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Temperature and Exports

– Evidence from the United States

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Abstract

IPCC estimates anthropogenic global warming to have reached 1°C compared to pre-industrial levels. This study evaluates the relationship of temperature fluctuations and exports, using high-resolution panel data of daily weather and monthly exports in U.S. states. I find significantly negative effects of both low and high temperatures, where one additional day with temperatures below -10°C and above 25°C reduces U.S. exports by 0.22% and 0.24%, respectively. The optimal daily average temperature for exports is estimated to approximately 10°C. These new findings contradict previous research on temperature and exports, which has not found significant effects in rich countries. Under a 'business as usual' scenario with a continued rise in CO_2 emissions, I project an average reduction in U.S. exports by 12.7% at the end of this century. My result implies stronger economic incentives for rich countries similar to the United States to invest in climate change mitigation, and to plan for future adaptation against a warming climate.

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Contents

1 Introduction

IPCC evaluates the impacts of continued global warming reaching the 2°C threshold, compared to pre-industrial levels (Masson-Delmotte et al., 2018). The predicted consequences are more frequent extreme weathers, such as heavier precipitation, heat waves and a sea level rise. According to the report, regions will face different future climate scenarios, where tropical countries are predicted to experience the highest increases in the number of hot days. At the same time, extreme cold nights are expected to become 6°C warmer in high-latitude countries. The increased awareness of the magnitude and regional distribution of future climate change have motivated economists to study the linkages between weather and socioeconomic outcomes. 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 stability. While microeconomic impacts have been found in a broad range of countries, few studies have estimated significant effects on aggregated economic outcomes in rich countries. Recent studies have shown that the temperature-economy relationship exhibits a nonlinear shape, which can explain the lack of significant results in rich-country studies (Burke et al., 2015). Given that rich countries tend to be located in moderate climates, the possibility to capture the effect of extreme temperatures depends heavily on the econometric specification, since the distribution of adverse temperature outcomes is sparse.

The empirical studies in this field of economics are closely related to policy through so-called Integrated Assessment Models (IAMs). IAMs are climate-economy models that combine physical climate model projections in the distant future with economic damage functions, and are used to estimate the social cost of an additional unit of carbon emission (Howard & Sterner, 2017). By comparing the market and non-market costs of future global warming with the cost of carbon abatement, IAMs calculate the optimal policy of the price of carbon and the corresponding temperature pathway, based on welfare functions from economic theory (Nordhaus, 2014). The damage functions of climate impacts used in these models are thereby central to climate policy decision-making, as they (among other factors) determine the optimal price on carbon. The IAMs used by U.S. administrations (DICE, PAGE and FUND (Interagency Working Group on Social Cost of Carbon, 2013)) have been criticized for underestimating the total damage of climate change, where they assume global GDP to be around 1 – 4% less from a global temperature increase of 4°C (Revesz et al., 2014). Diaz and Moore (2017) describe a 'disconnect' in the policy-targeted cost-benefit analyses and the current literature on climate impacts, where IAMs fail to incorporate key scientific findings in modern research. In a meta-analysis, Howard and Sterner (2017) control for apparent biases in earlier meta-analyses that have been the foundation of previous damage functions (such as Tol (2009)) and re-estimate the damage of a 4°C temperature increase to approximately 17 – 19% of global GDP. The substantially higher climate damage alters the net present value of investing in carbon emission reduction, making the 2°C target of future global warming an optimal trajectory for climate policy. The results are in the direction of Burke et al. (2015), who find a 23% reduction in global GDP at the end of this century under a 'business as usual' scenario, calculating economic damages alone. Non-market impacts are not included in their study, suggesting an even higher total damage of climate change.

With this paper, I aim to reconcile the contradictory findings from previous micro and macroeconomic research, using high-resolution panel data of monthly exports and daily temperatures in the United States. I develop an econometric specification that estimate different marginal effects depending on the level of temperature, to capture the effect of extreme temperatures not seen in annual averages. Whether high-income countries are economically affected by temperature has implications for their incentives to engage in climate change mitigation and for future adaptation planning against a warming climate. The results are directly connected to policy and the estimated social cost of carbon, through the climate damage functions employed by current IAMs. Using exports as a dependent variable also highlights how domestic temperature shocks are transmitted to the global economy through cross-country supply chains. Studying the effect of temperature on exports in the United States, a large exporter to the world (Central Intelligence Agency, 2017), thus have relevance for international trade in a future climate scenario.

Several microeconomic studies, such as Graff Zivin and Neidell (2014) and Cachon et al. (2012), have linked temperature shocks to productivity losses in the United States. Based on these findings, I develop a theoretical model of temperature and international trade, where firm-productivity is the main determinant of which firms that choose to export to foreign economies (as in Melitz (2003)). By assuming productivity to be a function of temperature, I hypothesize temperature shocks to have an effect on aggregate exports in U.S. states. The high temporal frequency of daily weather outcomes improves the possibility to find the threshold where temperature becomes detrimental to exports, which is difficult when only using annual averages (Burke et al., 2015). I thereby hypothesize the higher temporal resolution of the temperature variables to yield a more kinked estimated impact function, in comparison with papers applying more aggregate measures.

Following the notion that the effect of temperature on economic outcomes is nonlinear, I count the number of days the daily average temperature is realized in different temperature intervals in a given month. The econometric specification allows high flexibility in the estimation of different levels of temperature, as the global structure inherent to polynomial equations is removed. The effect of temperature in different intervals can thus be estimated as separate variables, independent of each other. The result suggests that both very low and very high temperatures are detrimental to U.S. exports, where the optimal 24-h daily average temperature is estimated to approximately 10°C. Accordingly, I find that one additional day below -10°C and above 25°C reduces monthly exports by 0.22% and 0.24%, respectively, compared to days between 5 – 10°C. Additionally, I find heterogeneity in the response functions across sectors. Agricultural exports are negatively associated with high temperatures, while light manufacturing exports are negatively associated with low temperatures. Exports from heavy industry seem to be significantly reduced by both extremes. Raw material exports show no significant relationship with temperature in this study.

In a hypothetical experiment, I measure the impact on exports of current temperature distributions on an average year, compared to an optimal allocation of temperature days in the 5 – 10°C interval. I estimate U.S. exports to be on average 35.1% lower due to the current climate, compared to an optimal temperature distribution. The states experiencing the most adverse temperatures are located in the warmer South, indicating that high temperatures are of larger concern to

U.S. exports than low temperatures. Interpreting the numerical reductions with caution (since the counterfactual scenario represents a climate outcome unlikely to be realized) the heterogeneity across states indicates which locations that are experiencing the most adverse temperature distributions.

Extrapolating my results to a future climate change scenario using the downscaling climate model LOCA (Pierce et al., 2014), I project an average reduction in U.S. exports by 12.7% at the end of this century, under a 'business as usual' CO_2 emission pathway. The projected export reductions range between 1.2 – 30.2% over states, where the highest reductions are found in the Northwest, a region which seems to be only moderately affected by its current climate. The variation across states is driven by differences in future temperature increases in the climate model projection. The relatively higher rate of future warming in colder states can thus lead to a convergence in harmful temperature distributions in the United States, reducing the comparative advantage in climate for Northern states. Although, there is a risk of underestimation in the effect of high temperatures well beyond the levels in the observed dataset. Due to the nonlinearity in the effect of temperature found in previous research, there is a probability that small temperature increases in locations with an already warm climate are more harmful than large increases in cold climates (Hsiang et al., 2017). The projected reductions in exports in Southern states are hence subject to additional uncertainty. Nevertheless, the projected reductions in exports give support to the critique against the damage functions incorporated in most IAMs, where e.g. the total damage of market and non-market costs are estimated to below 10% in the latest version of DICE (Howard & Sterner, 2017).

The remainder of this paper is organized as follows. In the following subsection, I review the relevant findings in previous research. The second section provides economic theory and hypotheses related to the results. The third section describes the data collection and discusses potential limitations. The fourth section describes the empirical framework of the estimations. The fifth section presents the results. The sixth section discusses implications of the results, while the last section concludes.

1.1 Literature Review

The previous empirical studies on the effect of weather on the economy vary in their time span and economic aggregation. A large number of papers have investigated the impacts on productivity at micro-level, using individual or firm-level data. Cachon et al. (2012) estimate significant losses in production in U.S. automobile plants caused by extreme rain, snow, heat and wind. Both Cai et al. (2018) and Zhang et al. (2018) find reductions in worker productivity in Chinese manufacture plants, an effect not likely to stem from increases in absenteeism. The latter study finds similar effects in labor-intensive firms as in capital-intensive firms. Other papers study the effect on labor supply, where the occurrence of high daily temperatures has been shown to reduce the number of hours worked in industries with high exposure to outdoor climate in U.S. counties (Graff Zivin & Neidell, 2014).

At a macro-level, several studies have estimated the impact of weather on GDP growth. Dell et al. (2012) use panel data on a large number of countries' growth in GDP, combined with changes in annual average temperature and precipitation. They estimate significant, negative impacts of a 1°C increase in average temperature on growth, but only for poor countries. Rich countries appear unaffected by changes in temperature, which is suggested to relate to differences in resources allocated to weather adaptation and institutions. Burke et al. (2015) question their results, as previous research at micro-level has found substantial negative effects on economic performance also in rich countries. By adding a squared term to temperature, they reproduce the paper by Dell et al. (2012) and state that the effect of annual temperature on economic growth is globally valid for all countries in the sample, however nonlinear. The larger effect seen in poor countries seem to come from that poor countries tend to have a warmer baseline climate. Burke et al. (2015) estimate a growth function of average annual temperature which is increasing up to 13°C, after which it declines sharply. In a similar paper to this study, Colacito et al. (2018) find that growth rates in U.S. states are negatively affected by increases in average summer temperature. However, they do not discuss the implications of nonlinearity in the effect of temperature, which is likely to be the driver of the result. By exploiting changes in seasonal averages, they risk underestimating the effect of high temperatures, since the effect of a 1°C increase in summer temperature is different depending on the baseline climate of each state. This is especially apparent by their heterogeneity analysis showing that Southern states are driving the negative effects of temperature increases. Zhao et al. (2018) focus on within-country growth, and provide results that are consistent with Burke et al. (2015) and with a trend in the recent literature where higher parametric precision and higher spatial resolution seem to decrease measurement errors and yield estimates of higher magnitudes and significance levels.

A similar innovation in methodology has been, to a large extent, absent in the literature covering the impacts of weather shocks on international trade. An early paper by Jones and Olken (2010) finds results in line with Dell et al. (2012), as they predict a country's growth rate in exports to drop by 2.0-5.7 percentage points for each 1°C increase in annual average temperature, but again finding that the effect is entirely driven by the impact on poor countries. Dallmann (2019) investigates in a similar study the linear effect of weather changes on international trade, by looking at variations in yearly bilateral trade flows. Her results are in line with early findings on trade and production, although the heterogeneity in her study comes from a country's distance from the equator instead of income differentials. However, it is problematic to empirically separate a fixed effect as geography from income levels due to the potential omitted variables bias, especially as poor countries tend to be located in tropical climates (Burke et al., 2015). Although recently published, Dallmann (2019) fails to take into account the nonlinearity in the effect of weather fluctuations on economic performance that has been found in previous research. Even so, the results of Jones and Olken (2010) and Dallmann (2019) indicate that the exporting sectors most sensitive to weather shocks are agriculture and labor-intensive industries.

An example in the trade literature taking the nonlinearity in weather impacts into account is Li et al. (2016), who study the effect of extreme heat on exports using daily weather and firm-level data in China. They count the number of days of each month with an average temperature above 30°C, and find a significant cumulative effect indicating that firms maintain their export levels after one additional day above 30°C for 3 months, after which exported output declines for 14 months, without any signs of recovery. The magnitudes are substantial, as one additional hot day reduces annual exports by almost 1.67%.

I contribute to previous research in several aspects. First, by applying an econometric specification which allows high flexibility in the estimation of a nonlinear relationship of temperature and exports, I increase the precision of the result. Second, I use high temporal and spatial resolution data, in order to reduce measurement errors and thereby reduce the likelihood of underestimating the effect of temperature fluctuations. Third, I focus my study on the United States, an industrialized country where a significant effect of temperature on exports not has been found. As a large exporter to the world, impacts on U.S. exports are likely to have substantial consequences for global trade patterns. The result may also be extrapolated to other industrialized countries, similar to the United States.

2 Theoretical Framework

The theoretical framework of this paper broadly follows Chen and Yang (2017), who derive a firm's profit as a function of temperature and productivity, and Li et al. (2016), who extend the model by Melitz (2003) on firm productivity and self-selected exporters (where only highly productive firms choose to export). The difference from Melitz (2003) is the dynamic shock to the model, coming from temperature fluctuations instead of trade exposure. It is thereby a model focusing on the supply-side. As mentioned above, the effect on productivity has been suggested by studies on micro-level as a possible channel in how weather shocks affect the economy, thus motivating the use of productivity as a principal argument in the theoretical framework. Consistent with mentioned papers, the weather variables are represented by temperature in this section. However, the model is generally valid for other weather outcomes affecting the economy (e.g. precipitation). The model starts by linking temperature shocks to productivity and production and ends with the effect on exports.

2.1 A Model of Temperature and International Trade

Chen and Yang (2017) assume a competitive market, where a profit-maximizing firm produces at constant returns to scale. The production function $Y(\cdot)$ takes N

inputs $x = \{x_1, x_2, \ldots, x_N\}$, each having an input-specific productivity represented by the input productivity vector $\lambda_x(\cdot)$. A firm's output can thereby be described by:

$$y = Y(\lambda_x(\cdot) \times x) \tag{1}$$

As the purpose of the model is to provide an estimation framework of the total effect from temperature shocks, the output market price $P_y(\cdot)$ and the input price vector $P_x(\cdot)$ are also allowed to be endogenously determined by temperature, although not empirically estimated specifically. The indirect effect on prices will instead be subsumed in the total effect of temperature shocks on trade. Importantly, input productivity is a function of temperature. However, the impact on productivity might be dampened by firms' (or local governments') ability to adapt in response to adverse temperature shocks, an effort denoted as $A(\cdot)$.

An important contribution of this paper is to allow the estimated marginal effect to change depending on the level of temperature. In my main specification, I divide the temperature variable into m number of bins, each representing a given interval in degrees Celsius. The temperature variable is thereby transformed into a vector of possible temperature outcomes, denoted $\mathbf{T} = \{T_1, T_2, \ldots, T_m\}$. This approach requires few assumptions on the level at which temperature becomes detrimental, as both extremes of the temperature scale are estimated as separate variables. In addition, to cover the potentially persistent effects of previous periods' temperature outcomes on current periods' production, each k of m bins is also a vector through L previous time periods, where $T_k = \{t_{k,0}, t_{k,-1}, \ldots, t_{k,-L}\}$. The somewhat modified maximization problem for domestic profits in Chen and Yang (2017) for a competitive firm can thereby be described as:

$$\pi^D = max\{P_y(\mathbf{T}) \times y - P_x(\mathbf{T}) \times x - A(\mathbf{T})\} \tag{2}$$

$$\text{s.t. } y = Y(\lambda_x(\mathbf{T}, A(\mathbf{T})) \times x)$$

The adaptation effort intuitively appears as a cost in the profit function, and as a determinant in the input productivity vector, potentially mitigating the loss in productivity due to weather shocks. The temporal dimension of the temperature variable has two motivations. First, firms that are located in warmer regions are more experienced to high temperatures. This might affect adaptation effort, as more experienced firms are better at anticipating frequent temperature shocks. Second, given the short-term fluctuations in monthly trade flows, detrimental effects of temperature shocks might follow a temporal lag distribution. As mentioned, Li et al. (2016) find that the negative effect of temperature on exports does not appear until 3 months after the shock, possibly due to the rate of stock turnover of the firm.

The maximization problem is now extended to a firm's exporting decision. The theoretical motivation comes from Melitz (2003), who builds a model based on empirical findings suggesting that it is the most productive firms in each sector that choose to export, as low-productivity firms are not sufficiently profitable to pay the additional cost of exporting. Within-country heterogeneity in productivity across firms leads to some (efficient) firms being exporters, while other (inefficient) firms choose to only serve the domestic market. The derived production function is applied to the framework by Li et al. (2016), who let the profit-maximizing firm choose the quantity q of goods to export, which is a function of total production y and its exports in previous periods, q_{-1}. The firm's additional profit from exported goods is

$$\pi^E = P^E(\mathbf{T}, \mathbf{Z}) \times q(y, q_{-1}) - c(\mathbf{T}, \mathbf{X}, \mathbf{Z} | q > 0) \tag{3}$$

where $P^E(\mathbf{T}, \mathbf{Z})$ is the market price of the exported good and $y = Y(\lambda_x(\mathbf{T}, A(\mathbf{T})) \times x)$ is defined above. Including the production function is intuitive, as firms must produce to be able to export. Also previous exporting experience might affect propensity to export in current periods, as goods already have been tested on consumers in foreign markets. The total cost of exporting is represented by $c(\mathbf{T}, \mathbf{X}, \mathbf{Z})$, given that the firm is exporting. The cost function is dependent on $\mathbf{T}$, as infrastructure and storage cost are possibly affected by temperature shocks. Also, the cost of exporting is affected by region-specific characteristics $\mathbf{X}$ (e.g. distance to ports, size and other weather types potentially correlated with temperature and trade costs) and exogenous effects $\mathbf{Z}$ (e.g. demand shocks and agricultural seasonality). As previously, the market price of the exported good is potentially affected by domestic temperature shocks $\mathbf{T}$, but also by cyclical patterns on the global market $\mathbf{Z}$.

Following Li et al. (2016), firms will choose to export (represented by export status $E = 1$) as long as profits from exports are positive:

$$E = \begin{cases} 1, & \text{if } \pi^E \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

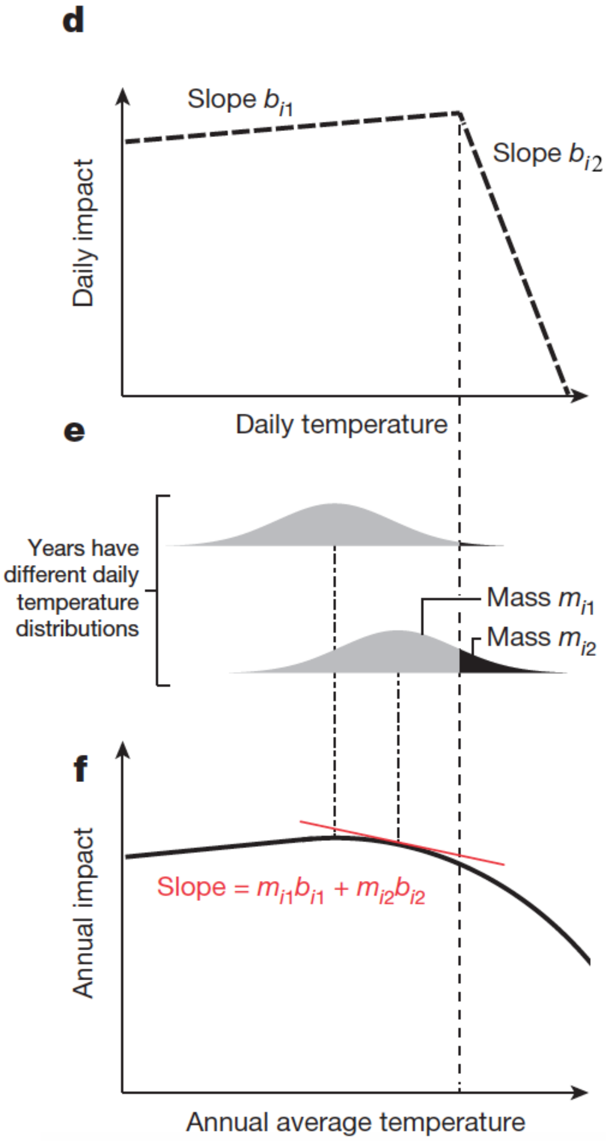
2.2 Hypotheses

In this setting, the effect of temperature shocks on exports has two main channels. First, detrimental temperature outcomes might decrease firm productivity. As firms produce less efficiently, more inputs are needed in production and profits from exports are reduced. The impact on productivity is potentially valid for both labor and capital, although the effect might be heterogenous across inputs. Second, temperature shocks might affect the total cost of exporting, which alters the profits from exports. The cost of exporting might covary with temperature if the performance of the transportation of the exported good (through intermediaries) is also affected by temperature. As seen above, a reduction in firms' export profits decreases the likelihood of firms serving foreign markets. The impact of temperature on an aggregated regional level can thus be analyzed accordingly. When affected by a regional adverse temperature shock, productivity in all firms declines, which can make some exporting firms stop serving foreign markets, as the threshold for being a profitable exporter has been raised. The result is a reduced number of exporting firms in the region, reducing the exported output to the world. This leads to the first hypothesis:

Hypothesis 1: *Temperature shocks have an effect on aggregate export levels.*

Furthermore, the temporal frequency of the data has implications for the shape of the predicted export-temperature curve. Figure 1 by Burke et al. (2015) provides a stylized theoretical description of how daily impacts of different temperature levels are captured in annual averages. The threshold after which temperature is assumed to be detrimental to economic activity is apparent in Figure 1d, where the slope of the impact curve becomes negative. A shift in the distribution of daily temperatures towards higher values (as in Figure 1e) leads to a larger proportion of daily temperatures that are realized above the detrimental level. When aggregated to annual average temperature, this shift results in a smooth move along a continuous curve (which is shown in Figure 1f), whose slope is a function of the slopes before and after the kink in the daily impact curve. A change in annual (or monthly) average temperature thereby captures a shift in the distribution of daily temperatures. This leads to the second hypothesis:

Hypothesis 2: *The higher temporal resolution of the temperature variables, the more kinked is the estimated impact function.*



Note: Graph retrieved from Burke et al. (2015) (Figure 1 (d-f), p. 235).

Figure 1: A Model of Daily Temperatures and Annual Averages

3 Data

3.1 Export Data

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 – October 2018, and to ensure geographic compatibility with the weather data, 50 states are included. For each state, the data is disaggregated according to the Harmonized System 2-digit commodity classification (HS2), which groups trade flows into 98 product categories. Two of these categories are excluded from the sample, as they represent special cases not related to this study[1]. I exclude commodities in states which are not typically exported during the time period, as in Jones and Olken (2010). Consequently, the data only includes state-commodity pairs with a positive value of exports for all time periods. To investigate the heterogeneity in the effect of temperature on exports, I group the commodities into sector categories. I follow Jones and Olken (2010) to maintain comparability with previous research, and thereby cluster exports into agriculture, light manufacturing, heavy industry and raw materials.

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, 2019) completes the inflation indices for the relevant months of 2018 which the previous series does 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 Data

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 U.S.. The variables collected from the weather stations include daily maximum and minimum temperature (°C), average temper-

[1]These product categories are 'Special Classification Provisions, nesoi' and 'Special Import Provisions'.

ature (°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).

In order to create representative averages of daily weather outcomes, I use population-weighted averages for each state, following the methodology of Dell et al. (2012). Population data is collected from the U.S. Census Grids (Summary File 1), 2010 (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 km. The population counts are time-invariant and based on the year 2010, which means that the population counts are likely to be different years before and years after. 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. 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, since these are the stations that will be used to create the daily state averages. This means that each weather variable has a corresponding state population total, that varies over time. The procedure described above is showed by the following three equations:

$$State\ Population_{R,w,t} = \sum_{s=1}^{I_{R,w,t}} Population_s \tag{5}$$

$$Station\ Weight_{s,w,t} = \frac{Population_s}{State\ Population_{R,w,t}} \tag{6}$$

$$State\ Average_{R,w,t} = \sum_{s=1}^{I_{R,w,t}} [Weather\ Outcome_{s,w,t} \times Station\ Weight_{s,w,t}] \tag{7}$$

Here, s refers to a specific station, w to one of the weather variables, R to a specific state and t refers to a date. I is the list of stations that have non-missing values for the corresponding weather variable within the state, and varies over time. The aggregation of daily weather data into monthly frequency is described in Section 4.

3.3 Limitations

A common problem when using ground weather stations for time series analysis is that stations sometimes are de-activated and replaced. This creates discontinuities in the time series of each station. For this reason, stations usually contain large shares of missing values for the chosen weather variable. When weather stations are used in panel data estimations with fixed effects, variation caused by stations being activated or disconnected might constitute a large part of the total variation in a continuous weather outcome (Auffhammer et al., 2013). When a large part of the variation in the regressors is the result of fluctuations in the number of active weather stations, the measurement errors are higher, which leads to a classical attenuation bias and a possible underestimation of the effect of temperature on exports (Wooldridge, 2015). However, the data coverage over the United States is high in comparison with other regions (NCEI/NOAA, 2019).

Also mentioned by Auffhammer et al. (2013), there are several weather outcomes that 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. For example, variables not included in the regressions that are likely covariates to temperature are humidity and sunshine, whose effect on exports is uncertain. Still, I believe the included control variables (precipitation, wind speed and snow depth) to be sufficient to be able to obtain interpretable results when estimating the separate effect of 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 10 in Appendix A displays the spatial distribution of four end-scale temperature variables used in the main estimation of this paper. Figure 10a and 10b show that extreme daily averages (below -10°C and above 25°C) are rare occurrences, appearing only in very few states. Moderate intervals at the end of the temperature scale (Figure 10c and 10d) 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 the majority of states have not experienced the temperature outcomes in question during the studied time period. This issue relates to the role of adaption to climate (see Section 2), since states have had the time to integrate their long-run climate into the economy, and thereby into their individual response functions. This means that states with an experience of the tails of the temperature distributions are likely to be better prepared for these outcomes. Consequently, states that do not experience frequent temperature extremes are likely less prepared, and thereby more sensitive to these levels. In terms of estimating a country average of the effect on exports (controlling for state fixed effects), the results are possibly an underestimation of the effect, if the drivers of the results are better adapted to temperature extremes than the average state. However, the opposite holds if the sensitivity to temperature changes depends on income levels, rather than past adaptation. If states with a moderate climate are on average richer, they might have more resources to counteract negative effects on exports, which would lead to an overestimation of the national effect of temperature. Figure 8 in Appendix A shows that there is a negative relationship between high annual average temperature and state GDP per capita, although the majority of states are located in the $7-15$°C range where variation in income level is large. Nevertheless, this does not affect the causality nor the unbiasedness of the results, but rather the generalizability of the effect of temperature to a U.S. average.

4 Empirical Framework

As previous studies have used different econometric specifications, yielding different results, I apply various specifications to estimate a nonlinear effect of temperature on U.S. exports. I start by estimating an Ordinary Least Square regression that fits a 2-degree polynomial function of temperature, for comparison with previous studies (such as Burke et al. (2015)).

$$\begin{aligned} ln(Y_{i,R,t}) = {} & \alpha_R + \beta_1 Temp_{R,t} + \beta_2 Temp_{R,t}^2 + \mathbf{X}_{R,t} \\ & + \tau_t + \theta_t + \varepsilon_{i,R,t} \end{aligned} \tag{8}$$

The dependent variable is the natural logarithm of exports of HS2 commodity i in state R in month t. The variables of interest are monthly average temperature $Temp_{R,t}$ and its squared term. I control for state-level fixed effects α_R and additional weather outcomes $\mathbf{X}_{R,t}$, which are likely correlated with temperature. I also include a linear time trend τ_t and month fixed effects θ_t to account for cyclical effects during a year. By including month-specific dummy variables, I can remove the potential bias in the effect of temperature on exports that stems from season-specific circumstances, such as growing season for crops. Figure 9 in Appendix A graphs the subannual pattern of U.S. exports for an average year, showing that there is seasonality in the dependent variable. $\varepsilon_{i,R,t}$ 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. Alternative estimations are also tested to further investigate the nonlinear relationship of exports and temperature.

Following the previous estimations, I estimate what is the main specification of this paper:

$$ln(Y_{i,R,t}) = \alpha_R + \sum_{l=0}^{L}\sum_{k=1}^{m-1}[\beta_{k,l}Tbin_{R,k,t-l}] + \sum_{l=0}^{L}[\mathbf{X}_{R,t-l}] + \tau_t + \theta_t + \varepsilon_{i,R,t} \tag{9}$$

In this equation, the continuous temperature variables are replaced by $m-1$ temperature bins. 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. Each k temperature bin is also lagged through 11 previous time periods ($L = 11$), to allow the effect of temperature to follow a temporal lag distribution. I choose to include 11 lags to be able to evaluate the effect for an entire year. Lags of the covarying weather controls are also added to maintain the specification in all time periods. This specification enables the highest flexibility in the estimation of a nonlinear effect of temperature on exports, 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. The implications are discussed in Section 2.2.

The estimation models reflect the theoretical framework of firms' exporting decisions described in Section 2.1, where the region-specific characteristics $\mathbf{X}$ are controlled for by state-level fixed effects α_R and time-variant weather variables $\mathbf{X}_{R,t}$. Cyclical patterns $\mathbf{Z}$ are mainly captured by month fixed effects θ_t. The temperature vector $\mathbf{T}$ is best captured by the 8 temperature bins in Equation (9). Adaptation A is not controlled for, which has implications for the interpretation of the estimated effect. U.S. states that have experienced a given climate for a long time period have had the chance to specialize in industries that are suitable for that climate. This self-selection by states is integrated in the U.S. economy, which makes adaptation a part of the average effect of temperature on U.S. exports. The estimated effect might thereby be driven by states that are adapted to certain climates. However, as long-run average temperature is a fixed effect, an analysis investigating the heterogeneity in adaption across states will be endogenous, since biases due to e.g. institutions cannot be ruled out.

The standard errors are clustered at commodity-level, to allow for correlation in the error terms within each HS2 classification (Wooldridge, 2015). As the states vary in the number of HS2 categories they export to foreign economies, the number of clusters will be different in estimations with a sectoral disaggregation. I cluster at commodity-level since firms within these are subject to the same national regulation, and might respond similarly to economic cycles.

Table 1 provides descriptive statistics over the weather variables included in the estimations, and exports disaggregated by sector. Heavy industry is the sector with most observations in the dataset, and raw materials account for the fewest observations. Among the exporting sectors, heavy industry was also, on average, the largest contributor to state GDP in 2017. The minimum and maximum of average temperature show that a large range of the temperature scale is captured in the data. As mentioned, the geographic distribution of low and high daily temperatures is presented in Figure 10 in Appendix A.

Table 1: Descriptive Statistics

	Mean	SD	Min	Max	Obs	Average Share of 2017 State GDP (%)
Weather Variables						
Average Temperature (°C)	12.73	9.55	-18.19	32.09	597,516	–
Average Precipitation (mm)	2.91	1.87	0.00	17.16	597,516	–
Average Snow Depth (mm)	14.15	46.52	0.00	855.16	597,516	–
Average Wind Speed (m/s)	3.02	0.92	0.04	6.95	597,516	–
Exports						
Agriculture	10,401.82	41,875.97	1.79	1768,333	142,814	0.9
Light Manufacturing	14,668.86	56,403.08	1.88	1386,760	196,748	1.2
Heavy Industry	43,233.71	171,915.6	2.06	3735,792	236,946	4.3
Raw Materials	53,899.24	330,564	2.10	7911,475	21,008	0.7
All Industries	26,355.72	131,430.10	1.79	7911,475	597,516	7.1

Note: Exports in 1000's $US. State GDP is collected from Bureau of Economic Analysis (2019). Since only state-industry pairs with positive exports for the entire period are included in the sample, the average share of 2017 GDP is an underestimation of the correct value.
The Central Intelligence Agency (2017) provides an approximate estimate of 8% as the share of total exports of GDP in 2017. The remaining average values are based on monthly frequencies, without grouping. The mean of e.g. 'Average Temperature (°C)' is thereby affected by the number of commodities that are exported by each state, since a higher number of commodities that a state exports increases the weight of that state's temperature when constructing the average. Likewise, the mean of e.g. agricultural exports represents the ungrouped average of rows with commodities in the agriculture sector.

5 Result

5.1 Main Results

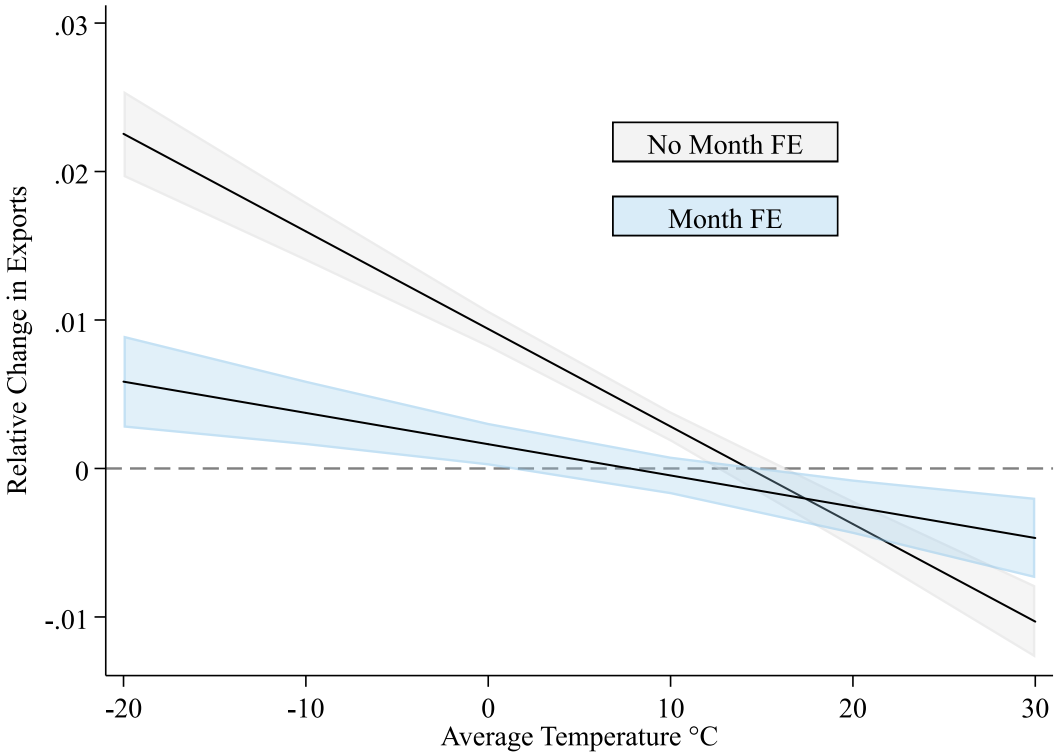
The first estimation, following Equation (8), is presented in Table 2 and shows how the estimated effect of temperature on exports changes when adding control variables to the regression. The result indicates that average temperature has a significantly positive but marginally decreasing effect on exports, with positive coefficients for the linear term and negative coefficients for the squared term. The null hypothesis of no effect of temperature on exports is rejected at the 1% significance level for almost all specifications. When including additional weather controls, as recommended by Auffhammer et al. (2013), the effect of temperature decreases and leaves the quadratic term insignificant. When including a linear time trend and state fixed effects, the positive linear temperature term decreases in magnitude, while the squared term becomes more negative and highly significant, suggesting a change in the concavity of the export-temperature relationship. In the full specification (6), which also controls for month fixed effects, the linear term drops sharply in magnitude. Figure 2 visualizes the estimated marginal effect over different temperature levels, using the complete set of control variables. Both very low and very high temperature outcomes seem to be significantly harmful to U.S. exports. When controlling for month fixed effects, the threshold where the effect of an increase in monthly average temperature becomes negative is lowered from 14.3°C to 7.8°C. The latter value is low in comparison with previous findings, as Burke et al. (2015) derive a global economic growth function that maximizes at an annual average temperature of 13°C. In terms of magnitude, an increase in monthly temperature from 20°C to 21°C is associated with a reduction in exports by 0.42%, with month fixed effects included. On the opposite extreme, an increase in monthly temperature from -15°C to -14°C is associated with an increase in exports by 0.31%

Figure 3 shows the effect of temperature on exports when controlling for month fixed effects, disaggregated by sector. Sectors exporting agricultural and light manufacturing goods are most sensitive to temperature fluctuations. Heavy industries do not seem to respond largely to changes in temperature. The large standard

Table 2: Polynomial Regression

Outcome: Exports (in logs)	(1)	(2)	(3)	(4)	(5)	(6)
Average Temperature	0.0160***	0.0250***	0.0136***	0.0099***	0.0094***	0.0016**
	(0.0015)	(0.0024)	(0.0022)	(0.0006)	(0.0006)	(0.0007)
Average Temperature^2		-0.0004***	-0.0001	-0.0003***	-0.0003***	-0.0001***
		(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Weather Controls						
Average Precipitation			0.0134	0.0040***	-0.0018**	-0.0019***
			(0.0095)	(0.0009)	(0.0007)	(0.0007)
Average Snow Depth			-0.0012***	0.0004***	0.0003***	0.0001***
			(0.0003)	(0.0000)	(0.0000)	(0.0000)
Average Wind Speed			-0.0394	-0.0390***	-0.0183***	-0.0334***
			(0.0238)	(0.0062)	(0.0055)	(0.0062)
Observations	597,516	597,516	597,516	597,516	597,516	597,516
R-squared	0.0054	0.0058	0.0065	0.1322	0.1390	0.1393
Weather Controls	NO	NO	YES	YES	YES	YES
Time Trend	NO	NO	NO	NO	YES	YES
Month FE	NO	NO	NO	NO	NO	YES
State FE	NO	NO	NO	YES	YES	YES

Clustered standard errors by commodity in parentheses
*** p<0.01, ** p<0.05, * p<0.1

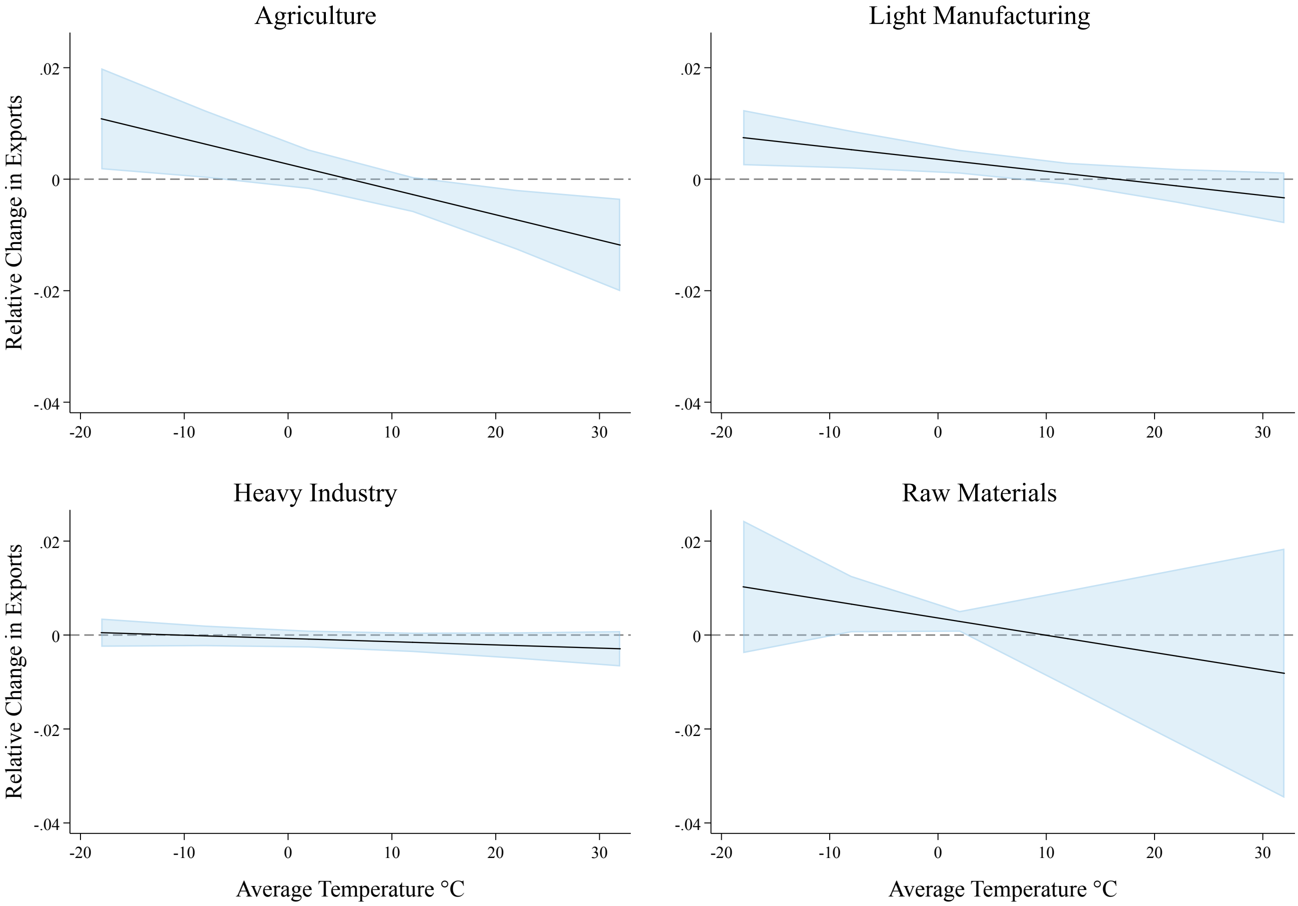


Note: 95% Confidence Intervals.

Figure 2: The Marginal Effect of Temperature on Exports

errors for raw material goods limit the analysis of the export-temperature relationship, which is likely to come from fewer observations. The heterogenous results are in line with previous studies, where agricultural and labor-intensive exporters have shown to be affected by temperature (Dallmann, 2019; Jones & Olken, 2010). For agricultural exports, which is the most temperature-sensitive sector, an increase from 20°C to 21°C in monthly temperature is associated with an average decrease by 0.91%. A similar increase from -15°C to -14°C is associated with an average increase in agricultural exports by 0.68%.

When fitting a 2-degree polynomial function of temperature on exports, the estimation forces 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

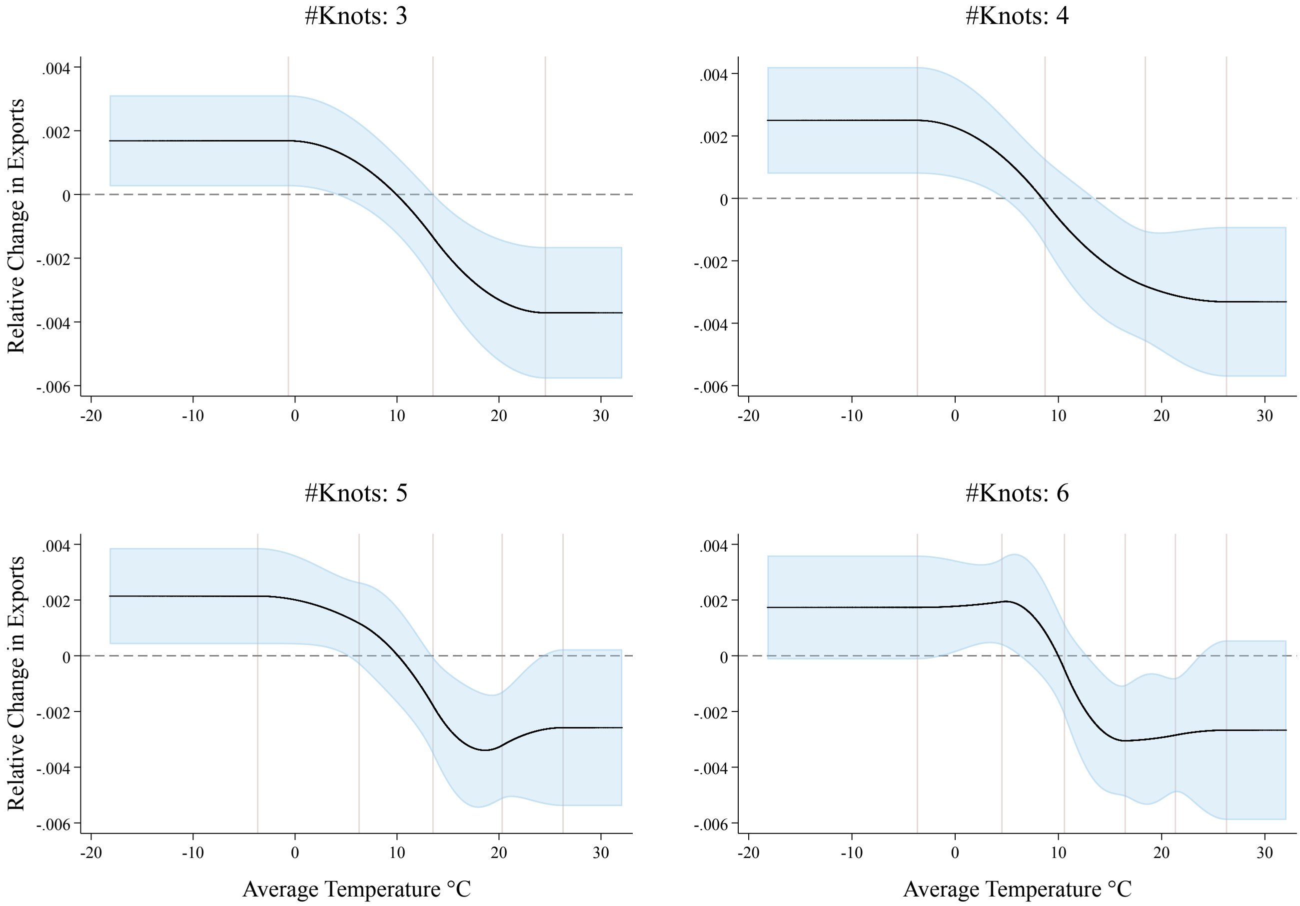


Note: 95% Confidence Intervals.

Figure 3: The Marginal Effect of Temperature by Sector

(as in Figure 1d), the smooth regression line will be a poor representation of the export-temperature relationship. The intersection of the derivative function on the temperature axis will thereby depend partly on the slope before the kink in the export function, and partly on the slope after the kink. 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 correct, but rather reflect a more or less sharp decline where temperature becomes detrimental.

In order to reduce the global structure of a polynomial function, I apply a restricted cubic spline (RCS) regression, using the full set of control variables. RCSs allow the estimated marginal effect to change flexibly between different intervals of the regressor (Desquilbet & Mariotti, 2010). The marginal effect is restricted in two ways. First, it is set to be constant at the extreme values of the regressor, where observations are few and inference less certain. This makes the regression less sensitive to noisy data at the tails of the distribution. Second, the slope of the marginal effect is constant over the end of an interval to the beginning of the next interval. This leads to a smooth function, continuous for all levels of temperature. A cubic polynomial function of temperature is estimated within each interval, which allows the function to assume a concave or convex shape, independent of the curvature of the previous interval. The result is a flexible estimation of a nonlinear relationship of export and temperature, presented in Figure 4. The knots are the levels of temperature that limit the intervals, in which the separate slopes are estimated. The location of the knots 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 knots correspond to equally spaced percentiles of temperature. As seen in Figure 4, the estimated effect of temperature on exports is increasingly nonlinear as the number of knots increases. Using six knots, which give five temperature intervals, the estimated marginal effect resembles a derivation of the theoretical impact function in Figure 1d, suggesting a sharp decline in exports around 10°C. The shape of the marginal effect at this point might explain the relatively low optimal temperature of 7.8°C derived above.



Note: 95% Confidence Intervals. Knots are represented by vertical lines.

Figure 4: Restricted Cubic Spline Regression

A different approach to investigate the nonlinearity in the result, is to estimate the effect piecewise for different temperatures. I construct five temperature intervals ranging over 10°C, and estimate a linear effect of temperature separately for each. The estimations are presented in Table 4 in Appendix A. The result indicates a significantly negative effect of temperatures below -10°C, where an increase by 1°C is associated with an increase in exports by 4.34%. The insignificant estimates of the regressions for temperatures between -10 – 0°C and 0 – 10°C, respectively, suggest that temperature changes have no effect within this range. In the 10 – 20°C interval, an increase by 1°C in monthly temperature has a significantly negative effect on exports by 0.43%. The coefficient is insignificant for temperature increases above 20°C. However, whether temperatures above 20°C are detrimental to U.S. exports, compared to the entire temperature scale, cannot be tested with this approach. The result from the piecewise linear regressions highlights the negative effect of very low temperatures, and give support to the RCS regressions indicating a change in the marginal effect around 10°C.

The estimations above indicate that temperatures below -10°C and above 10°C are detrimental to U.S. exports. Following this result, I estimate the main specification of this paper (see Equation (9)). I divide the temperature variable into 8 bins, each containing the number of days the daily average temperature is realized within an interval for a given month. Estimating the effect using separate variables for different levels of temperature enables high flexibility and increases the temporal resolution of the regressors of interest. The result is presented in Table 3. 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. The specification with all industries included estimates significant negative effects of one additional day below -10°C and above 25°C at the 1% significance level, reducing exports by 0.22% and 0.24%, respectively, holding all other factors constant. The negative effect seems to increase in magnitude and significance the further away from 5 - 10°C the daily temperature is, with the only insignificant exception of temperatures in the -10 – 0°C range. The effect is, however, heterogenous across sectors. Agricultural exports are (once again) the most sensitive sector to days with high temperatures, as one additional day above 25°C is associated with a 0.48% reduction in exported goods. On the other hand, days with low temperatures have no significant effect on agricultural exports. The opposite holds for light manufacturing goods, where only days with low temperatures are associated with an economically significant reduction in exports. Exported goods in heavy industries seem to be negatively affected by days in both ends of the temperature scale, with significant coefficients similar to the estimation with all industries. Raw material goods are not significantly affected by different temperatures.

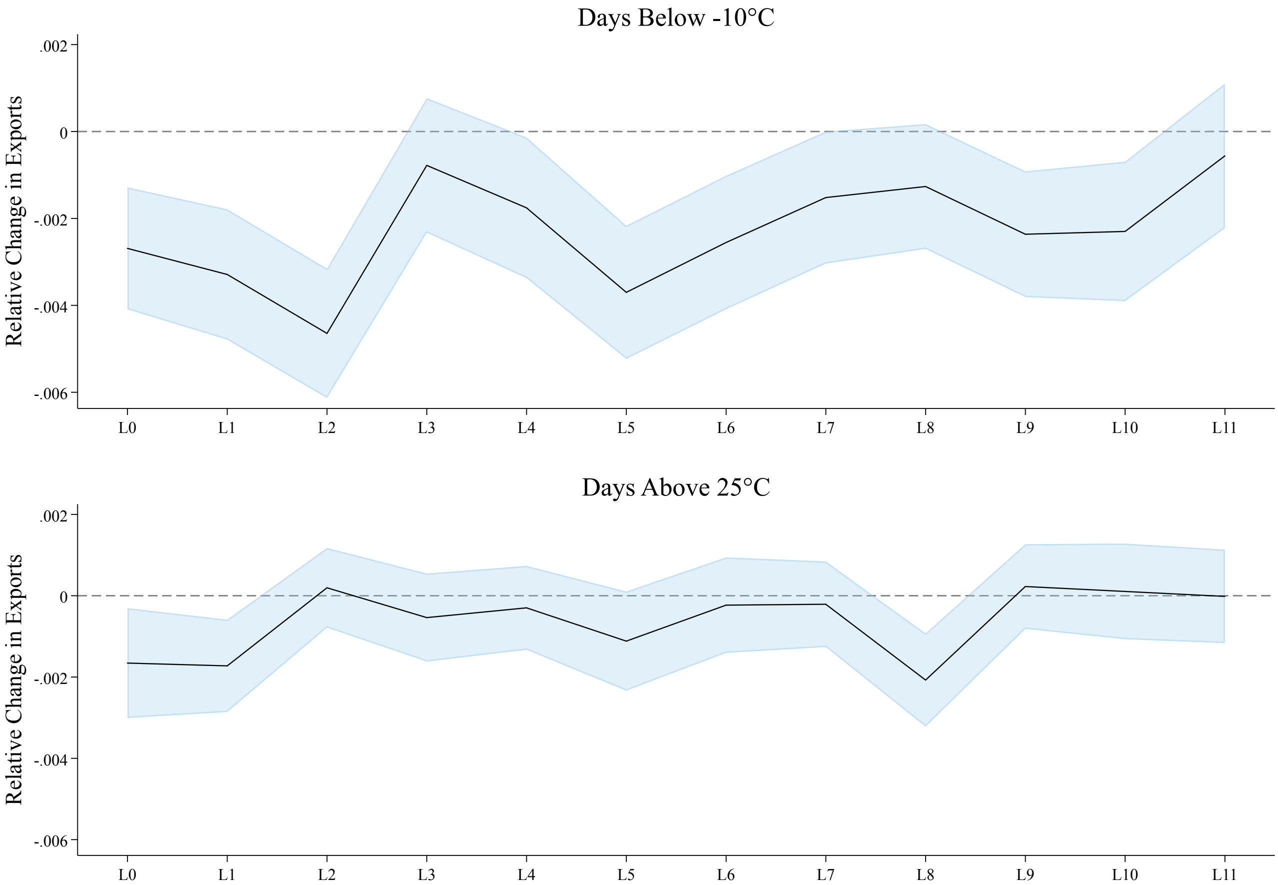
To see whether severe temperature days have a persistent effect on U.S. exports, I include 11 lags of the temperature variables, which captures the cyclical effect of a temperature day during one year. I also add lagged variables of the additional weather controls, in order to keep the full set of control variables in all the time dimensions. Figure 5 shows the result for the number of days below -10°C and above 25°C. Despite larger standard errors from autocorrelation in the temperature variables (Wooldridge, 2015), the effect of days with both low and high temperatures remains significant for at least one month after the contemporaneous shock. For days below -10°C, the magnitude of the estimate does not seem to reach its maximum until two months after the shock, where exports are associated with a lagged reduction by 0.46%. The results give some support of a temporal lag distribution of the effect of extreme temperature days, possibly due to the stock turnover rate of exporters. The estimated effects are, however, not as persistent as in Li et al. (2016), who find reductions in Chinese exports up to 14 months after one additional day above 30°C.

In order to understand the geographic dimension of the estimated coefficients, I apply the counterfactual scenario where each state's daily temperature distribution can be allocated to the optimal temperature bin, as in Deryugina and Hsiang (2014). I multiply the average value of each temperature bin for each state with the corresponding coefficient from column (1) in Table 3. The coefficient for the optimal interval (5 – 10°C) is set to zero, as this is the omitted benchmark variable in the estimations. The outcome is thereby the change in exports due to current temperature distributions, compared to the counterfactual scenario where all temperature days are located in the optimal 5 – 10°C interval. I choose to include the coefficient for the -10 – 0°C interval, although its p-value of 0.127 is higher than any conventional significance level. However, the variable is significant

Table 3: Main Estimation

Outcome: Exports (in logs)	(1) All Industries	(2) Agriculture	(3) Light Manufacturing	(4) Heavy Industry	(5) Raw Materials
Days < -10°C	-0.0022***	-0.0022	-0.0020*	-0.0023**	-0.0038
	(0.0007)	(0.0019)	(0.0010)	(0.0009)	(0.0015)
Days in -10 – 0°C	-0.0007	-0.0014	-0.0023***	0.0010**	0.0006
	(0.0004)	(0.0012)	(0.0007)	(0.0005)	(0.0014)
Days in 0 – 5°C	-0.0009**	-0.0004	-0.0020***	-0.0006	0.0029
	(0.0004)	(0.0007)	(0.0006)	(0.0006)	(0.0032)
Days in 10 – 15°C	-0.0007**	-0.0009	-0.0009**	-0.0005	0.0013
	(0.0003)	(0.0009)	(0.0004)	(0.0005)	(0.0025)
Days in 15 – 20°C	-0.0007*	-0.0016	-0.0005	-0.0005	0.0021
	(0.0004)	(0.0011)	(0.0004)	(0.0005)	(0.0014)
Days in 20 – 25°C	-0.0017***	-0.0025**	-0.0009	-0.0022***	-0.0012
	(0.0005)	(0.0012)	(0.0006)	(0.0008)	(0.0029)
Days > 25°C	-0.0024***	-0.0048***	-0.0015	-0.0020**	-0.0020
	(0.0006)	(0.0015)	(0.0009)	(0.0010)	(0.0034)
Observations	597,516	142,814	196,748	236,946	21,008
R-squared	0.1393	0.2374	0.1499	0.2266	0.4005
Weather Controls	YES	YES	YES	YES	YES
Time Trend	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES

Clustered standard errors by commodity in parentheses
*** p<0.01, ** p<0.05, * p<0.1



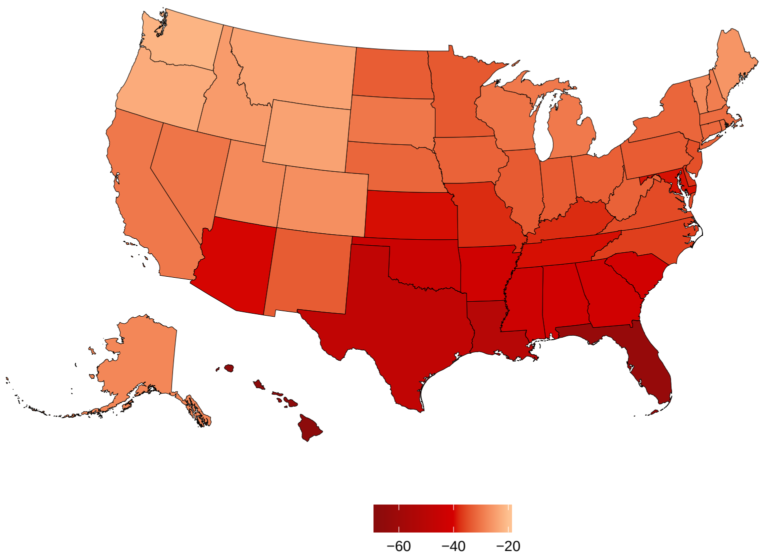
Note: 95% Confidence Intervals.

Figure 5: Monthly Lags of Temperature Days

for two of the sectors when disaggregated. I sum over the new temperature bin products, to obtain the total effect of the temperature distribution difference. The resulting reductions in exports are shown in Figure 6. The result suggests large negative impacts from current temperature distributions, as exports are on average 35.1% lower, compared to an optimal allocation of temperature days. Evidently, the states experiencing the most adverse temperatures are located in the warmer South, indicating that high temperatures are of larger concern to U.S. exports than low temperatures. Florida for example, is calculated to experience reductions in exports by 63.8% due to the current temperature distribution. The exact numbers cannot, however, be interpreted as reliable estimations, as this approach does not take into account the different response functions and adaptation efforts taken by states facing a new climate. Also, the counterfactual scenario represents a climate outcome which is unlikely to be realized, where all days in a given year have daily average temperatures in the 5 – 10°C interval. Between 2002 – 2018, the highest annual number of days within the optimal interval was 121. As a reference, I re-calculate the effect on exports by multiplying the coefficients with the difference in each temperature bin between the coldest and warmest year in the observed data for which all months are included, based on the U.S. annual average temperature. The state average change in exports going from the coldest to the warmest year is estimated to -0.43%, with a minimum and maximum of -10.02% and 6.82%. As there is a large difference between the calculated export reductions from the observed data and from the counterfactual scenario, the conclusion from these results regards which states that currently are the subjects of the most adverse temperature distributions, in relation to other states in the U.S..

Export Reductions Compared To

Optimal Temperature Allocation (%)



Note: Coloring towards red represents a larger reduction in current export levels (in %). The calculated changes in exports due to current temperature distributions are relative to the counterfactual scenario where all temperature days are located in the $5 - 10°C$ interval. The states of Alaska and Hawaii are relocated to reduce space.

Figure 6: The Effect of Current Temperatures on Exports

5.2 Climate Projections

I use the estimated coefficients of each temperature bin in Table 3 to extrapolate my result to a future climate change scenario. I obtain data from the downscaling climate model LOCA, which contains high-resolution future climate projections over the North American continent (Pierce et al., 2014)[2]. The projected temperature changes can be calculated under different scenarios of future human emissions of greenhouse gases (GHG) and economic development. Figure 11 in Appendix A shows the projected climate change at the end of this century, under the Representative Concentration Pathway (RCP) 8.5 scenario, which is a high-emission 'business as usual' scenario without climate mitigation policy targets (Riahi et al., 2011). In addition to a continued rise in GHG emissions, the RCP8.5 assumes high population growth and slow technological change. It is important to point out that climate models in combination with carbon emission pathways are not to be interpreted as forecasts of future climates, but rather as plausible scenarios relying on socioeconomic assumptions, without assigned probability weights. Using the Climate Data API service (Azavea, 2019), I extract monthly temperature data for the most populated city in each state for the period 2070-2099[3]. The time range of 30 years enables the future distribution of temperature to be interpreted as a changing climate, since individual abnormal years will have a small impact on the long-term distribution. For both observed and projected temperatures, I construct 30-year temperature averages by month and state. Following Schlenker and Roberts (2009), I add the projected month and state specific temperature increases to the daily temperatures in the observed dataset. This leads to a shift in the daily temperature distribution towards higher values, from which future temperature bin variables can be created. Finally, I sum over months and obtain the number of days the daily average temperature is realized in a given bin during an average year, for current and future climates.

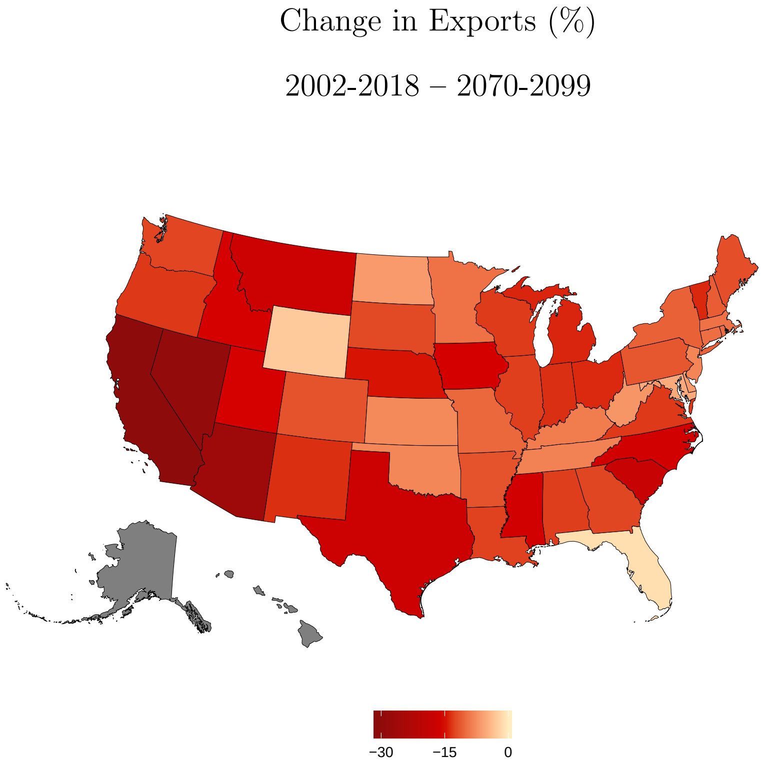
Comparing Figure 11a and 11b, one can see that a majority of states are ex-

[2]Data for the states of Alaska and Hawaii are missing for the climate projections. The following analysis is thereby based on the 48 remaining states.

[3]For North Dakota, West Virginia and Wyoming, the most populated cities were not available. Instead, data for these states are based on the cities Grand Forks, Buckhannon and Jackson, respectively.

periencing a substantially warmer climate under the chosen scenario at the end of this century. The temperature increases range from 1.2 – 12.9°C (with an average of 5.8°C), where states in the Northwest are subject to the highest increases. In order to compute the projected change in exports under the future climate scenario, I multiply the difference in observed and future value of each temperature bin, with the corresponding coefficient from column (1) in Table 3. The coefficient of the benchmark interval (5 – 10°C) is set to zero. As in the counterfactual simulation of an optimal allocation of the temperature distribution, I include the insignificant coefficient for the -10 – 0°C interval. Lastly, I sum the products of each temperature bin effect. This approach assumes that the economy does not adapt to future climate change, and that technology to reduce the impact of temperature is constant throughout the decades. These are strong assumptions, although, as the projected climate scenario in LOCA (RCP8.5) is not a forecast of future climate change, the projected export changes are not a prediction of future export levels. They rather serve as an alternative scenario, showing how future climate change might amplify the estimated effects of temperature experienced today. The result of the calculations is presented in Figure 7, and projects an average decrease in exports by 12.7%, compared to the current climate. However, as the climate model does not project a uniform warming over the United States, there is substantial heterogeneity across states. Florida, a state which today experiences a warm climate, faces the smallest reduction in exports (1.2%), whereas California and Nevada suffer the largest reductions in exports (30.2% and 29.2%, respectively). The estimated changes in exports follow the pattern in temperature changes only to some extent, since the projections in Figure 7 also take into account the varying effect of temperature across bins. Two states that have similar projected temperature changes might thereby differ in projected export change, if the different underlying baseline climate causes the shift in distribution of temperature days to spread over more detrimental temperature bins for one of the states, compared to the other.

To investigate the validity of using the average effect of temperature, estimated on all industries, I calculate each sector's average share of total exports, which is shown in Figure 12 in Appendix A. There seem to be relatively low specialization across states, which means that the average effect is more likely to be generalizable to the majority of states. Some states seem, however, to stand out in their sector ratio of total exports. These states might have a different exposure to future climate change, as the previous results indicate that the effect of temperature is heterogenous across sectors.



Note: Coloring towards red represents a larger reduction in future export levels (in %). The underlying temperatures are projections from the downscaling climate model LOCA using the RCP8.5 carbon scenario (Pierce et al., 2014). State values are extrapolated from the largest city in each state from the Climate Data API service (Azavea, 2019), taking the average of 'Average High Temperature' and 'Average Low Temperature'. The states of Alaska and Hawaii are relocated to reduce space, and do not have future climate projections (shown by grey colors).

Figure 7: Projection of Future Exports Under LOCA (RCP8.5)

5.3 Sensitivity Analysis

I evaluate the sensitivity of the results by estimating different combinations of fixed effects and standard errors. The alternative specifications are versions of column (1) in Table 3, which is the main estimation of this study. When clustering standard errors by state instead of commodity, the variables containing days with temperatures below -10°C, in 20 – 25°C and above 25°C remain significant at the 5% significance level. Controlling for state-commodity fixed effects yields the same magnitudes and significance levels for all temperature variables as controlling for state fixed effects.

To analyze the importance of major economic shocks in the United States to the result of temperature on exports, I add year fixed effects specific to periods of economic downturns. The time series of U.S. exports reveals a sharp drop during the financial crisis of 2008 – 2009, and a moderate decline in the years of 2015 – 2016. I estimate the main specification with four additional dummy variables, capturing the respective years of export decline. The results are small changes in significance levels over the temperature variables. The estimates are higher for very cold days and lower for very warm days, where one additional day with an average temperature below -10°C and above 25°C is associated with a reduction in exports by 0.32% and 0.13%, respectively. I also estimate the main specification adding year fixed effects, covering all years in the dataset. This leads to smaller magnitudes and significance levels, especially for days with high temperatures. The outer temperature bins are, however, still significant at the 5% and 10% significance levels.

Allowing the month fixed effects to be state-specific (by adding month and state dummy interaction terms to the main specification), does not change the significance levels and yields larger estimates for high temperatures. Interacting the month fixed effects with the four sectors instead of states, controlling for different seasonal patterns for each sector, leads to the same significance levels and magnitudes as in the main result. Adding sector-specific year fixed effects leads to the same result as with total year fixed effects. I do not allow the year fixed effects to be state-specific due to the large matrix size requirements for such an estimation.

I find no significant results from estimating the main specification on all observations, including state-commodity pairs without positive values of exports for all time periods. The number of observations increases from 597,516 to 969,600 (2,958 to 4,800 state-commodity pairs). Among the panels, 20.3%, 14.1% and 8.5% have a share of missing values in exports of more than 25%, 50% and 75%, respectively, of all observations in the dataset. This indicates that the original data suffers from a high level of noise, where untypical export commodities (commodities in states without positive values for all time periods) might respond less systematically to temperature changes and more to external factors causing them to stop exporting. The reason for missing values is however unknown, making a certain interpretation of the lack of result difficult.

I conclude that overall, the result is robust to econometric specifications in terms of fixed effects and standard error clustering. Higher temperatures seem to be more sensitive than low temperatures, although the temperature bin capturing days with average temperatures above 25°C remains significant at a lower significance level.

6 Discussion

The result of this study provides new evidence on the economic cost of temperature. Contrary to previous studies, I find significant, negative effects of high temperatures on exports in the United States, which previously only have been found in low-income countries (Dallmann, 2019; Jones & Olken, 2010). In addition, I find that low temperatures are equally harmful to U.S. exports as high temperatures, an effect which has not been emphasized in earlier research. However, in the current climate, high temperatures seem to be causing larger export reductions than low temperatures (see Figure 6). My result also supports the nonlinear economy-temperature relationship found by Burke et al. (2015) at the global level. The restricted cubic spline regressions in combination with the temperature bin estimations confirm the hypothesis that a higher temporal resolution leads to a more kinked impact function, where temperature thresholds determine the marginal effect of an additional temperature increase. The heterogeneity across sectors is also in line with previous findings, where agriculture and light manufacturing exports are associated with significant reductions from extreme temperatures. The significantly negative estimates for the heavy industry sector correspond to the result in Zhang et al. (2018), who find a significant relationship of productivity and temperature in capital-intensive firms. Raw materials is the only sector that is unaffected by temperature changes throughout the estimations.

Interestingly, agriculture and light manufacturing seem to be sectors with opposite response functions to outcomes in the end of the temperature scale. Agricultural exports are only significantly affected by days with high temperatures, whereas light manufacturing exports show a negative relationship only for days with low temperatures. Schlenker and Roberts (2009) show that corn and soybeans (which the United States is a large producer of) have yields responding positively to subdaily temperature increases up to 29°C and 30°C, respectively, and sharply negative to temperature increases beyond these levels. As the temperature variables in this study measure the 24-h daily averages, the temperature bins counting the days within 20 – 25°C and above 25°C might capture the higher thresholds of 29°C and 30°C experienced during a few hours of the day. The lack of significance of very low temperatures could result from the relative importance of weather in specific months, when e.g. yield levels of crops are affected the most. If the winter months are irrelevant for the growth of crops in season, the low temperatures of these months are unlikely to affect aggregate agriculture exports. In an empirical assessment of the effect of climate change on crop yields in California, Adams et al. (2003) implicitly assume winter temperatures to have no effect, as they base their temperature measure on the months corresponding to growing season. The light manufacturing sector, on the other hand, is characterized by labor-intensive industries, such as knitted products and the production of musical instruments. Oksa and Rintamäki (1995) find that cooling decreases performance in exercises which are 'very short lasting and dynamic, utilising fast movement velocities and/or elastic properties of the working muscles'. They also find negative effects of low temperatures on the co-ordination ability among the subjects of the experiment. These micro effects on the human body could explain the detrimental effects of days with temperatures below moderate levels, as the exercises described could be frequently occurring for workers in the light manufacturing sector. The insignificant result of high temperatures indicates that firms are better prepared to protect workers from outside heat, possibly through indoor climate control, than from outside cold. However, the aggregate export data does not enable any firm-level analysis to conclude the true mechanism of the varying effects.

When analyzing the estimated effects of temperature in the context of future climate change, the heterogenous projections of export reductions raise questions related to the trend in state export differentials. The climate projections in Figure 7 indicate that overall, the states facing the largest reductions in exports compared to current levels, are those who today experience the least harmful temperature distributions. This implies that although all states are projected to have reductions in exports due to future temperatures, there is a possible convergence in the impact from temperature among states. The comparative advantage of a beneficial climate might therefore be smaller in the future. There is, however, a substantial risk of underestimation of the negative impacts of very high temperatures in Southern states, since the marginal effects used in the projection are limited by the observed temperatures in the estimations. As I only observe days with average temperatures up to 32°C during the studied time period, temperatures well beyond this level at the end of this century are restricted to the marginal effect of an additional day above 25°C. Due to the nonlinearity in the effect of temperature, there is a probability that small temperature increases in locations with an already warm climate are more harmful than large increases in cold climates. In an economic assessment model of climate damage in the U.S., Hsiang et al. (2017) find larger effects in Southern areas when evaluating the impacts on agriculture, crime, coastal storms, energy, human mortality, and labor, although future warming in this region is smaller in absolute terms. They mention a more frequent distribution of extreme heat waves in currently warm counties (becoming slightly warmer) as a mechanism of the projected regional differences.

In terms of IAMs, the result of the climate projection gives support to the current research advocating damage functions with larger climate impacts than what have been applied in previous assessments (Diaz & Moore, 2017). The projected average reduction in exports by 12.7% at the end of this century (potentially both an under- and overestimation) represents an economic cost of a warming climate in a developed country. The updated version of the commonly used DICE model (DICE-2013R) expects total climate damages for a similar increase in temperature (around 6°C) to be below 10% of global GDP (Howard & Sterner, 2017). This includes both market and non-market costs. As climate damage is generally believed to be higher in developing countries (Dell et al., 2012), the result of this paper indicates that the damage functions used in the influential IAMs (such as DICE-2013R) are an underestimation. This, of course, assumes that exports in the United States can be used as a measure for the economy as a whole. Although some mechanisms might be specific to the exporting sector (such as the additional cost of exporting discussed above) leading to different sensitivities in outcome, it is not unlikely that overall economic activity has a similar response function to temperature as estimated in this paper. The effect on productivity for example, as theorized in this paper, is one channel which is likely to be valid for domestic sectors, as shown by micro-level research (Cachon et al., 2012; Graff Zivin & Neidell, 2014).

In summary, the policy implications of this paper are mainly related to the cost-benefit analyses of reducing future global warming. With a higher economic cost of climate change than previously estimated, the United States as a country should face larger benefits from investing in climate change mitigation. Such an investment can have large implications for future global warming, since the United States is a big country both in terms of economic size and CO_2 emission (Boden et al., 2017). The climate-export projection also indicates stronger incentives for states which are only moderately affected by their current climate to engage in mitigation and adaptation, as they risk being relatively more affected in the future. In addition, the estimated effect on exports shows how national temperature shocks can be transferred to foreign economies through international trade. If economies are heavily dependent on imports from other countries, they face an increased exposure to production shocks if the supplying countries follow the projected pattern as the United States in Figure 7. Countries that are highly integrated in the global economy thus have reasons to evaluate the possibilities of being supplied by their current trading partners in the future.

7 Conclusion

This paper studies the effect of temperature on exports in U.S. states, using panel data on monthly exports and daily temperature. Counting the number of days the daily average temperature is realized in different temperature intervals in a given month, I find that one additional day below -10°C and above 25°C (compared to days between 5 – 10°C) reduces monthly exports by 0.22% and 0.24%, respectively. The optimal 24-h daily average temperature for exports is estimated to approximately 10°C. The new evidence contradicts previous studies on temperature and exports, which have not found significant effects in rich countries. The heterogeneity analysis across sectors indicates different responses to temperature fluctuations. Agricultural exports are negatively associated with high temperatures, while light manufacturing exports are negatively associated with low temperatures. Exports from heavy industry are significantly reduced by both extremes. Raw material exports show no significant relationship with temperature in this study.

In the United States, the Southern states seem to be experiencing the most export-reducing temperature distributions, having a climate which is warmer than average. Assuming no further adaptation to temperature shocks, climate change is projected to reduce U.S. exports by 12.7% on average at the end of this century, under a 'business as usual' scenario with a continued rise in greenhouse gas emissions. The relatively higher rate of warming in states with a colder climate can lead to a convergence in harmful temperature distributions across states, reducing the comparative advantage in climate for Northern states. The risk of underestimating the impacts of high temperatures well beyond observed levels in current climates leaves, however, the projected reductions in exports in Southern states uncertain.

My result implies stronger economic incentives for the United States to invest in climate change mitigation, as the cost of especially high temperatures (and thereby future global warming) is seemingly higher than previously estimated. I thereby find additional evidence of underestimation in the climate damage functions in the Integrated Assessment Models used by U.S. administrations to evaluate the optimal mitigation policy. The variety of temperature impacts across the United States highlights the importance of a fair distribution of resources assigned to counter economic reductions today and in a future scenario. Future research should be directed towards efficient adaptation implementation and climate change mitigation investments, in order to reduce the economic damages of current climates and global warming.

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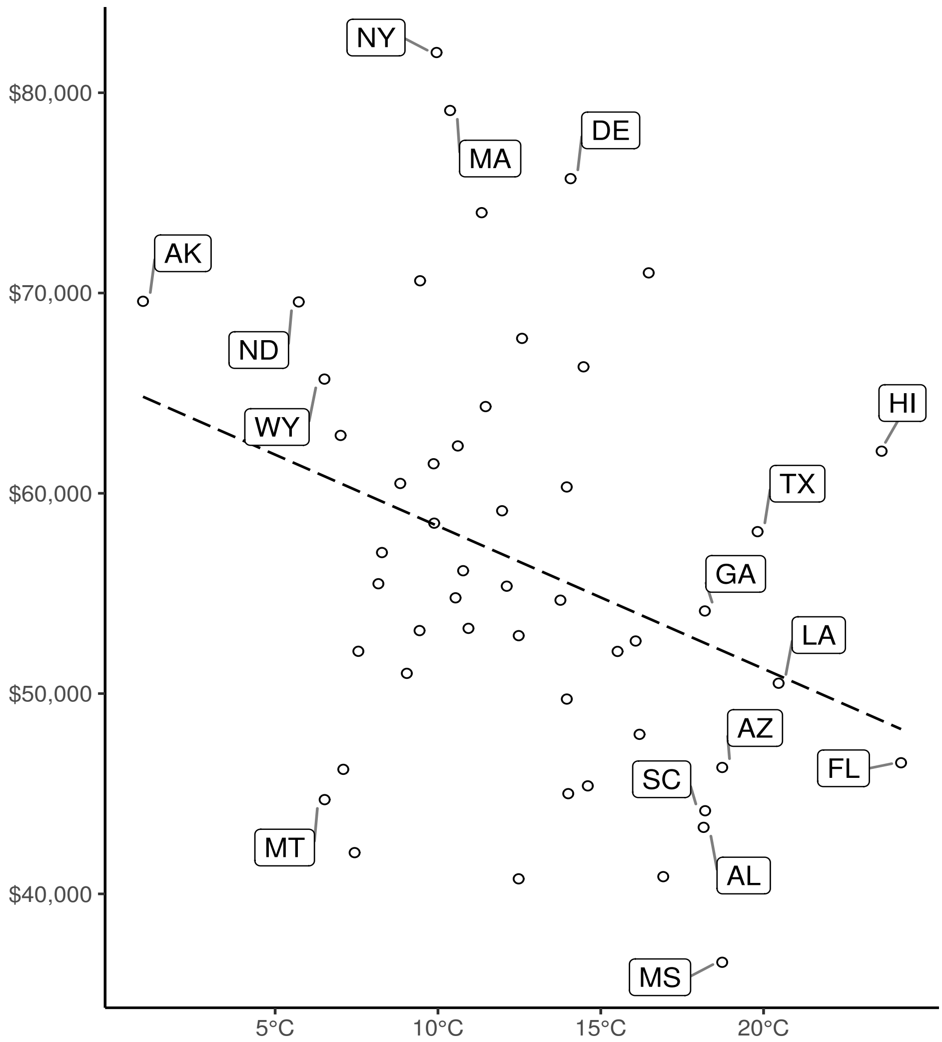
A Appendix

Table 4: Piecewise Linear Regression

Outcome: Exports (in logs)	(1) Below -10°C	(2) -10 – 0°C	(3) 0 – 10°C	(4) 10 – 20°C	(5) Above 20°C
Average Temperature	0.0434***	-0.0026	0.0002	-0.0043***	-0.0006
	(0.0105)	(0.0016)	(0.0014)	(0.0014)	(0.0018)
Observations	3,890	65,172	161,922	195,650	170,882
R-squared	0.1069	0.1213	0.1140	0.1430	0.1503
Weather Controls	YES	YES	YES	YES	YES
Time Trend	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES

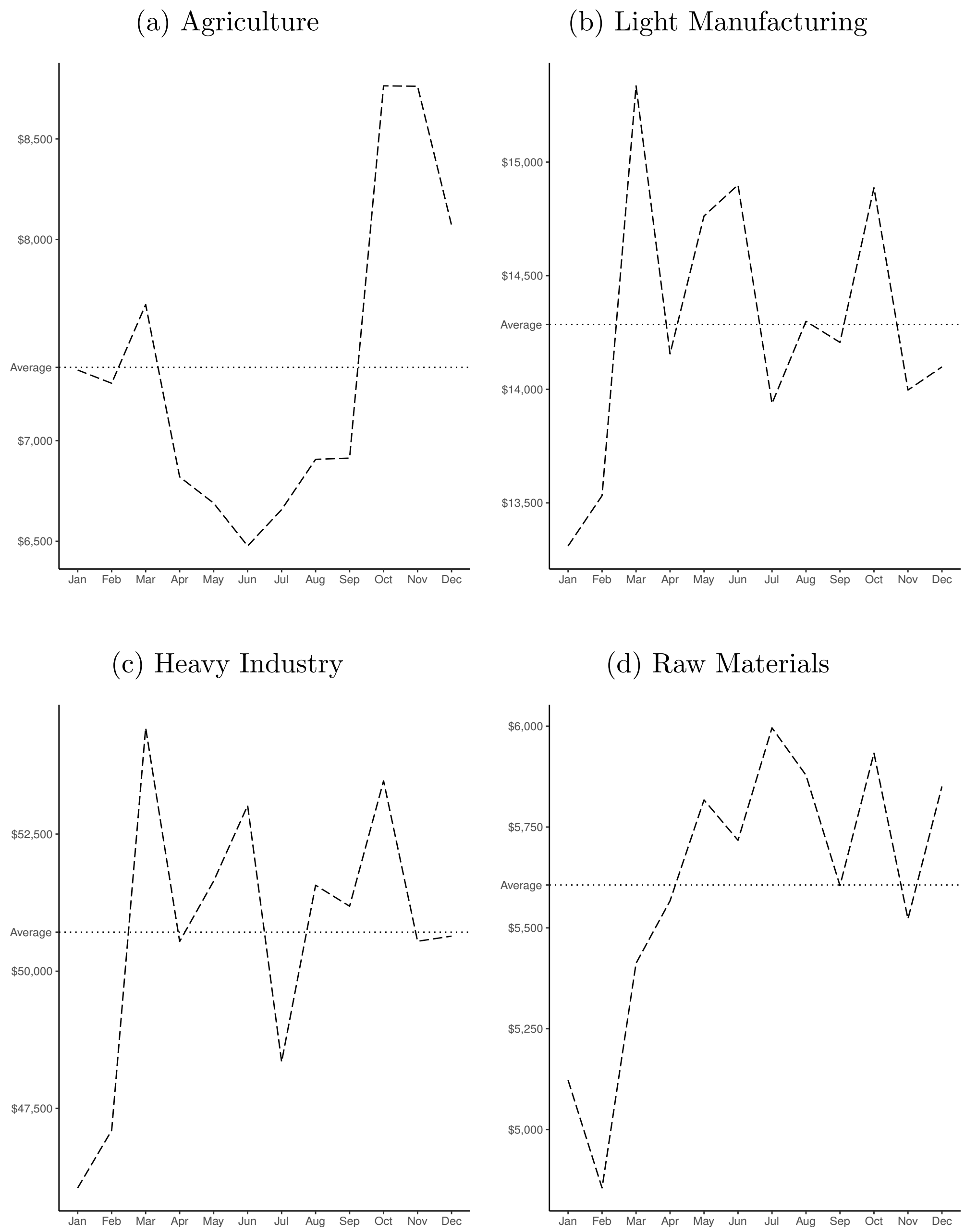
Clustered standard errors by commodity in parentheses

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



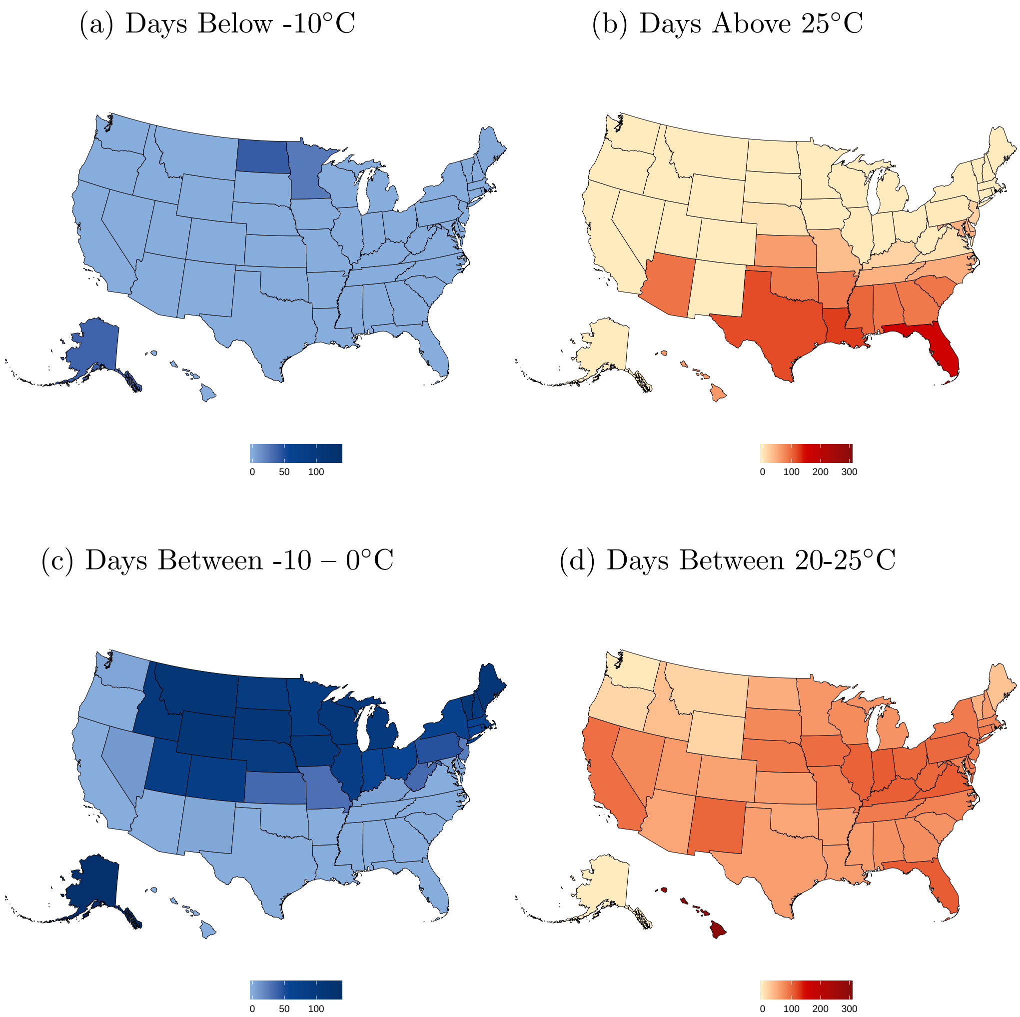
Note: The graph shows the relationship between State GDP per capita and annual average temperature in 2017. GDP per capita is measured in $US (2017 year's value) and collected from Bureau of Economic Analysis (2019). States in the ends of the regression line (dashed) are labeled with their corresponding state abbreviation.

Figure 8: State GDP per Capita and Temperature



Note: Exports are presented in million $US (2002 year's value), and calculated by summarizing exports for an average month over states and commodities.

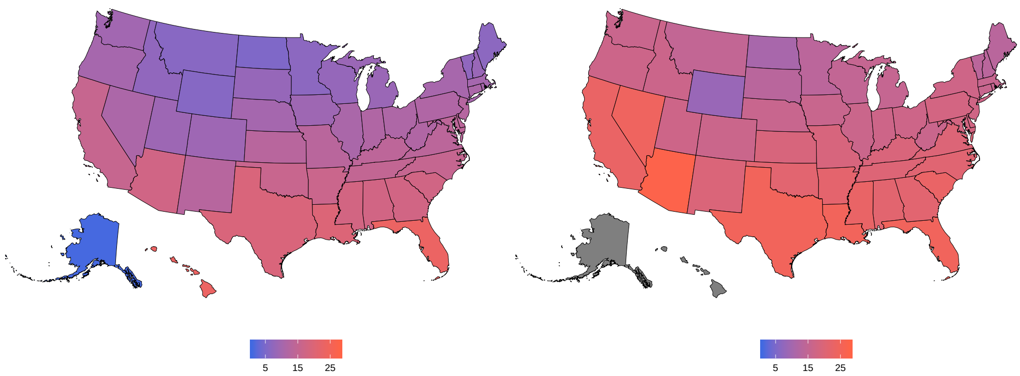
Figure 9: Subannual Patterns of U.S. Exports



Note: Higher color intensity represents a higher number of days in the respective interval for an average year. The states of Alaska and Hawaii are relocated to reduce space.

Figure 10: Annual Geographic Distribution of Temperature Days

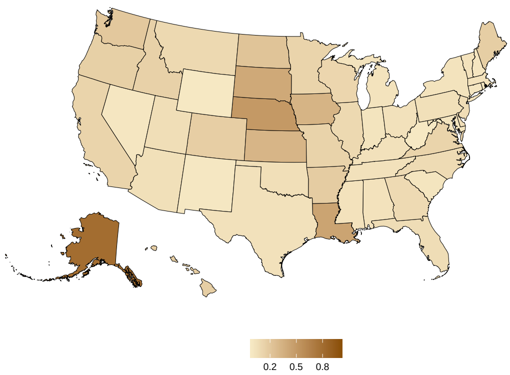
(a) 2002-2018 (b) 2070-2099 (RCP8.5)



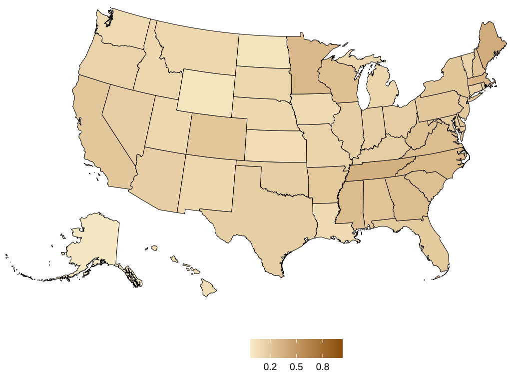
Note: Coloring towards orange represents a higher average temperature (°C). Temperatures in (b) are projections from the downscaling climate model LOCA using the RCP8.5 carbon scenario (Pierce et al., 2014). State values are extrapolated from the largest city in each state from the Climate Data API service (Azavea, 2019), taking the average of 'Average High Temperature' and 'Average Low Temperature'. The states of Alaska and Hawaii are relocated to reduce space, and do not have future climate projections (shown by grey colors).

Figure 11: Current Temperature and Future Climate Projection

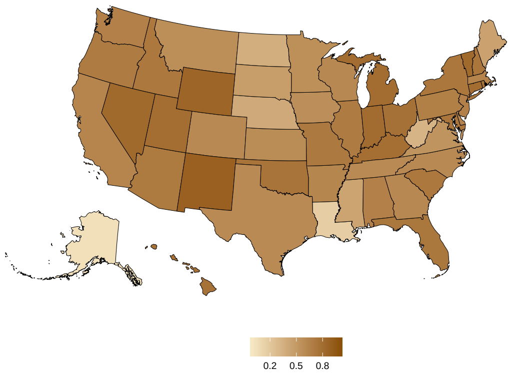
(a) Agriculture



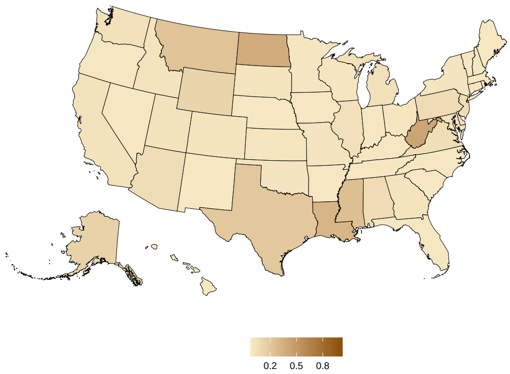
(b) Light Manufacturing



(c) Heavy Industry



(d) Raw Materials



Note: Higher color intensity represents a higher average export share of respective sector. The states of Alaska and Hawaii are relocated to reduce space.

Figure 12: Average Sector Share of Total Exports