production. The severity of this potential bias will therefore affect the extent to which the estimated effect of temperature on exports can be extrapolated to the producing economy in general. On the other hand, using exports instead of production as the dependent variable might decrease bias stemming from *domestic* demand. Empirically, it is more difficult to disentangle the temperature effects on demand and production when consumers and producers are located close to each other, as they will be subject to the same temperature shocks. Using exports as a proxy for production, where consumers are distributed across foreign importing countries, could then reduce the problem of simultaneous changes in domestic demand. However, using exports will only provide a complete solution as long as changes in domestic demand do not lead to changes in exports (e.g. if firms prioritize domestic markets over foreign markets), and, as explained above, if temperatures in the U.S. and its importing countries are sufficiently uncorrelated. These assumptions might for some industries and states be restrictive, and less likely to hold, depending on their location and the consumption pattern of the products in relation to temperature.

5 Results

5.1 The Effect on Exports

The first estimation following Eq. (4) is presented in Fig. 1, and shows a nonlinear and negative relationship between temperature and exports, where both very high and very low temperatures seem to be harmful to U.S. exports. For temperatures below 0 °C, a 1 °C increase in monthly temperature is associated with an increase in monthly exports by approximately 0.25%. For temperatures above 20 °C, a similar increase is associated with a decrease in exports by approximately 0.50%. The nonlinearity in the marginal effect is more striking as the number of intervals dividing the temperature variable increases (denoted "knots"), and the resulting function resembles a derivation of the theoretical impact function in Burke et al. (2015). The intersection of the marginal effect at zero indicates an optimum of the temperature-export relationship above 10 °C, which is lower than the optimal level in Burke et al. (2015) who derive a global economic growth function that maximizes at an annual average temperature of 13 °C, but comparable to the estimated optimal temperature for manufacturing income (9–12 °C) in the U.S. (Deryugina and Hsiang 2017). Overall, the graph demonstrates the importance of allowing for high flexibility in the estimated marginal effect, as the optimal temperature changes as flexibility

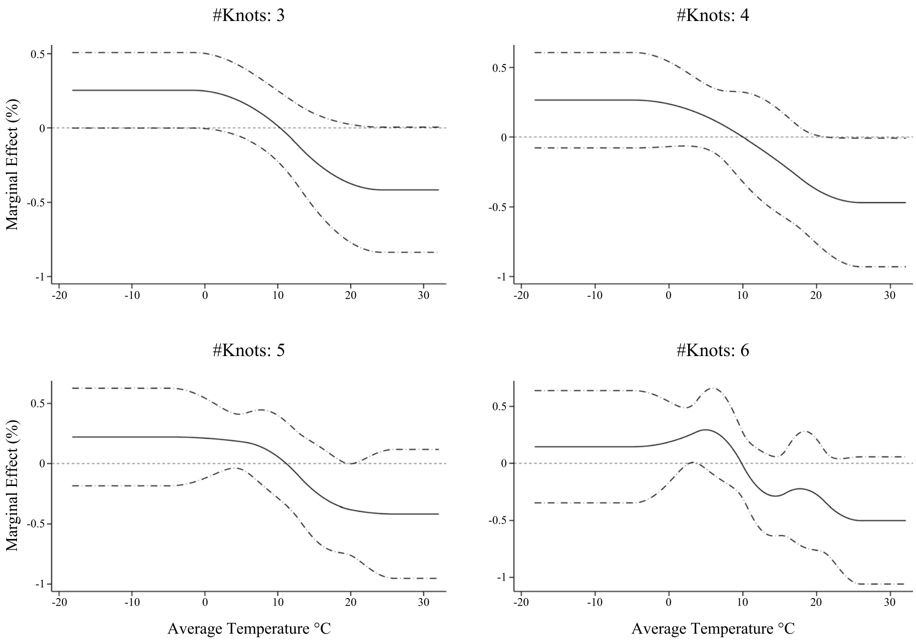

Fig. 1 Restricted cubic spline regression. The graph shows the marginal effect of temperature on exports, controlling for precipitation, snow depth and wind speed. Estimations include month-of-year FE, industry-year FE and state FE. The number of knots are the number of intervals corresponding to equally spaced percentiles of temperature. Standard errors are clustered at state-level and climate zone by month-of-sample. 95% confidence intervals shown by dashed lines. Models are estimated using the STATA package by Buis (2009)

around this point increases. However, one should note that the result is merely indicative, as standard errors are large.

The previous estimations indicate that both extremes of temperature are detrimental to U.S. exports. Following this result, I estimate the main specification of this paper using temperature bins [see Eq. (5)]. The result is presented in Table 2, where column (1) includes the full sample, and column (2) excludes the Oil and Gas sector. The latter estimation is added as a robustness check since the Oil and Gas sector also is subject to temperature-induced variation related to energy demand (Auffhammer and Mansur 2014). This sector will instead be further explored in the heterogeneity analysis of this paper. The variable measuring the number of days within 5–10 °C is omitted to avoid perfect multicollinearity, and is thereby the variable the other temperature bins are compared to. Both cold and hot days are negatively associated with exports at 5% and 1% significance levels. One additional day below −5 °C reduces exports by 0.20%, whereas a day above 25 °C

Table 2 Temperature bin regression

Outcome: Exports (in logs)	Full Sample (1)	Excl. Oil and Gas (2)
Days < 5 °C	−0.0020**	−0.0021**
	(0.0010)	(0.0010)
Days in −5 to 0 °C	−0.0009	−0.0010
	(0.0010)	(0.0010)
Days in 0–5 °C	−0.0015*	−0.0015*
	(0.0008)	(0.0008)
Days in 10–15 °C	−0.0006	−0.0006
	(0.0007)	(0.0007)
Days in 15–20 °C	−0.0011*	−0.0010
	(0.0006)	(0.0006)
Days in 20–25 °C	−0.0015*	−0.0012
	(0.0009)	(0.0008)
Days > 25 °C	−0.0027***	−0.0022**
	(0.0010)	(0.0010)
Precipitation	−0.0024	−0.0021
	(0.0015)	(0.0015)
Snow depth	0.0000	0.0000
	(0.0001)	(0.0001)
Wind speed	−0.0171**	−0.0163*
	(0.0087)	(0.0090)
Observations	244,800	242,556
R-squared	0.7004	0.7086
Month-of-year FE	YES	YES
State FE	YES	YES
Industry-Year FE	YES	YES

Estimations control for average precipitation, average snow depth and average wind speed, and month-of-year FE, state FE, and industry-year FE. 5–10 °C is the omitted bin of reference. Cameron et al. (2011) standard errors clustered by state and climate zone by month-of-sample in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

reduces exports by 0.27%, compared to a day in the 5–10 °C bin. The coefficients support the nonlinear relationship between export and temperature of the earlier estimations, since the negative effect increases both regarding magnitude and statistical significance as the distance from the omitted bin increases. The result is consistent with previous findings of the temperature effect on manufacturing output and exports in the United States (Deryugina and Hsiang 2017), China (Zhang et al. 2018; Chen and Yang 2019; Li et al. 2021), and India (Somanathan et al. 2015), and remains similar when excluding the Oil and Gas sector from the sample. Among the additional weather variables added as controls, I find a statistically significant effect only for wind speed, which has a negative association with monthly exports of −1.71% per m/s increase, all else equal. The negative effect is in line with factory-level evidence on the effect of high wind speed on weekly automobile production plants in the U.S. (Cachon et al. 2012). However, one should bear in mind the additional weather confounders omitted from the analysis when interpreting the coefficient, which is large in relation to the other estimates. It is plausible that the estimated effect of wind speed in this case is influenced by other correlated factors that are unobserved in the data.

5.2 Sectoral Heterogeneity

To investigate heterogeneity in the sensitivity to temperature, the effect is estimated for 28 sectors separately. The regressions thereby contain only one industry over a varying number of states, depending on the extent to which the industry is exported by states across the country. The result of the two lower and two upper temperature variables is presented in Fig. 2 for 27 of the 28 sectors. Estimates for the Oil and Gas sector is presented in Table 3 and discussed separately below. The overall impression is that confidence intervals are large for many of the sectors. At the 95% significance level, the effect of high temperatures is significant for 5 sectors. These are Fabricated Metal Products, Leather and Allied Products, Livestock and Livestock Products, Nonmetallic Mineral Products, and Plastics and Rubber Products. Hot days thereby seem to have a significant impact on sectors that are either related to animal products, or sectors characterized by more capital-intensive production processes, such as mineral, metal, plastics and rubber industries. This pattern partially supports the findings by Zhang et al. (2018), where both labor-intensive and capital-intensive firms are found to be responsive to high temperatures. In general, the majority of sectors estimated to be significantly affected by high temperatures in this paper are also observed in previous work, although temperature seems to have an impact on a larger number of sectors in studies covering developing countries compared to the United States (Zhang et al. 2018; Jones and Olken 2010; Somanathan et al. 2015).

The effect of cold temperatures is also significant for 5 sectors, namely Agricultural Products, Apparel and Accessories, Forestry Products, Nonmetallic Mineral Products, and Textiles and Fabrics. In contrast to the rather capital-intensive industries above, the two sectors producing apparel and textiles instead require a relatively low amount of capital per

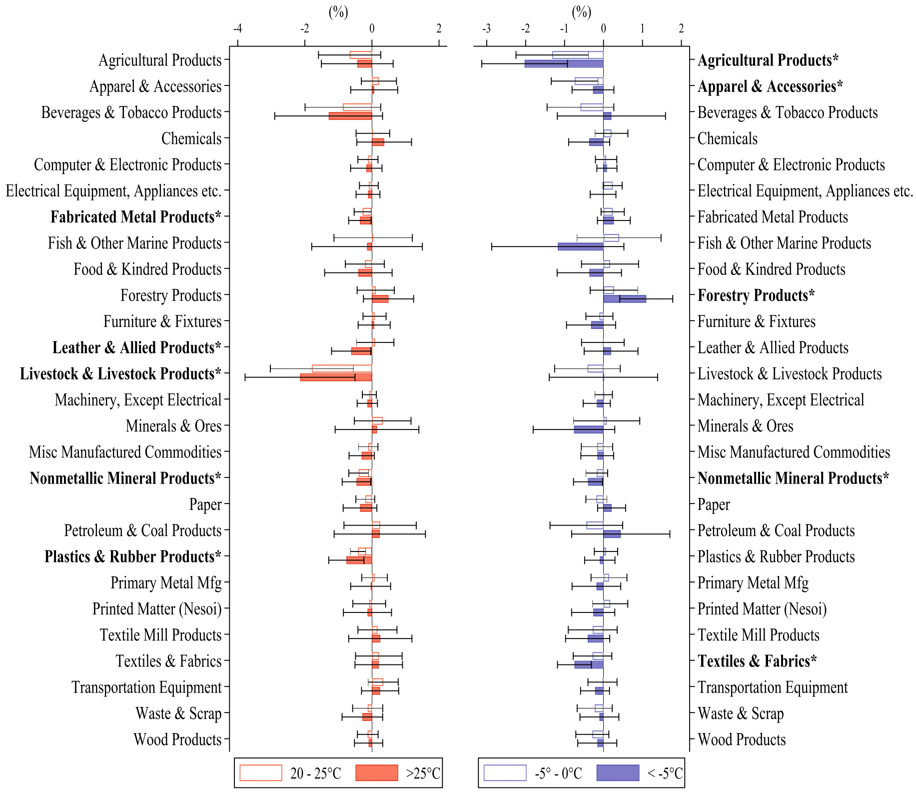

Fig. 2 Effect of extreme temperature days by industry. Point estimates are represented by bars and capped spikes show 95% confidence intervals. Dependent variable is monthly state-level exports (in logs). The effect is estimated for each sector separately controlling for precipitation, snow depth, wind speed, month-of-year FE, state FE and year FE using Cameron et al. (2011) standard errors clustered by state and climate zone by month-of-sample. Industries with an estimated effect statistically significant at the 5% level are highlighted in bold with *

worker. Interestingly, forestry products seems to be the only category which is positively affected by a temperature extreme, as a day below −5 °C is estimated to increase exports by 1.1% in this sector, compared to 5–10 °C. Figure 2 also suggests that agricultural exports are more negatively affected by cold days compared to hot days (where the effect is not significant), having an associated decrease of more than 2% due to the former.

Table 3 The effect on Oil and Gas

Outcomes (in logs)	Consumption		Production		Exports
	Petroleum	Natural Gas	Petroleum	Natural Gas	Oil and Gas
	(1)	(2)	(3)	(4)	(5)
Days < -5 °C	0.0241***	0.0001	−0.0032	−0.0004	0.0093
	(0.0086)	(0.0055)	(0.0021)	(0.0040)	(0.0114)
Days in -5 to 0 °C	0.0046	−0.0060	−0.0040**	−0.0001	0.0020
	(0.0085)	(0.0045)	(0.0018)	(0.0028)	(0.0126)
Days in 0–5 °C	0.0030	0.0006	−0.0012	−0.0013	−0.0073
	(0.0051)	(0.0038)	(0.0019)	(0.0039)	(0.0112)
Days in 10–15 °C	−0.0117***	0.0022	−0.0039*	−0.0020	−0.0039
	(0.0045)	(0.0031)	(0.0024)	(0.0030)	(0.0096)
Days in 15–20 °C	−0.0116**	0.0114***	−0.0005	0.0007	−0.0108
	(0.0050)	(0.0040)	(0.0019)	(0.0023)	(0.0104)
Days in 20–25 °C	−0.0096	0.0290***	−0.0019	0.0009	−0.0328**
	(0.0066)	(0.0052)	(0.0027)	(0.0043)	(0.0147)
Days > 25 °C	−0.0206**	0.0441***	−0.0027	0.0017	−0.0546***
	(0.0083)	(0.0073)	(0.0037)	(0.0061)	(0.0191)
Observations	8568	9588	5712	4680	2244
R-squared	0.7674	0.9031	0.9741	0.9581	0.7418
Weather controls	YES	YES	YES	YES	YES
Month-of-year FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES

Consumption and production variables are measured in thousand barrels (petroleum) and thousand Mcf (natural gas). Weather controls include precipitation, snow depth and wind speed. All columns are subject to the constraint of having positive values for all time periods, resulting in 42, 47, 28, 30 and 11 covered states, respectively. Production columns refer to crude oil and 'consumer-grade' dry natural gas. Covered time periods are 2002–2018 for columns (1), (2), (3) and (5), and 2006–2018 for column (4). Consumption and production source: US Energy Information Administration (2020). Cameron et al. (2011) standard errors clustered by state and climate zone by month-of-sample in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

5.3 Oil and Gas

Considering that the correlation between temperature and exports of fuels might be confounded by the effect of temperature on domestic energy demand (Auffhammer and Mansur 2014), this sector is analyzed in more detail and presented in Table 3. One additional day above 25 °C reduces monthly exports in the Oil and Gas sector by as much as 5.5%, compared to baseline temperature, which is more than the impact on any other sector in the sample. The economic significance is non-negligible, considering that the monthly average of U.S. exports in this sector was \$6.4 billion in 2018 (current dollars). The magnitude thus corresponds to a reduction of monthly Oil and Gas exports by \$348 million. However, since hot days are known to increase domestic demand for cooling in buildings (Deschênes and Greenstone 2011), the estimated negative impact on exports could be the result of a shift in the share of production between markets; from the export market towards serving the domestic market to a greater extent. I explore this issue by estimating the model on monthly domestic electricity consumption and production of petroleum and natural gas for a similar time period disaggregated by state. The data is collected from the US Energy Information Administration (2020), and the result is presented in columns (1)–(4) in Table 3. Electricity consumption sourced from petroleum liquids are negatively associated with hot days, but positively affected by cold days, suggesting that this source of electricity is used for heating. The result for electricity from natural gas instead presents a clear positive relationship with hotter days, while being insignificantly correlated with the number of cold days. One additional day above 25 °C is estimated to increase monthly electricity consumption from natural gas by 4.41% compared to a day in the 5–10 °C interval. The magnitude is larger than the effect on petroleum, and is similar to the effect on monthly exports in the Oil and Gas sector. The effect on natural gas consumption is also proportional to the effect on annual U.S. residential electricity consumption of a day above 90 °F (32 °C) in Deschênes and Greenstone (2011). None of the temperature extremes seem to have a significant impact on the production of petroleum or natural gas. Thus, the different responses of the export and domestic market suggest that the higher effect of hot days on Oil and Gas exports is the result of a shift of (mostly natural gas) production in the designated market towards domestic consumers.

5.4 Temporal Displacement

As discussed in the literature (see e.g., Hsiang et al. 2017; Hsiang 2016; Deschênes and Greenstone 2011), I investigate the existence of displacement of the temperature effect over time. I re-run the regression of column (1) in Table 2 with 6 or 12 additional lags of each temperature bin and weather control to keep the full set of control variables in all time periods. I estimate the temporal displacement with two alternative number of lags since there is a trade off between modelling the true number of lags, without losing too much precision in the estimation of the coefficients. Estimating the total impact after both 6 and 12 lags could therefore be more informative compared to only reporting the total impact of only one set of lags. The output is presented in Tables 5 and 6 in the "Appendix", and the result for each table is based on a single estimation. The result does not indicate any significant delay in the effect of high temperatures. The coefficients of the two upper temperature bins are similar to the previously estimated contemporaneous effects, and do not seem to exhibit a clearly significant trend that neither offsets nor magnifies the negative impact in the following 6 or 12 months. The impact of very cold temperatures is less clear, but indicates the existence of some temporal displacement of the total effect over the 6 months following a shock, compared to the contemporaneous regression of Table 2. Column (8) and (14), respectively, present the cumulative relative impact across time periods. It is calculated as the average of the estimated coefficients (contemporaneous and lags), and the consistently negative signs in both tables confirm the lack of any offsetting effects in the months following a temperature shock. The estimated effect of temperature on monthly exports thereby seems to correspond to a change in levels that are not immediately counteracted. It should be noted, however, that this approach of investigating temporal displacement in the temperature effect suffers from high multicollinearity, due to the large number of variables with high correlation across bins and in time, which leaves the coefficients with a higher level of uncertainty. A rather surprising result is the strong effect of an extra day in the 0–5 °C interval, compared to 5–10 °C. The distributed effect is significant and remains in the approximate range of [−0.20%, −0.15%] over the 12 months following a shock. This leads to a cumulative reduction in exports by 0.17%, statistically significant at 1%, one year after a day with average temperature of 0–5 °C compared to a day in the 5–10 °C interval.

I separate the estimations with 6 or 12 lags for each sector, to allow the dynamics of the temperature effects to vary across sectors. There are in general few signs of sectors experiencing offsetting effects in the months following high or low temperatures, with the exception of Livestock and Livestock Products, where one can see positive impacts on exports during the months after a negative contemporaneous effect of high temperature. Rather, the pattern seems to be the opposite, as the negative impacts remain in the following months for many of the sectors in the sample. This is true for Leather and Allied Products and Plastics and Rubber Products (which had significant contemporaneous effects of high temperature), and for Agricultural Products, Apparel and Accessories, Nonmetallic Mineral Products, and Textiles and Fabrics (which had significant contemporaneous effects of low temperature). For example, exports of Leather and Allied Products is significantly estimated to be reduced by 0.69% in the 13 month period after one extra day above 25 °C, compared to a day in the 5–10 °C interval, including the contemporaneous effect. One can also find significant delayed impacts on sectors which were not significantly affected by contemporaneous temperature shocks, namely Electrical Equipment and Appliances (high temperatures), and Livestock and Livestock Products and Plastics and Rubber Products (cold temperatures). There is one indication of Agricultural Products exports being subject to a delayed reduction in the third month after a high temperature shock, although it only remains significant in the estimation including 6 lags. In addition, there are several sectors identified as the drivers of the previously estimated negative effect of days in the 0–5 °C interval, compared to 5–10 °C. These are Apparel and Accessories, Chemicals, Computer and Electronic Products, Electrical Equipment and Appliances, Food and Kindred Products, Leather and Allied Products, Livestock and Livestock Products, Machinery (Except Electrical), Misc. Manufactured Commodities, Plastics and Rubber Products, and Textiles and Fabrics. The sector-specific output tables are not presented in this paper, but available upon request.

6 Sensitivity Analysis

This section explores the sensitivity of the results to combinations of control variables in the main specification. The estimations are shown in Tables 4 and 7 in the "Appendix". The effect of days above 25 °C, compared to 5–10 °C, is robust to replacing the month-of-year and industry-year fixed effects with month-of-sample and industry fixed effects, as well as replacing state fixed effects with state-industry fixed effects. Although the effect of days below −5 °C loses significance, the magnitude remains approximately similar under the same change in econometric specification. The effect of days above 25 °C is still significant when clustering standard errors by state and year, instead of state and climate zone by month-of-sample, but only at the 10% significance level. The same does not hold for the effect of days below −5 °C, which again seems to be less robust than the effect of high temperatures. The main specification is also estimated using the unadjusted number of days each month, leading to less perfectly correlated temperature bins. The coefficients remain economically and statistically similar to the main result.

7 Discussion and Concluding Remarks

This paper investigates the effect of short-term temperature fluctuations on merchandise exports in the United States. I combine data on weather with high spatial and temporal frequency together with monthly exports disaggregated by state and 28 different sectors. The higher detail of the export statistics by industry offers a top-down analysis of the net effect of temperature on the U.S. economy, while still benefiting from the level of detail enabling a discussion about potential mechanisms, usually only available with bottom-up approaches. Hence, this paper contributes to the understanding of the temperature effect in the United States, which have been constrained by the lack of granularity in data on total production and national income. Consistent with the recent literature, I find a significant temperature-economy relationship, following an inverted U-shape with an optimal monthly temperature at approximately 10 °C. Compared to days with an average temperature between 5–10 °C, I estimate one additional day above 25 °C to reduce monthly exports by 0.22%. Likewise, one extra day below −5 °C is associated with a reduction in exports by 0.21%, compared to baseline temperature.

I find the sectors that export goods related to livestock or capital-intensive industries to be the drivers behind the negative effect of high temperatures on the U.S. exporting economy. The production processes of these industries include, but are not limited to, welding and assembling of fabricated metal, the transformation of hides into leather by tanning or curing, the keeping and feeding of animals, cutting and shaping of minerals in glass and cement production, and the processing of plastic and rubber materials (Bureau of Labor Statistics 2020). Although there are several other capital-intensive sectors in the sample that are seemingly unaffected by high temperatures, the amount of capital required in these manufacturing establishments indicates that the main channel of the temperature effect is not a reduction of overall labor productivity. Rather, the result suggests two principal scenarios explaining the outcome. Either, capital input productivity declines after a heat shock, leading to a reduction in output for capital-intensive industries. Or, heat exposure has a negative impact on labor productivity that is heterogeneous across sectors, where the effect on workers who operate machinery and other types of capital inputs is larger in terms of output loss, compared to workers employed in labor-intensive industries. Possible explanations to this disparity are different physical demands and exposure across occupations, where e.g. 92.3% of workers in construction and extraction occupations were exposed to the outdoors in 2018, compared to 33.3% of workers in all occupations (Bureau of Labor Statistics 2019b). The level of detail required for such hypothesis testing is, however, not available in the data used in this paper.

The effect of cold temperature seems to follow a different pattern. While agricultural goods are also adversely affected by cold days, most of the capital-intensive industries mentioned above are not significantly affected. Instead, cold days are associated with reductions of monthly exports in the labor-intensive industries of apparel and textiles. Examples of activities in these sectors are cutting, sewing and knitting fabrics in the production of garment, and the transformation of basic fiber into products such as yarn, sheets and apparel. This suggests that the effect of cold temperatures is mainly channeled through reductions in the productivity of workers occupied with light and repetitive tasks. The result is in line with previous research in physiology and ergonomics on the impact of cold temperature exposure, which shows a negative relationship between cold and dexterity and manual task performance (Phetteplace 2000; Cheung 2015; Heus et al. 1995). As for Forestry Products, which is the only sector in the sample experiencing an increase in exports after a temperature shock, scientific evidence supports the positive effect of cold days on forestry activities. Frozen soil eases the transportation of timber on winter roads, as it increases the passability of transportation routes in forested wetlands (Rittenhouse and Rissman 2015). Mild winters might thereby cause short-term problems in the supply chain in this sector, which otherwise is characterized by decadal production cycles (Bureau of Labor Statistics 2020).

The result also suggests that the short-term temperature impacts exhibit important temporal dynamics which differ across sectors. Another plausible factor, which is left out of the analysis of this paper, is the temporal dynamics of temperature-induced disruptions in upstream supply chains. If a firm depends on intermediate inputs produced in other states at different points in time, it might be subject to additional temperature effects stemming from shocks occurring in other locations. The interlinked temporal and spatial displacements that are propagated through supply chains make up a related economic impact of temperature shocks, but are yet not captured by the estimates presented in this paper, since they originate from shocks in locations that lie outside the regional entity of the regressor and dependent variable. Analyzing the complex dynamics of supply chain disruptions thus constitutes an interesting topic for future inquiry.

To evaluate the economic significance of the result, I calculate the impact of a uniform shift of the daily distribution of temperature by 2 °C and 4 °C, respectively, for an average year in my sample. For each state, I increase the daily temperature by 2 °C or 4 °C. Then, I create counterfactual temperature bins based on the increased temperature for each state and month. By comparing the sample bin counts with the counterfactual bin counts, and multiplying the difference with the corresponding coefficients for each temperature bin, I obtain state-level impacts for each month during an average year following either of the two temperature shifts. The coefficients are based on Column (2) in Table 2 (excluding Oil and Gas), where the coefficient in front of the baseline interval 5–10 °C is set to zero. For simplicity I do not consider temporal dynamics of the temperature effects. Finally, I average across months to obtain the average impact for each state under the respective temperature shift, which can thereby be interpreted as the average impact on annual exports. It should be noted that this is not a prediction of future climate change impacts, as this procedure does not take into account future adaptation or technology change, differences in the composition of industries across states, or how a temperature increase is most likely to be distributed within the United States. It is rather a way to present the dynamics of the total effect of all temperature bins. The result is presented in Table 8 in the “Appendix”. 33 states are negatively affected by a uniform shift in temperature by 2 °C, with an average impact across states by −0.20% on annual exports. State impacts range from −1.13% to 0.49%, where colder states are positively impacted by a temperature increase, as they are to a lesser extent exposed to adverse cold temperatures. Impacts following a 4 °C temperature shift range from −2.43% to 0.58%, with an average of −0.44%. Fewer states are positively impacted by a larger temperature increase, as 39 states have negative signs.

Even under simplifying assumptions, the exercise above highlights the complexity in estimating future economic damages from a warming climate. Temperature is expected to rise in all regions of the United States (KNMI Climate Explorer 2020), thereby mitigating a part of the negative effects of cold temperatures on the economy. State-specific economic impacts of future warming thus depend on the magnitude and regional variation of the shift in the distribution of temperature, which could result in net gains for communities located in cold climates (keeping other climate impacts fixed) (Berman and Schmidt 2019; Hsiang et al. 2017). Making use of more detailed sector-level estimates of temperature damages could thereby help identifying segments of the population belonging to regions and occupations with dissimilar vulnerabilities to a warmer climate, thereby improving upon the design of future policies (Hsiang et al. 2019).

Furthermore, the results of this paper point to the direction of where to allocate resources for climate adaptation. The estimated adverse impacts suggest that establishments in the manufacturing sector in the United States have not sufficiently invested in effective climate control to counter the negative impacts of outdoor weather. Investing in higher resilience against changes in weather could thereby result in a welfare gain. Future research is suggested to focus on micro-level analysis of sectors adversely affected by temperature shocks, in order to better identify the causal mechanisms suggested in this paper.

Appendix

Population-weighted weather In order to assign weights to specific weather stations, the coordinates of each station are used to extract population values from the gridded dataset. For each state, the values of the stations are summarized to create state totals. Consequently, the weight of a station is calculated by dividing its assigned population value by the calculated total for the corresponding state. The weighted daily averages of the weather outcomes thereby reflect the daily weather of the more populated areas within states, with the intention to lower the importance of stations which are remotely located. For 173 stations, the received population counts are missing. These stations are given the population count of the station with the minimum non-missing value in the state, so that weather stations with missing population data are not assigned a higher weight than the stations with the lowest weight within states. This precautionary approach is chosen since the reason for missing values in the population data is unknown. If the stations with missing population values instead are located in highly populated areas which are good representations of the state economies, this can lead to increased measurement errors, as the weather averages are weighted differently. However, in relation to the total number of 46,663 weather stations in the data, this is unlikely to have a substantial effect on the result.

Due to the time variation in the number of stations with non-missing values, the process of creating population-based weights has to be repeated for each date and weather variable, to ensure that the sum of weights equals 1 for stations within a state. This is accomplished by re-calculating the state totals each date, taking into account the number of stations with non-missing values for the specific weather variable. Each weather variable thus has a corresponding state population total, varying over time (Fig. 3; Tables 4, 5, 6, 7, 8).

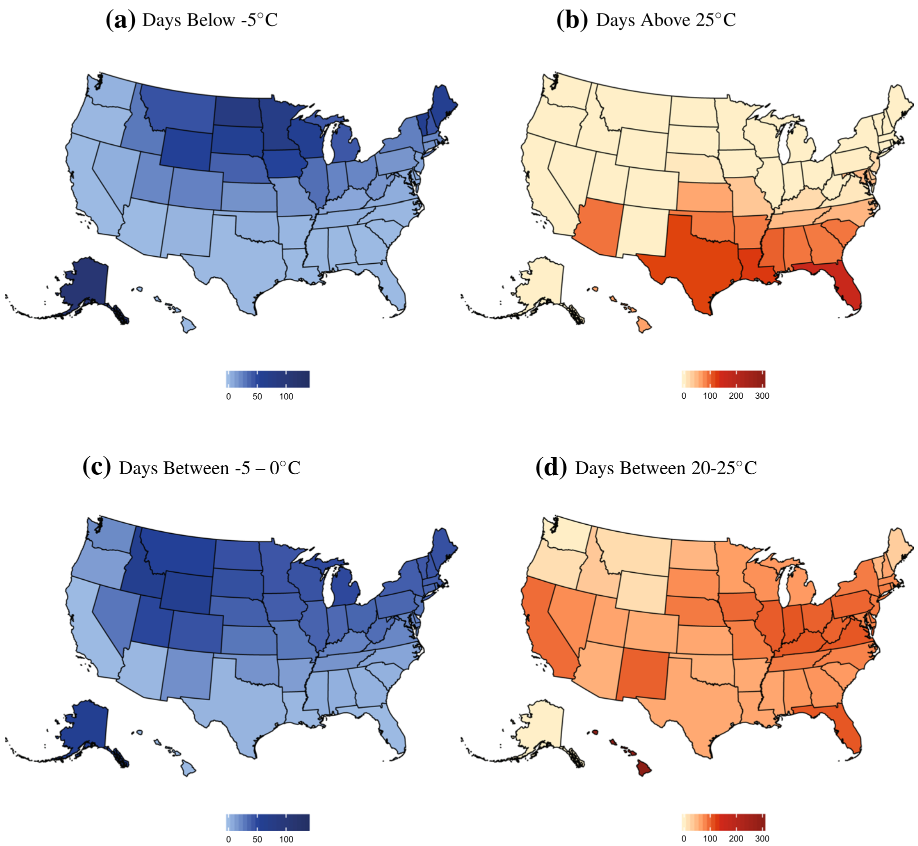

Fig. 3 Annual geographic distribution of temperature days. Darker color represents a larger number of days in the respective interval for an average year. Map shapefiles are based on *urbnmapr* by Urban Institute

Table 4 Temperature bin regression with unadjusted number of days per month

Outcome: Exports (in logs)	Full sample	Excl. Oil and Gas
	(1)	(2)
Days < -5 °C	−0.0020**	−0.0022**
	(0.0010)	(0.0010)
Days in -5 to 0 °C	−0.0007	−0.0007
	(0.0010)	(0.0010)
Days in 0–5 °C	−0.0015*	−0.0015*
	(0.0008)	(0.0008)
Days in 10–15 °C	−0.0006	−0.0006
	(0.0007)	(0.0008)
Days in 15–20 °C	−0.0010*	−0.0010
	(0.0006)	(0.0006)
Days in 20–25 °C	−0.0016*	−0.0012
	(0.0009)	(0.0008)
Days > 25 °C	−0.0028***	−0.0022**
	(0.0011)	(0.0010)
Precipitation	−0.0023	−0.0021
	(0.0015)	(0.0015)
Snow depth	0.0000	0.0000
	(0.0001)	(0.0001)
Wind speed	−0.0172**	−0.0163*
	(0.0087)	(0.0090)
Observations	244,800	242,556
R-squared	0.7004	0.7086
Month-of-year FE	YES	YES
State FE	YES	YES
Industry-year FE	YES	YES

Estimations control for average precipitation, average snow depth and average wind speed, and month-of-year FE, state FE, and industry-year FE. 5–10 °C is the omitted bin of reference. Cameron et al. (2011) standard errors clustered by state and climate zone by month-of-sample in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5 Temporal displacement

Variables	(1) L0	(2) L1	(3) L2	(4) L3	(5) L4	(6) L5	(7) L6	(8) Cumulative
Days < -5 °C	−0.0007	−0.0018	−0.0014	0.0006	−0.0001	−0.0009	−0.0028**	−0.0010
	(0.0011)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0007)
Days in -5 to 0 °C	−0.0010	−0.0014*	0.0003	0.0000	−0.0006	−0.0004	−0.0015*	−0.0006
	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0005)
Days in 0–5 °C	−0.0016*	−0.0016**	−0.0009	−0.0014*	−0.0016**	−0.0013*	−0.0010	−0.0013**
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0005)
Days in 10–15 °C	−0.0005	−0.0004	0.0004	−0.0004	−0.0007	−0.0017*	−0.0014*	−0.0007
	(0.0007)	(0.0009)	(0.0011)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0006)
Days in 15–20 °C	−0.0011	−0.0003	0.0003	−0.0003	0.0004	−0.0003	−0.0006	−0.0003
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0009)	(0.0005)
Days in 20–25 °C	−0.0012	−0.0003	0.0004	−0.0006	0.0001	−0.0007	−0.0014*	−0.0005
	(0.0010)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0005)
Days > 25 °C	−0.0024**	−0.0005	0.0005	−0.0008	0.0013	−0.0011	−0.0018	−0.0007
	(0.0012)	(0.0010)	(0.0011)	(0.0012)	(0.0011)	(0.0010)	(0.0012)	(0.0007)
Constant	16.3534***	16.3534***	16.3534***	16.3534***	16.3534***	16.3534***	16.3534***	
	(0.2753)	(0.2753)	(0.2753)	(0.2753)	(0.2753)	(0.2753)	(0.2753)	
Observations	237,600	237,600	237,600	237,600	237,600	237,600	237,600	
R-squared	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	
Weather controls	YES	YES	YES	YES	YES	YES	YES	
Month-of-year FE	YES	YES	YES	YES	YES	YES	YES	
State FE	YES	YES	YES	YES	YES	YES	YES	
Industry-Year FE	YES	YES	YES	YES	YES	YES	YES	

Dependent variable is monthly industry-state-level exports (in logs). Columns represent current and delayed effects for 6 additional months following a contemporaneous treatment based on the same single regression. The last column is the average of coefficients over time periods for the respective temperature bin, and thereby represents the cumulative (relative) impact over the entire time period. Weather controls are average precipitation, average snow depth and average wind speed, including their corresponding lags. Standard errors clustered at state-level and climate zone by month-of-sample in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6 Temporal displacement

Variables	(1) L0	(2) L1	(3) L2	(4) L3	(5) L4	(6) L5	(7) L6	(8) L7	(9) L8	(10) L9	(11) L10	(12) L11	(13) L12	(14) Cumulative
Days < −5 °C	−0.0000	−0.0016	−0.0016	0.0001	−0.0000	−0.0011	−0.0016	−0.0008	−0.0002	0.0003	−0.0004	−0.0003	−0.0022	−0.0007
	(0.0011)	(0.0014)	(0.0014)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0014)	(0.0012)	(0.0014)	(0.0014)	(0.0014)	(0.0009)
Days in −5 to 0 °C	−0.0006	−0.0015	0.0000	−0.0005	−0.0011	−0.0005	−0.0013	−0.0016*	−0.0001	−0.0003	0.0003	−0.0003	−0.0010	−0.0007
	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0006)
Days in 0–5 °C	−0.0014	−0.0020**	−0.0014*	−0.0019**	−0.0021***	−0.0015*	−0.0013	−0.0015	−0.0021**	−0.0021**	−0.0011	−0.0015*	−0.0020**	−0.0017***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0008)	(0.0008)	(0.0006)
Days in 10–15 °C	−0.0003	−0.0004	0.0002	−0.0001	−0.0006	−0.0016*	−0.0009	−0.0013*	−0.0008	−0.0008	−0.0012	−0.0008	−0.0014**	−0.0008
	(0.0008)	(0.0009)	(0.0010)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0007)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0005)
Days in 15–20 °C	−0.0003	0.0000	0.0003	0.0001	0.0008	0.0000	0.0001	−0.0003	−0.0001	0.0004	−0.0001	−0.0004	−0.0006	0.0000
	(0.0008)	(0.0009)	(0.0010)	(0.0011)	(0.0012)	(0.0010)	(0.0011)	(0.0012)	(0.0013)	(0.0011)	(0.0010)	(0.0009)	(0.0008)	(0.0008)
Days in 20–25 °C	−0.0007	−0.0003	0.0000	−0.0002	0.0004	−0.0005	−0.0010	−0.0004	−0.0010	0.0004	−0.0012	−0.0008	−0.0005	−0.0004
	(0.0009)	(0.0010)	(0.0012)	(0.0013)	(0.0012)	(0.0010)	(0.0010)	(0.0011)	(0.0012)	(0.0012)	(0.0010)	(0.0009)	(0.0011)	(0.0008)
Days > 25 °C	−0.0018	−0.0009	−0.0003	−0.0008	0.0010	−0.0015	−0.0016	−0.0010	−0.0014	−0.0007	−0.0014	−0.0018*	−0.0012	−0.0010
	(0.0012)	(0.0012)	(0.0014)	(0.0015)	(0.0014)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0010)	(0.0011)	(0.0009)
Constant	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	16.5559***	
	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	(0.3486)	

Table 6 (continued)

Variables	(1) L0	(2) L1	(3) L2	(4) L3	(5) L4	(6) L5	(7) L6	(8) L7	(9) L8	(10) L9	(11) L10	(12) L11	(13) L12	(14) Cumulative
Observations	230,400	230,400	230,400	230,400	230,400	230,400	230,400	230,400	230,400	230,400	230,400	230,400	230,400	
R-squared	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	0.7004	
Weather controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	
Month-of-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	
Industry-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	

Dependent variable is monthly industry-state-level exports (in logs). Columns represent current and delayed effects for 12 additional months following a contemporaneous treatment based on the same single regression. The last column is the average of coefficients over time periods for the respective temperature bin, and thereby represents the cumulative (relative) impact over the entire time period. Weather controls are average precipitation, average snow depth and average wind speed, including their corresponding lags. Standard errors clustered at state-level and climate zone by month-of-sample in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 7 Sensitivity analysis with alternative econometric specifications

Outcome: Exports (in logs)	(1)	(2)	(3)	(4)	(5)
Days < −5 °C	−0.0020**	−0.0020	−0.0020	−0.0018	−0.0020*
	(0.0010)	(0.0012)	(0.0014)	(0.0011)	(0.0012)
Days in −5 to 0 °C	−0.0009	−0.0009	−0.0009	−0.0011	−0.0009
	(0.0010)	(0.0011)	(0.0013)	(0.0009)	(0.0011)
Days in 0–5 °C	−0.0015*	−0.0015	−0.0015	−0.0014*	−0.0015*
	(0.0008)	(0.0011)	(0.0012)	(0.0008)	(0.0009)
Days in 10–15 °C	−0.0006	−0.0006	−0.0006	−0.0005	−0.0006
	(0.0007)	(0.0009)	(0.0010)	(0.0007)	(0.0008)
Days in 15–20 °C	−0.0011*	−0.0011	−0.0011	−0.0009	−0.0011
	(0.0006)	(0.0007)	(0.0008)	(0.0006)	(0.0007)
Days in 20–25 °C	−0.0015*	−0.0015	−0.0015	−0.0015	−0.0015*
	(0.0009)	(0.0010)	(0.0012)	(0.0010)	(0.0009)
Days > 25 °C	−0.0027***	−0.0027**	−0.0027*	−0.0026**	−0.0027**
	(0.0010)	(0.0012)	(0.0014)	(0.0012)	(0.0011)
Precipitation	−0.0024	−0.0024	−0.0024	−0.0018	−0.0024
	(0.0015)	(0.0020)	(0.0022)	(0.0017)	(0.0016)
Snow depth	0.0000	0.0000	0.0000	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Wind speed	−0.0171**	−0.0171*	−0.0171*	−0.0191*	−0.0171**
	(0.0087)	(0.0099)	(0.0101)	(0.0098)	(0.0086)
Observations	244,800	244,800	244,800	244,800	244,800
R-squared	0.7004	0.7004	0.7004	0.6941	0.9390
Month-of-year FE	YES	YES	YES	NO	YES
State FE	YES	YES	YES	YES	NO
Industry FE	NO	NO	NO	YES	NO
Industry-year FE	YES	YES	YES	NO	YES
State-industry FE	NO	NO	NO	NO	YES

Table 7 (continued)

Outcome: Exports (in logs)	(1)	(2)	(3)	(4)	(5)
Month-of-sample FE	NO	NO	NO	YES	NO
SE by state	YES	YES	YES	YES	YES
SE by climate zone by month-of-sample	YES	NO	NO	YES	YES
SE by climate zone by Year	NO	YES	NO	NO	NO
SE by year	NO	NO	YES	NO	NO

Cameron et al. (2011) standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 8 Temperature impacts (%) after a uniform 2 °C or 4 °C increase

State	Δ 2 °C (%)	Δ 4 °C (%)	State	Δ 2 °C (%)	Δ 4 °C (%)
Alabama	−0.63	−1.06	Montana	0.17	0.07
Alaska	0.09	0.56	Nebraska	−0.21	−0.77
Arizona	−0.54	−1.08	New Hampshire	0.15	−0.19
Arkansas	0.08	−0.32	New Jersey	−0.44	−0.48
California	−0.62	−1.40	New Mexico	−0.36	−0.27
Colorado	−0.21	−0.66	New York	−0.26	−0.69
Connecticut	−0.31	−0.63	Nevada	−0.26	−0.22
Delaware	−0.19	−0.23	North Carolina	−0.24	−0.76
Florida	−0.39	−0.83	North Dakota	−0.06	−0.04
Georgia	−0.66	−1.06	Ohio	−0.38	−0.95
Hawaii	−1.13	−2.43	Oklahoma	0.10	0.08
Idaho	0.02	−0.32	Oregon	0.49	0.58
Illinois	−0.34	−0.93	Pennsylvania	−0.50	−0.71
Indiana	−0.57	−1.02	Rhode Island	−0.14	−0.46
Iowa	0.08	−0.24	South Carolina	−0.61	−1.11
Kansas	−0.47	−0.51	South Dakota	0.18	0.15
Kentucky	−0.28	−0.27	Tennessee	0.01	−0.23
Louisiana	−0.42	−0.84	Texas	−0.53	−0.90
Maine	0.20	0.26	Utah	−0.22	−0.72
Maryland	−0.14	−0.06	Washington	0.04	0.55
Massachusetts	−0.16	−0.57	Vermont	0.34	0.24
Michigan	0.28	−0.05	West Virginia	−0.29	−0.68
Minnesota	0.21	0.20	Virginia	−0.26	−0.28
Mississippi	−0.52	−1.04	Wisconsin	0.36	0.32
Missouri	−0.62	−0.53	Wyoming	0.42	0.58
Average impact	−0.20	−0.44			

Impacts are calculated by comparing temperature bin counts for an average year for each month with counterfactual temperature bin counts after increasing daily temperature with 2 °C or 4 °C in each state. Estimates are based on Column (2) in Table 4 (excluding Oil and Gas). Table rows present state-level impacts averaged across months. Bottom row presents the impact averaged across months and states

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Availability of data and material All data are collected from publicly available sources. The merged datasets used in this paper are available upon request.

Declarations

Conflict of interest The author declares that he has no conflict of interest.

Code availability The statistical softwares R and STATA have been used for data manipulation and estimation. Code scripts are available upon request.

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