

Beating the Heat: Temperature and Spatial Reallocation over the Short and Long-run

Christos Andreas Makridis and Tyler Ransom*

February 24, 2021

[PRELIMINARY AND INCOMPLETE](#), [click here for updates](#).

Abstract

Does temperature affect real economic activity? Using the annual Current Population Survey between 1963 and 2015, we show that there is no association between temperature and earnings, hours, or output after controlling for time-invariant spatial heterogeneity and time-varying demographic factors. These results are robust to five separate sources of micro-data, different sampling horizons, functional forms, spatial measures of temperature, and subsets of the data. This paper studies the relationship between temperature and productivity across space and time. Motivated by these null results, we develop a spatial equilibrium model where temperature can affect not only firm productivity, but also individual locational choice, industry choice, and labor supply. After estimating the model, we use it to disentangle the role of reallocation versus actual productivity losses in the U.S. economy between 1980 and 2015. Nearly all of the variation is driven by reallocation. We subsequently use the model to evaluate a counterfactual climate scenario and recover a new spatial equilibrium for the U.S. economy by 2050.

JEL: O44, J31, Q51, Q54, R11

Keywords: Climate, productivity, reallocation, weather, growth.

*Christos: MIT Sloan, makridis@mit.edu, www.christosmakridis.com. These views are ours only and do not represent those of affiliated institutions or the United States. Tyler: University of Oklahoma, 158 CCD1, 308 Cate Center Drive, Norman, OK, 73072, ransom@ou.edu. PRELIMINARY AND INCOMPLETE, do not cite. Thank you to Patrick Baylis, Judson Boomhower, Marshall Burke, Tatyana Deryugina, Rebecca Diamond, Lawrence Goulder, and Charles Kolstad for comments, as well as seminar audiences at Stanford and LERA/AEA 2019. We thank Dominik Gabinski and Jason Owens for research assistance in assembling the temperature data using geospatial software. We take ownership over any errors.

1. Introduction

The relationship between temperature and economic development has been the subject of significant economic inquiry dating back to Charles de Montesquieu’s *Spirit of Laws* that “excess heat makes men slothful and dispirited” and more recently from Gallup et al. (1999). Integrated Assessment Models (IAMs) have emerged as popular tools for modeling the costs of climate change on the aggregate economy. These studies apply general circulation models of the climate and environment with computable general equilibrium models of the economy in order to evaluate the effects of counterfactual policies. While they are effective at incorporating both environmental and economic margins, they have been labeled as a black-boxes (Pindyck, 2013), containing many parameters that have not been disciplined to micro-data in any shape or form.

This paper fills that void in understanding the relationship between temperature and productivity—a relationship that IAMs often invoke without empirical evidence. While there is recognition that climate fluctuations *will* affect economic activity, there is less evidence on *how*. This paper joins an emerging literature on the economics of climate fluctuations and its effects on real economic activity, including its effects on the quality of life (Albouy et al., 2015; Sinha and Cropper, 2016), propensity for conflict (Hsiang and Burke, 2014; Hsiang et al., 2011; Iyigun et al., 2016), temperament (Baylis, 2015; Lan et al., 2010), capital stock (Hsiang and Jina, 2014), mortality (Deschenes and Greenstone, 2011; Barreca et al., 2016; Greenstone et al., 2017), and even aggregate productivity (Dell et al., 2012; Deryugina and Hsiang, 2017). If the mean or standard deviation of climate changes (as some forecasts indicate), understanding the relationship between temperature and real economic activity will be a prerequisite to designing optimal mitigation and adaptation policies. The primary contribution of this paper is to quantify the impact of temperature on productivity by: (i) assembling the most comprehensive micro-database to date on individual and weather outcomes, (ii) estimating a series of reduced-form relationships between temperature and productivity, and (iii) developing a spatial equilibrium model that allows for the endogenous reallocation of workers across locations for long-run counterfactual analysis.

Temperature can affect real economic activity through the demand or supply of labor services. On the supply side, higher temperatures might discourage time spent outside since it makes physical activity more uncomfortable and/or strenuous. Inferring causality, however, from these regressions must reconcile the presence of non-random sorting based on preferences for market and non-market goods (Tiebout, 1956; Rhode and Strumpf, 2003; Banzhaf and Walsh, 2008; Makridis,

2014). For example, since individuals prefer colder climates over warmer ones (Albouy et al., 2015). On the demand side, higher temperatures might affect the distribution of spatial activity. Reallocation could be driven by either households deciding to move to another area based on underlying preferences, or by industries shifting their demand for labor based on their exposure to heat across locations. For example, the 1930s Dust Bowl had a significant impact on agricultural land values, which led to a large reallocation of workers (Hornbeck, 2012).

The first part of the paper brings new evidence on the reduced-form association between temperature and productivity by assembling micro-data from a number of sources at both the metropolitan statistical area (MSA) and county levels, including: monthly individual-level data from the Current Population Survey (CPS) between 1995-2015, annual individual-level data from the CPS between 1989-2015, decadal individual-level data from the Census Bureau between 1950-2015, occupation-by-industry-level data from the census between 1950-2015, and three-digit industry-by-metro from the Quarterly Census of Earnings and Wages (QCEW), and industry-by-county data from the Longitudinal Household-Employer Database (LEHD) and County Business Patterns (CBP). Remarkably, no matter how temperature is measured—in logs, levels, semi-parametrically, or either maximum or average temperatures—temperature has no statistically significant association in any of the datasets, conditional on controls and location fixed effects.¹

Do these results imply that climate has no causal effect on real economic activity? We motivate an alternative mechanism about the role of reallocation as an adaptation mechanism in response to climate fluctuations in two ways. First, the null association between temperature and earnings was not always the case. For example, Figure 12 plots the coefficients associated with regressions of logged occupational earnings scores on maximum temperature at a state-level, conditional on demographic controls, illustrating that the association between the two vanished by the late 1950s—precisely the era when air conditioning penetrated the marketplace (Barreca et al., 2016). Second, long-run changes in temperature are associated with significant changes in industrial composition. For example, Figure 2 shows that the growth in average county temperature between 1960 and 1970 is negatively correlated with the employment share of manufacturing (Panel A) and

¹Our results contrast with two recent empirical exercises, such as Dell et al. (2012) in the case of countries and Deryugina and Hsiang (2017) in the case of counties. The source of the differences with Deryugina and Hsiang (2017) appears to be in their inclusion of a lagged value of the dependent variable. In fixed effects models, dynamic panel regressions can produce biased estimates (Nickell, 1981). Our results indicate that there are three practical solutions: (i) using detailed micro-data to raise the sample size and reduce the potential for bias in smaller samples, (ii) omit the lagged dependent variable as a control, and (iii) add detailed demographic covariates as controls to reduce the ratio of the variance between the error and the lagged dependent variable. However, this is an ongoing issue that we are working to better understand.

agriculture (Panel B) between 1990 and 2000. While we interpret these merely as correlations, the fact that historical shocks have such a precise effect on future outcomes suggests that reallocation moderates the response among households and firms to changes in temperature.²

[INSERT FIGURES 12 and 2 HERE]

The second part of our paper develops a spatial equilibrium model estimated using techniques from [Diamond \(2016\)](#) to better understand the impact of temperature on the reallocation of economic activity. While our reduced-form evidence suggests that there is no direct effect on productivity, if climate shocks affect the spatial distribution of economic activity, then the central issue for policymakers is to understand the areas that are likely to be most adversely affected such that mitigation activities and transfers can be undertaken. We estimate our model using data between 1970 and 2010 for different states and industries.³ After showing our model does a good job characterizing the data, we use our model to conduct two quantitative experiments. First, we use it to decompose how reallocation costs versus direct costs of temperature affect productivity. Second, we use it to examine how changes in the distribution of temperature over the next 50 years would affect the spatial dispersion of economic activity.

Our paper is connected with two separate veins of literatures. The first literature is a series of reduced-form contributions that examine how temperature affects real economic outcomes. Our paper is closest to [Dell et al. \(2012\)](#) and [Deryugina and Hsiang \(2017\)](#) who use cross-country and county data to examine the impact of temperature on per capita GDP and income, respectively. We bring several sources of micro-data to the table and estimate similar econometric models, finding no evidence of a negative association between temperature and earnings once demographic characteristics and location fixed effects are introduced. Our paper is also closely related to [Albouy et al. \(2015\)](#) and [Sinha and Cropper \(2016\)](#) who estimate a demand-side sorting model to recover preferences over temperature. Our paper is also related with other areas of empirical environmental economics, including the impact of temperature on conflict ([Hsiang and Burke, 2014](#); [Hsiang et al., 2011](#); [Iyigun et al., 2016](#)), temperament ([Baylis, 2015](#); [Lan et al., 2010](#)), and

²The descriptive evidence suggests that a one percentage point (pp) rise in average temperature between 1960-70 is associated with a 0.63pp decline in the employment share of manufacturing and a whopping 5.60pp decline in the employment share of agriculture between 1990 and 2000. We also found similar evidence using other decades and looking at contemporaneous growth rates. We also found similar evidence when we work at a state-level.

³We use states rather than cities or commuting zones (CZs) in order to maintain tractability of estimation of the model. We focus on four industries: agriculture, manufacturing, high-skilled services (e.g. finance, real estate, administration, health care, and education), and low-skilled services (e.g. transportation, retail, and personal services).

capital stocks (Hsiang and Jina, 2014).

The second literature involves components of industrial organization and urban economics that estimate demand-side preference parameters and spatial sorting models, respectively. Ever since Berry et al. (1995), and more recently Berry et al. (2004), economists have been able to estimate structural models containing rich heterogeneity in preferences to conduct policy-relevant counterfactual analyses. We build specifically on a spatial equilibrium model from Moretti (2013) and Diamond (2016) with two new features: (i) temperature as an amenity that individuals sort on across locations, and (ii) different industries that individuals can work in and be more versus less susceptible to temperature shocks. Our focus on temperature is connected with a broader literature in urban economics focusing on the role of amenities and locational choice.⁴ Our paper is also closely connected with Costinot et al. (2016) who develop an international trade model to examine how climate change will affect cross-country trade flows, finding that reallocation is a primary channel through which markets adapt to these shocks.

2. Preliminaries

2.1. Why Does Temperature Matter?

There is a detailed literature on the effects of temperature fluctuations on agriculture dating all the way back to Mendelsohn et al. (1994). Schlenker et al. (2005) addressed a number of flaws in the early hedonic approach by accounting for cross-sectional heterogeneity in irrigation, water prices, and a number of other omitted variables, finding that a five degree Fahrenheit rise in temperature and 18% rise in precipitation is associated with a \$5.3-5.4 billion loss in dryland areas.⁵ There is also increasing evidence that higher temperatures raise the propensity of conflict by reducing agricultural productivity, thereby increasing resource scarcity (Iyigun et al., 2016; Hsiang and Burke, 2014; Burke et al., 2015). This paper, however, is not about the link between agriculture

⁴For example, Glaeser et al. (2001) argue that continued growth in per capita incomes has accelerated cities as centers of consumption and other amenities (e.g., climate). Rappaport (2007) also documents evidence of an increase in the hedonic price associated with nice weather as a consumption amenity and Rappaport (2008) subsequently shows that these spatial differences can generate substantial heterogeneity in population density. The paper is also related to another strand of literature on the relationship between climate / geography and economic growth (Gallup et al., 1999; Andersen et al., 2016; Michalopoulos and Papaioannou, 2013). Among two of the most prominent examples are Easterly and Levine (2003) and Acemoglu et al. (2002) who argue that omitted determinants of growth are highly correlated with geography and climate.

⁵Deschenes and Greenstone (2007) emphasized the importance of including fixed effects in these analyses to control for additional sources of heterogeneity, but Fisher et al. (2012) shortly reconciled the controversy.

and climate. These facts are generally already well-documented and the mechanism is straight forward since crops are sensitive to not only extreme heat, but also volatility in climate (Burke and Emerick, 2016; Roberts and Schlenker, 2011).

What are the potential mechanisms whereby temperature can impact aggregate productivity?⁶ Broadly speaking, there exist demand and supply channels. On the demand side, there are three main ways. The first way involves the impact of temperature on preferences. Higher temperatures, for example, might discourage time allocated to outside activities because those activities become more strenuous and uncomfortable. In these cases, individuals' willingness to pay for avoiding extreme heat might rise, giving rise to changes in mobility. Sinha and Cropper (2016) provide some of the first evidence using cross-sectional variation from the census, finding that prime-age (older) individuals are willing to pay \$518 (\$1,035) for a one degree increase in winter temperatures and \$627 (\$1,424) for a one degree decrease in summer temperatures. These estimates a little greater than those found in Albouy et al. (2015) who use a Roback-Rosen framework and cross-sectional data from the census. The second way involves affecting the relative productivity of individual activities.⁷ For example, Baylis (2015) uses millions of records from Twitter and finds a robust relationship between temperature and sentiment: higher temperatures tend to make people more irritable. Heal and Park (2014) provide additional cross-sectional evidence on the link between temperature and physiology, but cross-sectional estimates are inherently challenging to interpret as causal in light of omitted variables (Deschenes and Greenstone, 2011). Graff Zivin and Neidell (2014) use the American Time Use Survey and find that employees in industries that are relatively "climate-exposed" tend to reduce the number of hours they work. There is also some evidence in experimental setups that higher temperatures affects comfort, perceived air quality, and sick building syndrome symptoms (Seppanen et al., 2006).⁸ A third way involves the impact of temperature on mortality. While there was some early evidence documented in the scientific and health literature (Grover, 1938; Curriero et al., 2002), Deschenes and Greenstone (2011) and Burgess et al. (2014) provide more recent evidence about the link in the United States and India, respectively. Barreca et al. (2016) also illustrate the role of adaptation in mitigation the effects

⁶See Heal and Park (2015) for a survey.

⁷As an extreme example, a leading digital media company (Captivate Network) produced a study arguing that employee productivity and attendance declines by 20% and 19%, respectively, during summer months. These studies, however, fail to control for even the most basic omitted variables, such as seasonality and demographics.

⁸An important limitation of the experimental studies is the lack of external validity. Individuals have many adjustment mechanisms at their disposal, ranging from locating elsewhere to adjusting their schedule. What matters, therefore, is the equilibrium response to temperature fluctuations.

of temperature on mortality—that mortality declined by about 70% over the 20th century with most of the gains accruing after 1960 driven by the introduction of air conditioning.

On the supply side, temperature can affect productivity on both the intensive and extensive margins. On the intensive margin, hotter temperatures might make individuals in physically strenuous activities (e.g., construction), especially those without strong substitutes, less productive. However, heat exposure might be thought of more broadly. Certain types of consumer goods, for example, are less in demand in hotter climates. For example, pool repair companies are less likely to be found in New York than in Phoenix. On the extensive margin, expectations of permanently hotter temperatures might lead to the reallocation of firms from one geography. In these cases, weather behaves as a shock to their inputs, much like corporate taxes affect the profitability of firms producing in one location over another. While these supply-side effects are clearly large in agriculture (Schlenker et al., 2005; Fisher et al., 2012; Schlenker et al., 2006; Burke et al., 2015), there is some preliminary evidence from Somanathan et al. (2015) that weather may have a consequential impact on firms more generally. Using a panel of firms from Compustat, and proxying for the location of the firm using its headquarters location, Deryugina et al. (2016) find that higher temperatures are associated with increases in both revenues and costs. Using a panel of firms from the manufacturing sector in India, Somanathan et al. (2015) find that higher temperatures impact employee performance with the caveat that these estimates are specific to a developing country and a relatively manual-intensive sector. Zhang et al. (2018) also examines the effects of temperature on total factor productivity using a decade of data among manufacturing firms in China, finding adverse effects on output at very hot temperatures. While these differences in results may emerge due to differences in cross-country productivity and institutions, they also find null associations between hot temperatures and labor, which is our focus too.

The two papers that are most closely related to this one are Deryugina and Hsiang (2017) and Costinot et al. (2016). Deryugina and Hsiang (2017) use county-level data between 1969 to 2011 and focus on characterizing the reduced-form impact of temperature on productivity, which is proxied using county-level earnings.⁹ They find that every 1.8 degree Fahrenheit rise in temperature is associated with a 1.7% decline in an individual’s productivity within a day. After aggregating, they find that weekdays above 86 degrees Fahrenheit costs an average county \$20 per

⁹An important assumption in Deryugina and Hsiang (2017) is that the output process each day is the same, meaning that there is no cross-substitution or reallocation in productivity across days within a week. Since consumer demand declines at higher temperatures (e.g., fewer people go out to spend, rather they stay indoors), then higher temperatures are correlated with declines in output per person due to unobserved factors.

person. Compared to their results, ours suggest that the effects of temperature are muted in the short-run. While our exercises point to some possibilities in our diverging results, the main source is still not clear. To this end, our robustness exercises include data from six different sources at different levels of aggregation, geographic location, and frequency to help obviate concerns that our null effect is not driven by measurement error or other potential confounders. Costinot et al. (2016) focus on structurally modeling the ways in which changes in temperature might affect the location of agricultural production. For example, if temperatures in one region become warmer, agricultural production in that region may shift to another. However, many developing countries may simply lack the infrastructure or resources to adapt to climate shocks (Kahn, 2005).

2.2. Data and Measurement

Repeated Individual Cross-sections.—This paper leverages a number of sources of micro-data, including: the 1962-2015 annual Current Population Survey (CPS), the 1994-2015 monthly CPS, and the 1900-2015 Decennial Census (with an emphasis on 1970-2015). Each are accessed through the Integrated Public Use Microdata (IPUMS) data portal at the University of Minnesota. The advantage of the CPS is its ability to provide high frequency micro-variation in earnings and wages at local levels, whereas the advantage of the census is its long-run time series and large sample size.¹⁰ We restrict our samples to full-time workers between ages 20 and 65 with over \$5,000 in annual labor income and over \$2 hourly wages (both deflated using the 2010 real personal consumption expenditure index).

Individual rental rates are imputed for home owners as follows. Using self-reported housing values, we first impute housing values for renters by multiplying their annualized rental payments by 14. We subsequently estimate regressions of logged rental rates, which are missing for roughly 70% of the sample (home owners), on logged housing values, interacted with census division dummies, number of children dummies (one, two, three+ with zero as the base), number of rooms dummies (two, three, four+ with one as the base) and controls (race, age, marital status, gender). The implied R -squared is 0.99 and the correlation between actual and predicted rental rates (for non home owners) is 0.99.

¹⁰While the CPS was started in 1962, it was not until 1989 that an individual’s metropolitan area was tracked. For sufficiently large metro areas, the CPS is uniquely suited to examine high-frequency within-group movements between wages and temperature. For example, using the panel dimension of the CPS to create a new longitudinal database that identifies individuals who moved, Nekarda (2009) estimates a bound on the bias from geographic mobility and finds that it is quite minor, meaning that attenuation bias is an unlikely concern.

Longitudinal County-by-industry Panel.—The paper also leverages several administrative sources of industry-by-county data for robustness exercises, namely: the County Business Patterns (CBP), the Quarterly Census of Earnings and Wages (QCEW), and the Longitudinal Employer-Household Dynamics (LEHD).¹¹ Each of them are at the three-digit industry-by-geography-level where the geography for the QCEW is an MSA and for the CBP and LEHD is a county. The QCEW and LEHD are both at the quarterly frequency, whereas the CBP is annual. These datasets serve as consistent panels for investigating the effects of temperature shocks over a 25 year period.

Longitudinal County and Metropolitan Temperature Panel.—Measures of temperature and precipitation are obtained from two sources: (i) the PRISM database, which is used in ongoing work by Deryugina and Hsiang (2017) and provided by Wolfram Schlenker, and (ii) independently extracted measures from the National Ocean and Atmospheric Administration (NOAA) at daily, monthly, and annual frequencies.¹² These data are measured as the average temperatures within each grid (0.5 latitude \times 0.5 longitude degree) from large gridded raster files. Temperature is measured in several ways: (i) average temperature, (ii) maximum temperature, and (iii) the number of days within a certain duration of time (e.g., month) within a certain temperature range (e.g., 0-15 degrees Fahrenheit). Approach (iii) has been used in recent literature to flexibly characterize the impact of temperature on outcomes at different points of the distribution.

The Appendix details several basic descriptive statistics over the data—in particular, the extent of the variation at monthly frequencies over the past century—and documents the cleaning and validation procedures applied to the data.

3. Productivity’s Short-Run Invariance to Temperature

3.1. Empirical Specification

Consider the following baseline specification that relates temperature in a location j and period t , denoted T_{jt} , with real economic outcomes possibly at an individual level i , denoted y :

$$y_{ijt} = \alpha X_{jt} + \beta D_{it} + \psi f(T_{jt}) + \phi_j + \lambda_t + \epsilon_{ijt} \quad (1)$$

¹¹We also draw on the historical census records to obtain county-level population measures for weights when appropriate: <https://www.census.gov/population/www/censusdata/pop1790-1990.html>.

¹²http://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html

where X denotes a vector of individual covariates, D denotes a vector of location covariates, $f(\cdot)$ denotes an arbitrarily flexible function of temperature, and ϕ and λ are fixed effects on location and time, respectively. Recent literature has began emphasizing the potential non-linearities between temperature and real outcomes, which involves approximating $f(\cdot)$ in Equation 1 using a spline:

$$f(T_{jt}) = \sum_k \psi_k T_{jt}^k \quad (2)$$

T^k denotes the number of days in location j and period t that fall between the range $T^k \in [\underline{T}^k, \bar{T}^k]$. While the intervals on T^k in Equation 2 can be be arbitrarily flexible, we follow the literature in using 15 degrees Fahrenheit intervals, which is in the neighborhood of the norm in the literature (Deschenes and Greenstone, 2011; Deryugina and Hsiang, 2017).

The inclusion of location and time fixed effects in Equation 1 is hugely important because of the presence of “Tiebout” non-random sorting into locations based on preferences for non-market goods (Tiebout, 1956); see, for example, Albouy et al. (2015) and Sinha and Cropper (2016). To the extent fixed effects help absorb time-invariant sources of heterogeneity, it is also possible that demographic shifts are taking place and correlated with changes in temperature. Since, for example, temperature tends to move along the business cycle, migration flows may tend to bias the estimated gradient since inflows and outflows will affect the equilibrium wage (Saks and Wozniak, 2011; Molloy et al., 2011). In this sense, controlling for both individual and local characteristics helps mitigate bias arising from time-varying shocks. An additional side issue in this area is the fact that there is often measurement error in temperature data (Aufhammer et al., 2013), as well as the earnings data (Lemieux, 2006), which can introduce attenuation bias.

3.2. Individual-level Results

Having illustrated that county-level data do not appear to reflect a negative association between temperature and earnings, we now turn towards individual-level data. One reason that the county-level data (without the lagged dependent variable) may be close to zero is because it is pooling an array of compositional effects. For example, if certain sectors are affected, but not others, then the effects may wash out in the aggregate. Similarly, time-varying demographic shocks may be correlated with temperature and economic development, which may bias the estimates towards zero. The introduction of individual-level data addresses these concerns by allowing us to estimate heterogeneous treatment effects, controlling for demographic covariates.

While there are several sources of micro-data that are well-suited for this analysis, we begin by presenting results using the annual Current Population Survey (CPS) between 1963 and 2015, which contains individuals identified at a metropolitan-level. While a concern with the data is that it samples from larger metropolitan areas, the sample weights are created to help ensure that the data produces externally valid results. We also present and discuss results using the Decennial Census, which contains more comprehensive coverage. Figure 4 presents the results associated with Equation 29, conditional on a richer set of demographic controls, separately for four groups: those with versus without a college degree, and those in manufacturing versus services sectors.¹³ In each case, there is not an association between temperature and earnings, which is also robust to using personal income (rather than labor income).

[INSERT FIGURE 4 HERE]

Given that these results differ in some ways with some of the county-level data from [Deryugina and Hsiang \(2017\)](#), Appendix Section 8.2.1. begins by replicating their main results on the same sample and proceeds by examining potential sources of endogeneity, most notably through the inclusion of a lagged dependent variable as an additional control. We show that the correlation between mobility and lagged income likely creates an additional source of endogeneity that biases towards finding a negative association between temperature and per capita income.

Appendix Section 8.3.1. also presents a wide array of supplementary results. First, we show that there is also not an association with hours worked, which addresses the concern that earnings might not be affected simply due to changes in the intensive margin of labor services in response to temperature (see Figure 14). We also validate these results using the monthly CPS between 1994 and 2014. Second, we show a simpler set of results that simply examines the marginal effect of a change in mean and maximum metropolitan temperatures (see Table 9). Importantly, while there is a strong negative gradient in the cross-section, the inclusion of demographic controls cuts it in half and the inclusion of fixed effects completely eliminates it, consistent with our concern about demographic shifts. Third, we show that there is no evidence of lagged effects by estimating an impulse response function with up to 10 forward variables (see Figure 16).

¹³Manufacturing includes both durables and non-durables sectors. Services is defined as transportation, communications, utilities, retail and wholesale trade, finance, real estate, insurance, professional and management services, and personal services, entertainment, and accommodation. Demographic controls include a quadratic in educational attainment and age, number of children, gender, marital status, and race.

3.3. Industry-by-location-level Results

While the individual-level results do not point towards a meaningful association between temperature and earnings, one concern is that these individual-level data are fraught with measurement error and may, therefore, attenuate the main results; see, for example, Lemieux (2006) in the context of the CPS and Bound et al. (2001) more generally. Although measurement error is unlikely to play such a large role, especially across three separate datasets (annual CPS, monthly CPS, and Census), it is still possible. To overcome this concern, we turn towards three separate sources of administrative data at the county-by-industry level: annualized versions of the Quarterly Census of Employment and Wages (QCEW) between 1990 and 2014, the County Business Patterns (CBP) between 1984 and 2014, and the Longitudinal Employer-Household Dynamics (LEHD) between 1997 and 2014. To maintain brevity, we focus on the QCEW.

Using a three-digit industry-by-county panel between 1990 and 2014, Figure 5 plots the estimated coefficients associated with Equation 29 for four industries with an outcome variable set equal to logged annual wages. Like before, there is no association between temperature and earnings, even for heat-exposed industries, like agriculture, mining, utilities, and manufacturing. In fact, while there is a decline in the gradient for three of the four sectors, there is a much flatter gradient for the agricultural, mining, and utilities sector.

Appendix Section 8.3.2. presents a massive series of robustness exercises on the QCEW data. First, we replicate these results using total pay as an outcome variable, recognizing that there are other forms of compensation that might be curtailed in response to temperature shocks even if base salary is not adjusted (see Figure 17). Second, we replicate these results using a lagged value of the outcome variable as a control (see Figure 18). It is interesting to note that the same endogeneity bias that arose in the earlier results with the lagged dependent variable does not arise here.¹⁴Third, we replicate the results using completely separate temperature data collected at the metropolitan level, rather than county, data to address the potential concern that adjustment mechanisms take place at a broader labor market level (see Figure 19). In addition to these series of robustness exercises with the QCEW, we also present additional results in Appendix Section 8.3.2. using the CBP between 1984 and 2014 and the LEHD between 1997 and 2014.

[INSERT FIGURE 5 HERE]

¹⁴A series of diagnostics suggests that greater disaggregation mitigates the omitted variables bias problem that would result if the aggregation were at a county-level. In particular, migration flows at the county-level are less correlated with industry-by-county changes in wages and total pay.

3.4. Direct Productivity Measurements

While all these results provide evidence that there is not a reduced-form relationship between temperature and earnings, it is also possible that earnings is a poor proxy for actual productivity. To address this shortcoming, we turn towards recent data from the BEA on metropolitan GDP between 2001 and 2015. Appendix Section 8.3.2. presents additional evidence (see Figure 20) on the lack of a relationship between temperature and GDP when using the semiparametric measure, but Figure 6 below turns towards a similar characterization. In particular, it shows that there is an economically significant, but fairly imprecise, relationship between temperature and GDP concentrated in the agricultural and mining sectors. These results are consistent with evidence on the response of crop yields to temperature shocks (Schlenker et al., 2006; Schlenker and Roberts, 2009). However, the gradients decline in magnitude when weighting by metropolitan population since agriculture and mining activities are concentrated in less populated areas.

[INSERT FIGURE 6 HERE]

3.5. Motivating Evidence of Long-run Effects

The lack of a direct and contemporaneous effect of temperature on earnings is not (on its own) evidence that it has no impact on productivity. Indeed, climate may affect the spatial allocation of activity—that is, where an individual or firm decides to locate. Certain areas, for example, might be more productive for certain firms or individuals, or they simply might be preferable due to other idiosyncratic taste-related reasons. In either case, locational choice is an important mechanism that the earlier reduced-form results are not able to capture.

To measure the potential role of reallocation, we use decadal county-level data between 1970 and 2010 and allow for both medium and short run effects to impact median family income, which is used as a proxy for productivity. Following Iyigun et al. (2016) who implement a variant of this strategy, we estimate regressions of the form:

$$\Delta^{10}y_{ct} = \alpha\Delta^{10}D_{ct} + \psi\Delta^{10}\ln T_{ct} + \zeta\Delta^{20}\ln T_{ct} + \xi(\Delta^{10}\ln T_{ct} \times \Delta^{20}\ln T_{ct}) + \eta_c + \lambda_t + \epsilon_{ict} \quad (3)$$

where y denotes family income, D denotes a vector of demographic controls, T denotes temperature, η and λ denote fixed effects on county and year, and Δ^τ denotes a growth rate operator

for τ years, i.e., $\Delta^{10}x_{ct} = (x_{ct} - x_{ct-10})/x_{ct-10}$ and $\Delta^{20}x_{ct} = (x_{ct-10} - x_{ct-20})/x_{ct-20}$. While a special case of Equation 3 is simply a long-run first-differenced regression where $\zeta = \xi = 0$, here we allow for long-run temperature growth to affect family income, together with its interaction with medium-run temperature growth. In this sense, Equation 3 allows for the possibility that a sustained period of temperature growth can adversely affect productivity even more than if it is just a particular decade that is warmer than usual.

How should the parameter estimates be interpreted in light of the potential for adaptation? First, when $\psi < \zeta$, hotter temperatures might allocate individuals from one location to another. For example, individuals might reflect on growing temperatures and decide to move elsewhere. Second, when $\xi > 0$, hotter temperatures two decades prior are less costly based on actions taken in the prior decade. For example, individuals might reflect on growing temperatures and undertake mitigation activities today that reduce the costs of temperature shocks in the next decade.¹⁵

Table 1 documents these results. Columns 1 and 2 present a simplified version of Equation 3 where the 20-year growth rate and interaction with the 10-year growth rate is not included. Both suggest that there is a statistically significant and strong negative relationship between increases in temperature and family income, which offers a different perspective from the results presented earlier. Not surprisingly, growth in population, marital status, and the share of college graduates are associated with large increases in income with and without county and year fixed effects. In contrast, increases in the growth rate of unemployment are associated with declines in income.

While the negative gradient on temperature might appear to offer a counter perspective to the earlier results, the remaining columns in Table 1 allow for a more nuanced set of adaptation mechanisms. For example, turning towards columns 5 and 6, which present estimates of Equation 3 with and without population weights, there is a negative association between 10-year temperature growth rates, but a positive association between 20-year temperature growth rates and the interaction term. Since these data are roughly a complete census of the population, we focus on the unweighted results as the baseline. In this sense, a one percentage point rise in the 10-year temperature growth rate is associated with a direct 0.78 percentage point (pp) decline in the growth rate of family income, whereas a comparable rise in the 20-year temperature growth rate is associated with a 1.22pp rise in the growth rate of family income.

While the fact that $\zeta > \psi$ is consistent with the notion that individuals adapt, potentially

¹⁵Compared to Iyigun et al. (2016), these signs are flipped since they are looking at a negative amenity (conflict), whereas we are looking at a positive amenity. Even holding fixed the signs, these results would be consistent with “intensification”, which is good in the setting of productivity as an outcome variable.

through mitigation activities, what is especially remarkable is the consistency and magnitude of the interaction effect between 10-year and 20-year growth rates in temperature. Despite the large coefficient estimate on the interaction, the mean level is actually quite small, and thus must be scaled to have a realistic interpretation. Since the mean of $\Delta^{10}T$ is 0.0055pp and the mean of $\Delta^{20}T$ is 0.0072pp, the product of the two is roughly 0.000012pp, or 0.0012 percent, which makes the mean effect of 38 roughly 0.04 percent ($= 38 \times 0.00122$)—comparable to the other elasticities. The fact that the interaction is robustly positive is consistent with the presence of reallocation of economic activity from hotter areas to more temperature areas. Finally, Table 1 shows that not only are the medium-run effects of temperature shocks larger in areas with high shares of agriculture and mining—a significant elasticity of -1.44 versus an insignificant elasticity of 0.30—but also the long-run adaptation and reallocation effects are larger—an elasticity of 55 versus 21. In this sense, areas with more exposed industrial sectors reallocated more heavily due to the greater adverse effects they may have faced.

[INSERT TABLE 1 HERE]

4. A Spatial Equilibrium Sorting Model

This section introduces a spatial equilibrium model for inferring the valuation of temperature using information on housing rents, wages, and population. While the model builds upon the canonical Rosen (1974) and Roback (1982) sorting models, we develop extensions to Moretti (2013) and Diamond (2016) by introducing sectoral heterogeneity and climate amenities into a general equilibrium structure. Incorporating both these features is important since they allow for climate to affect not only productivity directly through firm-side effects, but also indirectly through the sorting patterns of households (which feed back into firm optimality conditions). Several recent contributions have pointed towards sorting based on climate amenities as an important mechanism (Chen and Rosenthal, 2008; Albouy et al., 2015; Sinha and Cropper, 2016). We do not, however, allow for search frictions and intersectoral linkages as in Beaudry et al. (2012).

4.1. Technology

Suppose that each location, indexed by j , contains a unique composition of four sets of industries, indexed by $k \in \{A, M, S, B\}$ for agriculture, manufacturing, services, and business with sectoral

production functions that combine capital and labor:

$$Y_{jkt} = N_{jkt}^{\theta_k} K_{jkt}^{1-\theta_k} \exp(z_{jkt}) \quad (4)$$

where z denotes total factor productivity that is decomposed into:

$$z_{jkt} = \alpha_k T_{jt} + u_{jkt} \quad (5)$$

where T denotes the temperature (e.g., average) in location j and u denotes idiosyncratic variation in productivity. Under the assumption of perfect competition, then the equilibrium demand for labor and capital is given by

$$w_{jkt} = \theta_k N_{jkt}^{\theta_k-1} K_{jkt}^{1-\theta_k} \exp(z_{jkt}) \quad (6)$$

$$\kappa_t = (1 - \theta_k) N_{jkt}^{\theta_k} K_{jkt}^{-\theta_k} \exp(z_{jkt}) \quad (7)$$

where the assumption on capital is that capital markets are frictionless and can be supplied elastically at a price κ across all cities. Substituting out the level of capital, the logged county-level demand curves for labor are given by:

$$\ln w_{jkt} = c_t + \theta_k \ln N_{jkt} + \alpha_k T_{jt} + u_{jkt} \quad (8)$$

$$c_t = \ln \left[\theta_k \left(\frac{1 - \theta_k}{\kappa_t} \right)^{(1-\theta_k)/\theta_k} \right] \quad (9)$$

which means that $Y_{jkt} = w_{jkt} N_{jkt} / \theta_k$. It follows that the aggregate production function can be written as follows:

$$Y_{jt} = \exp(z_{jt}) \left[\sum_k \chi_k (w_{jkt} N_{jkt} / \theta_k)^\rho \right]^{1/\rho} \quad (10)$$

$$w_{jkt} = \exp(z_{jt}) Y_{jt}^{1-\rho} \theta_k N_{jkt}^{\theta_k} \exp(-\alpha_j T_{jt})^{\rho-1} N_{jkt}^{(\theta_k-1)} \exp(-\alpha_j T_{jt}) \quad (11)$$

which can be re-written after taking logs as

$$\ln w_{jkt} = (1 - \rho) \ln Y_{jt} + (\theta_k \rho - 1) \ln N_{jkt} - \alpha_j T_{jt} + z_{jkt} \quad (12)$$

where z can be decomposed into a set of time-varying covariates (e.g., educational attainment, age) and a permanent fixed effect

$$z_{jt} = \beta X_{jt} + \phi_j + \lambda_t + \varepsilon_{jt} \quad (13)$$

where $E[w_{jt}^k | \varepsilon_{jt}, X_{jt}, \phi_j, \lambda_t] = 0$ must hold in order to consistently recover the coefficient estimates associated with each of the right hand side variables. The equilibrium wage equation shows that temperature can affect productivity in two ways: directly by influencing an industry's productivity of labor and indirectly by influencing aggregate output through the elasticity of substitution across sectors (governed by ρ).

Before continuing, it is useful to take stock of several assumptions. The first is the abstraction of capital. Since the analysis is conducted over decades, perfect mobility of capital is a reasonable assumption, meaning that introducing capital in an additively separable way would leave the labor demand equations unaltered. We also allow the factor shares on labor to vary by industry. Moreover, to our knowledge, there is no available micro-data on capital at a metro-by-industry level that would enable us to explicitly incorporate it in a data-driven way. The second is the abstraction of additional industries. However, the four that are included is a relatively parsimonious set given data constraints and the available frontier of knowledge on structural transformation, which emphasizes the shift from agriculture to manufacturing to services (Herrendorf et al., 2014). The third is the parametric structure on temperature. Since the effects of temperature may vary depending on the units (e.g., Fahrenheit versus Celsius), taking logarithmic transformations can generate coefficient estimates that are not fully comparable (see Hsiang (2016)). The specification here allows for temperature to reduce productivity, albeit in a somewhat parametric form.

4.2. Preferences and Labor Supply

Individuals, denoted by i , also make decisions about where to locate by choosing the location that offers the highest utility. Preferences are Cobb-Douglas over a local good, denoted M , with a price R_{jt} , a national good, denoted O , with a price P_t , and location-specific temperatures T such that

the representative household maximizes utility:

$$\max_{M,O} \left\{ \ln(M^\zeta) + \ln(O^{1-\zeta}) + g_i(T_{jt}) \right\} \quad (14)$$

subject to a budget constraint:

$$P_t O + R_{jt} M = W_{jt}^k \quad (15)$$

where $0 \leq \zeta \leq 1$ denotes the relative preference (and share of income) for the national good over the local good, and $g(\cdot)$ denotes an arbitrarily flexible functional form over temperature and allows for individual heterogeneity in the preferences for temperature. The implied indirect utility function is given by

$$V_{ijt} = \underbrace{\ln\left(\frac{W_{jt}^k}{P_t}\right)}_{w_{jt}^k} - \zeta \underbrace{\ln\left(\frac{R_{jt}}{P_t}\right)}_{r_{jt}} + g_i(T_{jt}) \quad (16)$$

The demand for local goods is given by:

$$D_{ijt} = \zeta W_{jt}^k / R_{jt} \quad (17)$$

Given our indirect utility function in Equation 16, we simply need to specify a functional form for temperature and take our preferences to the data. We allow for temperature to flexibly affect locational choice through both mean and distributional channels, decomposing residual variation of preferences into location and industry fixed effects, respectively denoted ξ_j and ξ_k , and an idiosyncratic component, denoted ε_{ijkt} , which is distributed with an extreme value type I distribution as in McFadden (1973):

$$\begin{aligned} v_{ijkt} &= (w_{ijkt} - \zeta r_{jt}) \beta^w + \eta_{ik} T_{jt}^{mu} + \pi_{ik} T_{jt}^{sd} + \beta_{ik}^{st} x_j^{st} + \beta_{ik}^{div} x_j^{div} + \xi_j + \xi_k + \varepsilon_{ijkt} \\ &= \beta_i x_{ijkt} + \beta_{ik}^{st} x_j^{st} + \beta_{ik}^{div} x_j^{div} + \xi_j + \xi_k + \varepsilon_{ijkt} \end{aligned} \quad (18)$$

where w_{ijkt} is the individual's expected log earnings for working in location j and industry k (estimated from a Mincerian wage regression), r_{jt} denotes a location's logged median housing values, and T^{mu} and T^{sd} denote the mean and standard deviation of logged temperature within a location; x is simply short-hand for all these. x^{st} and x^{div} are indicators for if an individual was

born in the same state or Census division as location j . Including these accounts for additional important determinants of location choice as shown in the literature on internal migration in the United States (Kennan and Walker, 2011; Bishop, 2012; Diamond, 2016; Ransom, 2018). What is essential to Equation 18 is that we allow for rich heterogeneity in the underlying preference parameters, specifically η and π since different types of individuals will be more versus less vulnerable to temperature fluctuations (e.g., older versus younger). We accomplish this by estimating the preference parameters on individual data in a similar fashion as Diamond (2016).¹⁶

4.3. Housing Supply

Housing prices vary by location and capitalize the value of both housing costs and the price of local market goods and services (Rosen, 1974). Following Diamond (2016), developers use construction materials (“construction costs”) and land (“land costs”) order to produce a homogeneous housing good that they sell equal to their marginal costs, parameterized as:

$$R_{jt} = \iota_t MC(CM_{jt}, LC_{jt}) \quad (19)$$

where ι is the interest rate. Houses are owned by landlords who rent housing to their local residents. From Equation 17, land costs are a function of the aggregate demand for local goods. When wages rise or prices for the local good fall, the demand for the local good rises, which in turn impacts the demand for housing. Following Diamond (2016), these housing supply equations are specified as:¹⁷

$$\ln R_{jt} = \ln \iota_t + \ln(CM_{jt}) + \gamma \ln(HD_{jt}) \quad (20)$$

$$HD_{jt} = \sum_{k \in \{A, M, S, B\}} N_{jt}^k \frac{\zeta W_{jt}^k}{R_{jt}} \quad (21)$$

¹⁶We estimate our model on decennial Census data from 1970-2000 and the 2010-2014 ACS, all provided by Ruggles et al. (2018). We restrict attention to household heads who are working full-time full-year and are between the ages of 25–55, and who live in the contiguous 48 states.

¹⁷The setup here differs slightly from Diamond (2016) who allows for heterogeneity in the housing supply regulation across metropolitan areas. However, we focus on a different layer of aggregation, but control for these factors using location fixed effects.

where HD denotes the aggregate demand for the local good. We use data from the Lincoln Institute to measure construction costs, which are available for 46 metropolitan areas.¹⁸ We crosswalk into economic areas and subsequently impute the remaining construction costs using demographic characteristics across these locations.

4.4. Equilibrium

The equilibrium is defined by a sequence of wages and rents, $\{w_{jkt}, r_{jt}\}$ with employment levels $\{N_{jkt}\}$ such that:

- The demand for workers in industry k equals the supply of those workers:

$$N_{jkt} = \sum_{i \in j_k} \frac{\exp(\delta_{ijkt})}{\sum_{i' \in j_k} \exp(\delta_{i'jkt})} \quad (22)$$

$$\ln w_{jkt} = (1 - \rho) \ln Y_{jt} + (\theta_k \rho - 1) \ln N_{jkt} - \alpha_j T_{jt} + z_{jkt} \quad (23)$$

- The demand of housing equals the supply:

$$\ln R_{jt} = \ln \iota_t + \ln(CM_{jt}) + \gamma_j \ln(HD_{jt}) \quad (24)$$

$$HD_{jt} = \sum_{k \in \{A, M, S, B\}} N_{jkt} \frac{\zeta W_{jt}^k}{R_{jt}} \quad (25)$$

- Indirect utilities are given by

$$\delta_{ijkt} = w_{jkt} - \zeta_i r_{jt} + \psi_i D_{jt} + \eta_i T_{jt} + \sum_{m=1}^M \eta_i^m d_{jt}^m T_{jt} + \xi_{jkt} \quad (26)$$

¹⁸<http://datatoolkits.lincolnst.edu/subcenters/land-values/metro-area-land-prices.asp>

4.5. Estimation and Identification

We estimate the model in two stages. First, we recover preference estimates via maximum likelihood estimation of a conditional logit model. We then combine our preference estimates with estimates of labor demand and impose the equilibrium conditions via GMM (Berry et al., 2004). We provide further details in the Appendix.

5. Quantitative Evaluation

5.1. Parameter Estimates and Model Fit

Table 6 begins by presenting a measure of model fit to validate our simulation results. We find a close correspondence between the data and model, although we tend to overestimate the manufacturing employment share, but underestimate the shares in business and services. Table 3 presents similar results across states. Overall, the choice probabilities, however, fit the data quite well.

We now present our estimates for the underlying wage parameters in Table 4. Our first specification contains demographic characteristics and fixed effects on year, industry, and state, whereas our second specification adds in state by industry fixed effects. We defer to the latter because it controls for changes in structural transformation that could be correlated with individual wages.

Not surprisingly, we find statistically significant and positive associations between GDP and wages, which reflects not only an exogenous causal link, but also likely endogeneity in the allocation of labor. While we find positive gradients on employment in each sector in the first specification, we find a negative association on services employment in the second specification. The negative association could reflect, at least in part, Baumol’s cost disease, which characterizes settings when a less productive sector in an economy expands and begins reducing aggregate GDP.

Turning towards temperature, we find a positive association between it and wages, but a negative association between its square and wages. We also find a positive association between the volatility of temperature and wages. These patterns may reflect the presence of compensating differentials: wages are higher in hotter areas because they are a disamenity to households who demand higher wage compensation.

Table 5 subsequently presents estimates associated with our preference parameters. We include a detailed set of interactions between temperature and demographic characteristics to allow for

greater heterogeneity in the taste for climate amenities, time-invariant location amenities, and time-invariant industry amenities.

[INSERT TABLE 4 HERE]

[INSERT TABLE 5 HERE]

5.2. The Long-run Effect of Temperature

Having estimated and validated our model, we now explore the effects of long-run changes in temperature on U.S. economic activity, specifically wages, GDP, and employment across sectors. Given our parameters, we simulate our model under the assumption that state-level temperature remained at 1970s levels for every subsequent decade—that is, we obtain counterfactual predictions under the assumption that temperature remained invariant from 1970 onwards.

Figure 7 summarizes one of our exercises. We plot the actual difference in average temperature across states between 2010 and 1970 with the counterfactual change in state employment shares, which is obtained by holding fixed the 1970 distribution of temperature. We see a strong correlation between the two series: a 10 degree increase in actual temperature between 1970 and 2010 is associated with a 1.7pp rise in counterfactual state population shares. Although the comparison of the two series may seem counterintuitive, these results are sensible given our parameter estimates: since individuals dislike hotter and more volatile temperatures, shutting down the increase in temperature means that more people would have moved to the states (in the counterfactual) that (in the actual) became hotter.

[INSERT FIGURE 7 HERE]

5.3. Disentangling Demand and Supply Factors

While our parameter estimates suggest that changes in the demand for labor are not quantitatively important for explaining the observed patterns, we can more formally test our intuition by simulating our model under counterfactuals where we shut down the two channels sequentially. That is, we can assume that there is no link between temperature and output in the production function, or that there is no link between temperature and residential sorting.

Our findings indicate that labor supply is more responsive to changes in temperature than is productivity. We examine this by comparing the result of Figure 7 (where we shut down temperature’s effect on labor reallocation) with the result of Figure 8 (where we shut down temperature’s effect on productivity as measured by wages). In Figure 7 we measure an increased inflow of labor supply of 0.17% for each degree increase between 1970–2010. In Figure 8, we measure a decrease in productivity of 0.03% for each 1970–2010 degree increase.

5.4. Projecting the Effects of Climate Change

Using state-of-the-art climate projection models, we can obtain state-level projections for temperature by 2099 from the NASA Earth Exchange (NEX) Downscaled Climate Projections (NEX-DCP30) dataset (<https://cds.nccs.nasa.gov/nex/>) and simulate our model under that new distribution.¹⁹ We specifically focus on the moderate (“stabilization”) scenario because it is a more likely outcome, according to climate researchers.

6. Conclusion

Integrated Assessment Models (IAMs) have become routine tools for evaluating the costs of climate change and counterfactual environmental policies. However, they impose an important assumption on the relationship between temperature and aggregate productivity. Using an array of individual and industry datasets covering multiple decades, this paper evaluated the empirical content of this assumption by examining the effect of temperature fluctuations on earnings, weekly wages, hourly wages, and other measures of productivity. Understanding the relationship between temperature and productivity comes at an important time as emerging environmental models forecast increasing weather fluctuations and higher temperatures in the years ahead.

¹⁹The dataset provides data on minimum and maximum temperature at a monthly time-step mapped to a 30 arc-second (1kilometer) grid. Version 5.0 of the Community Atmosphere Model - Community Earth System Model (CESM-CAM5) (<http://www.cesm.ucar.edu/models/cesm1.0/cam/>) was used for deriving the temperature values in 2099. In addition, the Representative Concentration Pathway (RCP) 6.0 was selected. RCP 6.0 is characterized as a stabilization scenario where greenhouse gas emissions stabilize shortly after 2100 (<https://skepticalscience.com/rcp.php?t=3>). The data was downloaded for the period 2096–2099 for the continental USA via a climate data portal <https://esgf.nccs.nasa.gov/search/nex-dcp30/>. We used the `ncdf4`, `raster`, `rgdal` and `maptools` libraries in R. The raw data (in NetCDF format) was converted to a spatial points layer – where each point was placed at the center of the grid cell and given the underlying attribute of interest: `tasmin` and `tasmax`. A shapefile of USA states was overlaid over the point data and used to match the points to individual states. The temperature values were extracted, averaged per state, and converted from Kelvin to Fahrenheit.

The results suggest that temperature is not statistically or economically associated with any of these measures of productivity after controlling for time-invariant differences across geography and time-varying demographic differences. Our results are robust to different functional forms and inclusion of dynamic effects. Our empirical setting offers several important advantages over earlier work. First, because the granularity of our data is at the individual-level, we are not only able to leverage more cross-sectional variation, but also control for differences in the composition of the labor force within narrow geographies over time. These compositional differences account for much of the variation in the unconditional correlation between temperature and earnings. These mobility patterns are also correlated with temperature, which generates downwards bias in prior estimates. Second, using micro-data on consumption expenditures, we show that the cyclicity of product demand coincides with the seasonal cycles of temperature fluctuations. In this sense, just as temperature is beginning to cool down in many areas, consumer spending rises, generating downwards bias in prior estimates.

While we have worked hard to create a simultaneously tractable and realistic model that captures the general equilibrium effects of temperature fluctuations, we have abstracted from a number of potentially interesting and important factors. For example, we have abstracted from technological change, which is important for understanding not only output growth over the long-run, but also industrial composition (Kongsamut et al., 2001; Ngai and Pissarides, 2007). Second, we have abstracted from other spatial amenities, which are important for understanding residential choice (Diamond, 2016). While we do not think that either condemn the implications of our analysis, future work should continue using additional micro-data to discipline more realistic models of the economy and environment. Adding additional structure will not only help separate between selection versus real effects associated with climate fluctuations, but also reveal the mechanisms through which individuals and geographies adapt to climate fluctuations.

References

- ACEMOGLU, D., S. JOHNSON, AND J. A. ROBINSON (2002): “Reversal of fortune: Geography and institutions in the making of the modern world income distribution,” *Quarterly Journal of Economics*, 117, 1231–1294.
- ALBOUY, D., R. KELLOGG, W. GRAF, AND H. WOLFF (2015): “Extreme temperature, climate change and the American quality of life,” *Journal of the Association of Environmental and Resource Economists*.

- ALDY, J. AND W. K. VISCUSI (2008): “Adjusting the value of a statistical life for age and cohort effects,” *Review of Economics and Statistics*, 90, 573–581.
- ANDERSEN, T. B., C.-J. DALGAARD, AND P. SELAYA (2016): “Climate and the emergence of global income differences,” *Review of Economic Studies*, forthcoming.
- ARELLANO, M. AND S. BOND (1991): “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations,” *Review of Economic Studies*, 58, 277–297.
- AUFHAMMER, M., S. M. HSIANG, W. SCHLENKER, AND A. SOBEL (2013): “Using weather data and climate model output in economic analyses of climate change,” *Review of Environmental Economics and Policy*, 7, 181–198.
- BANZHAF, S. H. AND R. P. WALSH (2008): “Do people vote with their feet? An empirical test of Tiebout’s mechanism,” *American Economic Review*, 93, 843–863.
- BARRECA, A., K. CLAY, O. DESCHENES, M. GREENSTONE, AND J. S. SHAPIRO (2016): “Adapting to climate change: The remarkable decline in the U.S. temperature-mortality relationship over the 20th century,” *Journal of Political Economy*, 124, 105–159.
- BAYER, P., F. FERREIRA, AND R. MCMILLAN (2007): “A unified framework for measuring preferences for schools and neighborhoods,” *Journal of Political Economy*, 115, 588–638.
- BAYLIS, P. (2015): “Temperature and temperament: Evidence from a billion tweets,” *Berkeley Job Market Paper*.
- BEAUDRY, P. D., D. A. GREEN, AND B. M. SAND (2012): “Does industrial composition matter for wages? A test of search and bargaining theory,” *Econometrica*, 80, 1063–1104.
- BELLEMARE, M. F., T. MASAKI, AND T. B. PEPINSKY (2016): “Lagged explanatory variables and the estimation of causal effects,” *Working paper*.
- BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): “Automobile prices in market equilibrium,” *Econometrica*, 63, 841–890.
- (2004): “Differentiated products demand systems from a combination of micro and macro data: The new car market,” *Journal of Political Economy*, 112, 68–105.
- BISHOP, K. (2012): “A dynamic model of location choice and hedonic valuation,” *Working paper*.
- BOUND, J., C. BROWN, AND N. MATHIOWETZ (2001): “Measurement error in survey data,” *Handbook of Econometrics*, 5.
- BURGESS, R., O. DESCHENES, D. DONALDSON, AND M. GREENSTONE (2014): “The unequal effects of weather and climate change: Evidence from mortality in India,” *Working paper*.

- BURKE, M. AND K. EMERICK (2016): “Adaptation to climate change: Evidence from US agriculture,” *American Economic Journal: Economic Policy*, 8, 106–140.
- BURKE, M., S. M. HSIANG, AND E. MIGUEL (2015): “Global non-linear effect of temperature on economic production,” *Nature*, 527, 235–239.
- CHEN, Y. AND S. S. ROSENTHAL (2008): “Local amenities and life-cycle migration: Do people move for jobs or fun?” *Journal of Urban Economics*, 64, 519–537.
- CHETTY, R. (2012): “Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply,” *Econometrica*, 80, 969–1018.
- COSTINOT, A., D. DONALDSON, AND C. SMITH (2016): “Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World,” *Journal of Political Economy*, 124, 205–248.
- CROPPER, M. AND A. ARRIAGA-SALINAS (1980): “Inter-city wage differentials and the value of air quality,” *Journal of Urban Economics*, 8, 236–254.
- CROPPER, M. L. (1988): “Measuring the benefits from reduced morbidity,” *American Economic Review*, 71, 235–240.
- CURRIERO, F., K. HEINER, J. SAMET, S. ZEGER, L. STRUG, AND J. PATZ (2002): “Temperature and mortality in 11 cities in the Eastern United States,” *American Journal of Epidemiology*, 155, 80–87.
- DELL, M., B. F. JONES, AND B. OLKEN (2012): “Temperature shocks and economic growth: Evidence from the last half century,” *American Economic Journal: Macroeconomics*, 4, 66–95.
- DERYUGINA, T. AND S. M. HSIANG (2017): “The marginal product of climate,” *NBER working paper*.
- DERYUGINA, T., D. MURAVYEV, AND N. PEARSON (2016): “Wall street and climate change: How do weather fluctuations affect large corporations,” *Working paper*.
- DESCHENES, O. AND M. GREENSTONE (2007): “The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather,” *American Economic Review*, 97, 354–385.
- (2011): “Climate change, mortality and adaptation: Evidence from annual fluctuations in weather in the US,” *American Economic Journal: Applied Economics*, 3, 152–185.
- DIAMOND, R. (2016): “The determinants and welfare implications of U.S. workers’ diverging location choices by skill: 1980-2000,” *American Economic Review*, 106, 479–524.
- EASTERLY, W. AND R. LEVINE (2003): “Tropics, germs and crops: How endowments influence economic development,” *Journal of Monetary Economics*, 50, 3–39.

- FISHER, A. C., W. M. HANEMANN, M. J. ROBERTS, AND W. SCHLENKER (2012): “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment,” *American Economic Review*, 102, 3749–60.
- GALLUP, J. L., J. D. SACHS, AND A. D. MELLINGER (1999): “Geography and economic development,” *International Regional Science Review*, 22, 179–232.
- GLAESER, E. L., J. KOLKO, AND A. SAIZ (2001): “Consumer city,” *Journal of Economic Geography*, 1, 27–50.
- GRAFF ZIVIN, J. S. AND M. NEIDELL (2014): “Temperature and the allocation of time: Implications for climate change,” *Journal of Labor Economics*, 32, 1–26.
- GREENSTONE, M., O. DESCHENES, AND J. S. SHAPIRO (2017): “Defensive investments and the demand for air quality: Evidence from the NOx budget program and ozone reductions,” *American Economic Review*, 107, 2958–2989.
- GROVER, M. (1938): “Mortality during periods of excessive temperature,” *Public Health Reports*.
- HEAL, G. M. AND J. PARK (2014): “Feeling the heat: Temperature, physiology and the wealth of nations,” *Working paper*.
- (2015): “Temperature stress and the direct impact of climate change: A review of an emerging literature,” *Review of Environmental Economics and Policy*, forthcoming.
- HERRENDORF, B., R. ROGERSON, AND A. VALENTINYI (2014): “Growth and structural transformation,” *Handbook of Economic Growth*, 2B, 855–941.
- HORNBECK, R. (2012): “The enduring impact of the American dust bowl: Short and long run adjustments to environmental catastrophes,” *American Economic Review*, 102, 1477–1507.
- HSIANG, S. M. (2016): “Climate econometrics,” *NBER working paper*.
- HSIANG, S. M. AND M. BURKE (2014): “Climate, conflict and social stability: What does the literature say?” *Climatic Change*, 123, 39–55.
- HSIANG, S. M. AND A. S. JINA (2014): “The causal effect of environmental catastrophe on long run economic growth: Evidence from 6,700 cyclones,” *NBER working paper*.
- HSIANG, S. M., K. C. MENG, AND M. A. CANE (2011): “Civil conflicts are associated with the global climate,” *Nature*, 476, 438–441.
- HSIANG, S. M. AND D. NARITA (2012): “Adaptation to cyclone risk: Evidence from the global cross-section,” *Climate Change Economics*, 3.

- IYIGUN, M., N. NUNN, AND N. QIAN (2016): “The long-run effects of climate change on conflict, 1400-1900,” *Working paper*.
- KAHN, M. E. (2005): “The death toll from natural disasters: The role of income, geography and institutions,” *Review of Economics and Statistics*, 87, 271–284.
- KEANE, M. AND R. ROGERSON (2012): “Micro and macro labor supply elasticities: A reassessment of conventional wisdom,” *Journal of Economic Literature*, 50, 464–476.
- KENNAN, J. AND J. R. WALKER (2011): “The effect of expected income on individual migration decisions,” *Econometrica*, 79, 211–251.
- KONGSAMUT, P., S. REBELO, AND D. XIE (2001): “Beyond balanced growth,” *Review of Economic Studies*, 68, 869–882.
- LAN, L., Z. LIAN, AND L. PAN (2010): “The effects of air temperature on office workers’ well-being, workload and productivity-evaluated with subjective ratings,” *Applied Ergonomics*, 42, 29–36.
- LEMIEUX, T. (2006): “Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill?” *American Economic Review*, 96, 461–498.
- MAKRIDIS, C. (2014): “The Elasticity of Air Quality: Evidence from Millions of Households Across the United States,” *Working paper*.
- McFADDEN, D. (1973): “Conditional logit analysis of qualitative choice behavior,” *Academic Press, New York*, *Frontiers in Econometrics*.
- MENDELSON, R., W. D. NORDHAUS, AND D. SHAW (1994): “The impact of global warming on agriculture: A ricardian analysis,” *American Economic Review*, 84, 753–771.
- MICHALOPOULOS, S. AND E. PAPAIOANNOU (2013): “Pre-colonial ethnic institutions and contemporary African development,” *Econometrica*, 81, 113–152.
- MOLLOY, R., C. L. SMITH, AND A. WOZNIAK (2011): “Internal migration in the United States,” *Journal of Economic Perspectives*, 25, 173–196.
- MORETTI, E. (2013): “Real wage inequality,” *American Economic Journal: Applied Economics*, 5, 65–103.
- NEKARDA, C. J. (2009): “A longitudinal analysis of the Current Population Survey: Assessing the cyclical bias of geographic mobility,” *Working paper*.
- NGAI, L. R. AND C. A. PISSARIDES (2007): “Structural change in a multisector model of growth,” *American Economic Review*, 97, 429–443.
- NICKELL, S. (1981): “Biases in dynamic models with fixed effects,” *Econometrica*, 49, 1417–1426.

- PINDYCK, R. (2013): “Climate change policy: What do the models tell us?” *Journal of Economic Literature*, 51, 860–872.
- RANSOM, T. (2018): “LaborMarket Frictions and Moving Costs of the Employed and Unemployed,” Working paper, University of Oklahoma.
- RAPPAPORT, J. (2007): “Moving to nice weather,” *Regional Science and Urban Economics*, 37, 375–398.
- (2008): “Consumption amenities and city population density,” *Regional Science and Urban Economics*, 38, 533–552.
- REED, W. R. (2013): “On the practice of lagging variables to avoid simultaneity,” *Working paper*.
- RHODE, P. W. AND K. S. STRUMPF (2003): “Assessing the importance of Tiebout sorting: Local heterogeneity from 1850 to 1990,” *American Economic Review*, 93, 1648–1677.
- ROBACK, J. (1982): “Wages, rents and the quality of life,” *Journal of Political Economy*, 90.
- ROBERTS, M. J. AND W. SCHLENKER (2011): “The evolution of heat tolerance: Implications for climate change,” *University of Chicago Press*.
- ROSEN, S. (1974): “Hedonic prices and implicit markets: Product differentiation in pure competition,” *Journal of Political Economy*, 82, 34–55.
- RUGGLES, S., S. FLOOD, R. GOEKEN, J. GROVER, E. MEYER, J. PACAS, AND M. SOBEK (2018): *IPUMS USA: Version 8.0 [dataset]*, Minneapolis, MN: IPUMS.
- SAKS, R. E. AND A. WOZNIAK (2011): “Labor reallocation over the business cycle: New evidence from internal migration,” *Journal of Labor Economics*, 29, 697–739.
- SCHLENKER, W., W. M. HANEMANN, AND A. C. FISHER (2005): “Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach,” *American Economic Review*, 95, 395–406.
- (2006): “The impact of global warming on U.S. agriculture: An econometric analysis of optimal growing conditions,” *Review of Economics and Statistics*, 88, 113–125.
- SCHLENKER, W. AND M. J. ROBERTS (2009): “Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change,” *Proceedings of the National Academy of Sciences*, 106, 15594–15598.
- SEPPANEN, O., W. J. FISK, AND Q. LEI (2006): “Effect of temperature on task performance in the office environment,” *Lawrence Berkeley National Lab*.
- SINHA, P. AND M. L. CROPPER (2016): “Household location decisions and the value of climate amenities,” *RFF Discussion Paper*.

SMITH, V. K. (1983): “The role of site and job characteristics in hedonic wage models,” *Journal of Urban Economics*, 13, 296–321.

SOMANATHAN, E., R. SOMANATHAN, A. SUDARSHAN, AND M. TEWARI (2015): “The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing,” *Working paper*.

TIEBOUT, C. M. (1956): “A pure theory of local expenditures,” *Journal of Political Economy*, 64, 416–424.

VISCUSI, W. (1979): “Employment hazards: An investigation of market performance,” *Cambridge: Harvard University Press*.

ZHANG, P., O. DESCHENES, K. MENG, AND J. ZHANG (2018): “Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants,” *Journal of Environmental Economics and Management*, 83, 8–31.

7. Tables and Figures

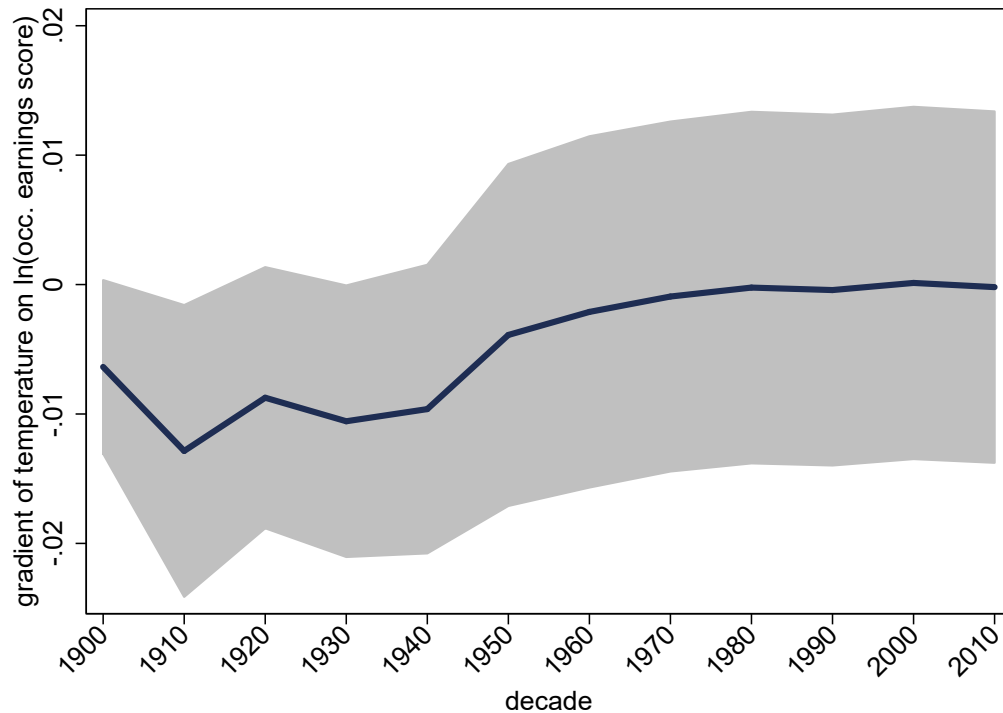


Figure 1: Changes in the Relationship between Temperature and Productivity, 1900-2010

Notes.—Sources: Census Bureau and NOAA. The figures plot the estimated coefficient from a regression of logged annual labor income at the occupation-level on average maximum temperature (within a month) at the state-level interacted with year fixed effects. 1900 is the omitted group. Controls include a quadratic in age and educational the fraction of people who are male, white, black, and married. Standard errors are clustered at the state-level.

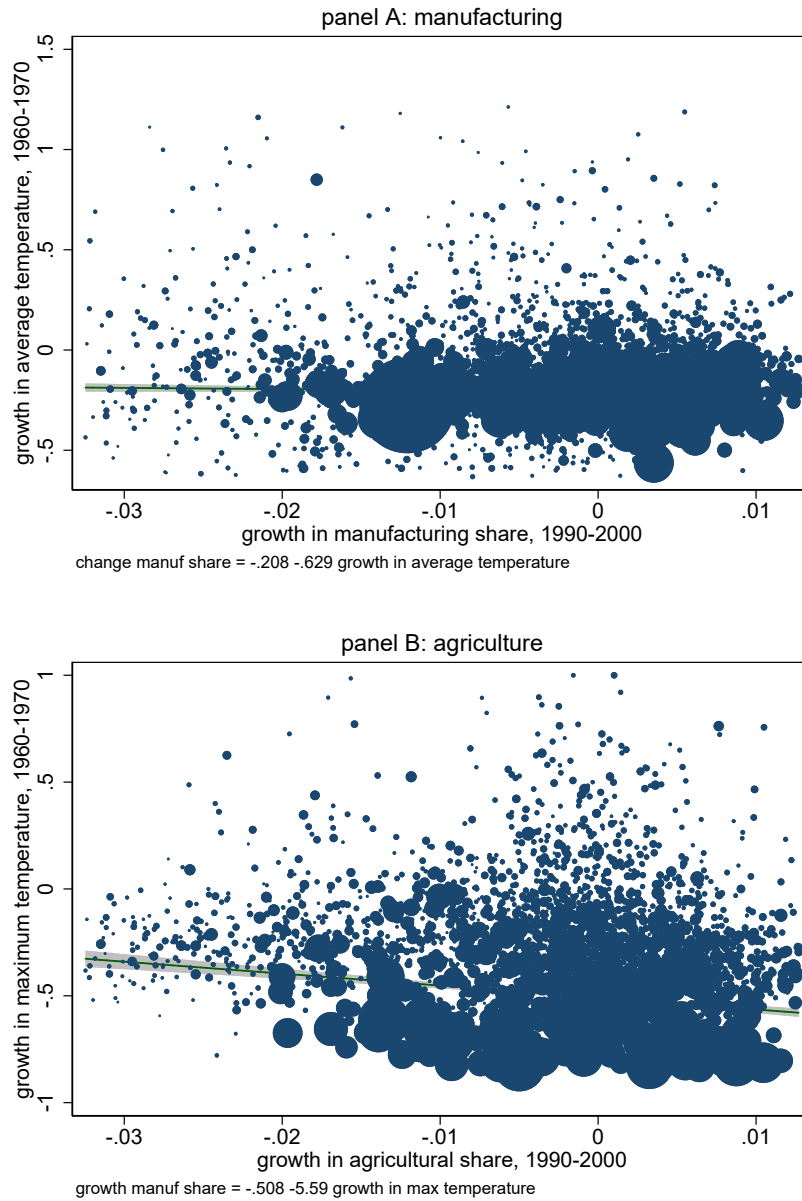


Figure 2: Growth in Average Temperature (1960-1970) and Sectoral Employment Shares in Manufacturing and Agriculture (1990-2000)

Notes.—Sources: Census Bureau (SocialExplorer) and PRISM. The figure the growth in average temperature between 1960 and 1970 with the growth in the employment share of manufacturing and agriculture between 1990 and 2000 for each county. Observations are weighted by county population and standard errors are clustered by county.

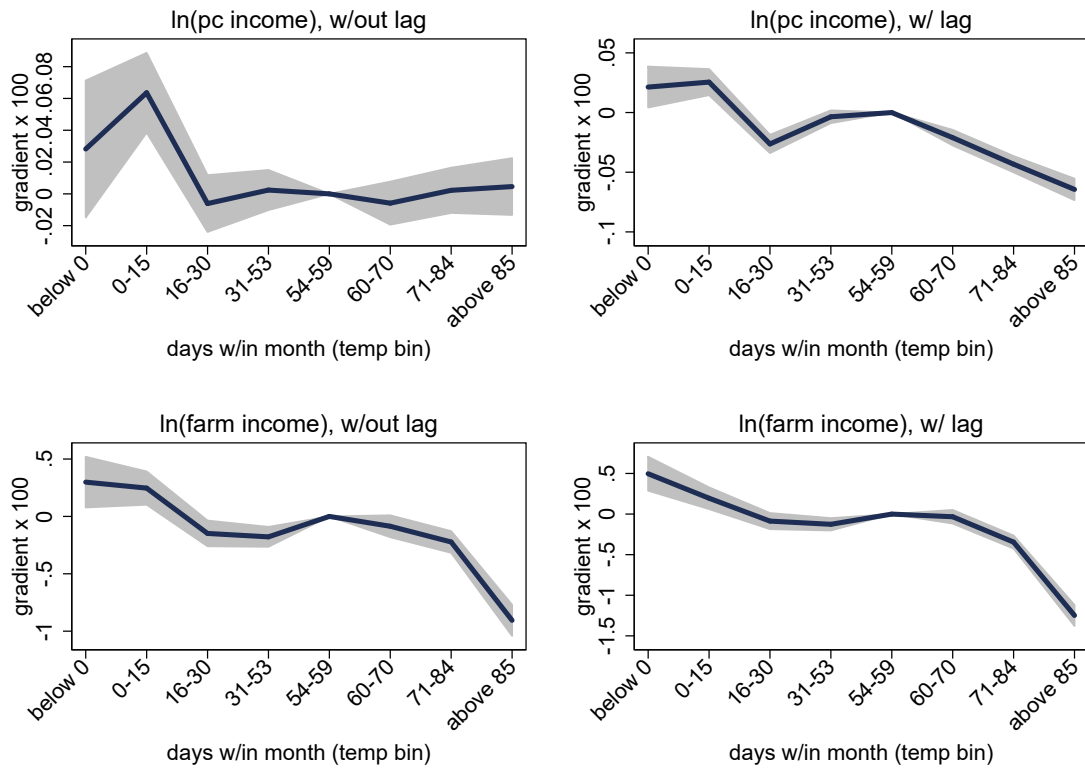


Figure 3: (Average Daily) Temperature and Per Capita Income / Farm Income

Notes.—Sources: PRISM and BEA regional data, 1970-2014. The figure plots the coefficients associated with regressions of logged county per capita income and logged county farm earnings on counts of the days in different temperature bins (based on average daily) and precipitation (as well as their one-year lags), conditional on county and year fixed effects. The difference between the specifications is that two contain lagged values of the outcome variable as additional controls to allow for dynamic effects. Observations are unweighted by county population. The sample is restricted to counties with at least 340 days of temperature records observed.

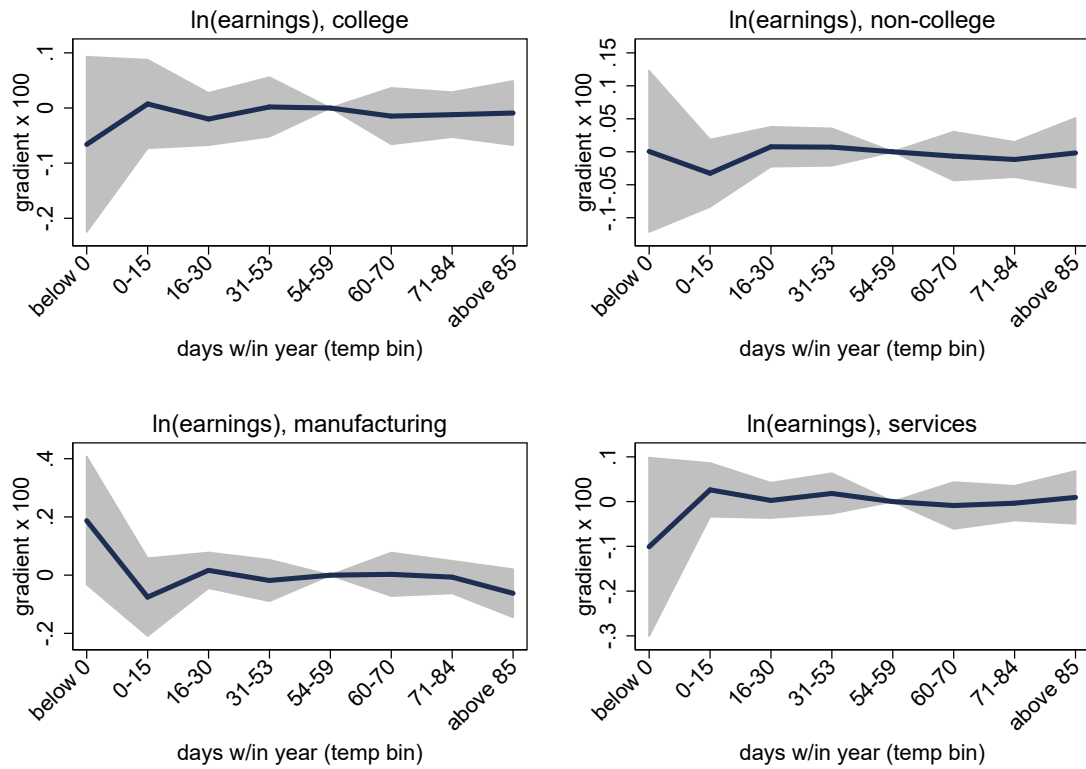


Figure 4: Semiparametric Response of Earnings to Temperature, 1963-2015

Notes.—Sources: NOAA, Current Population Survey (CPS) from 1963-2015. The figure reports the coefficients associated regressions of logged earnings (deflated using the 2010 personal consumption expenditure index) on bins for the number of days in a year that fall within the corresponding bin (e.g., number of days in a year below zero degrees Fahrenheit), which is unique at the metropolitan level. Controls include: a quadratic in both educational attainment and age, number of children, gender, marital status, and race. Standard errors are clustered at the metropolitan level (2013 OMB codes) and observations are weighted by the survey sample weights.

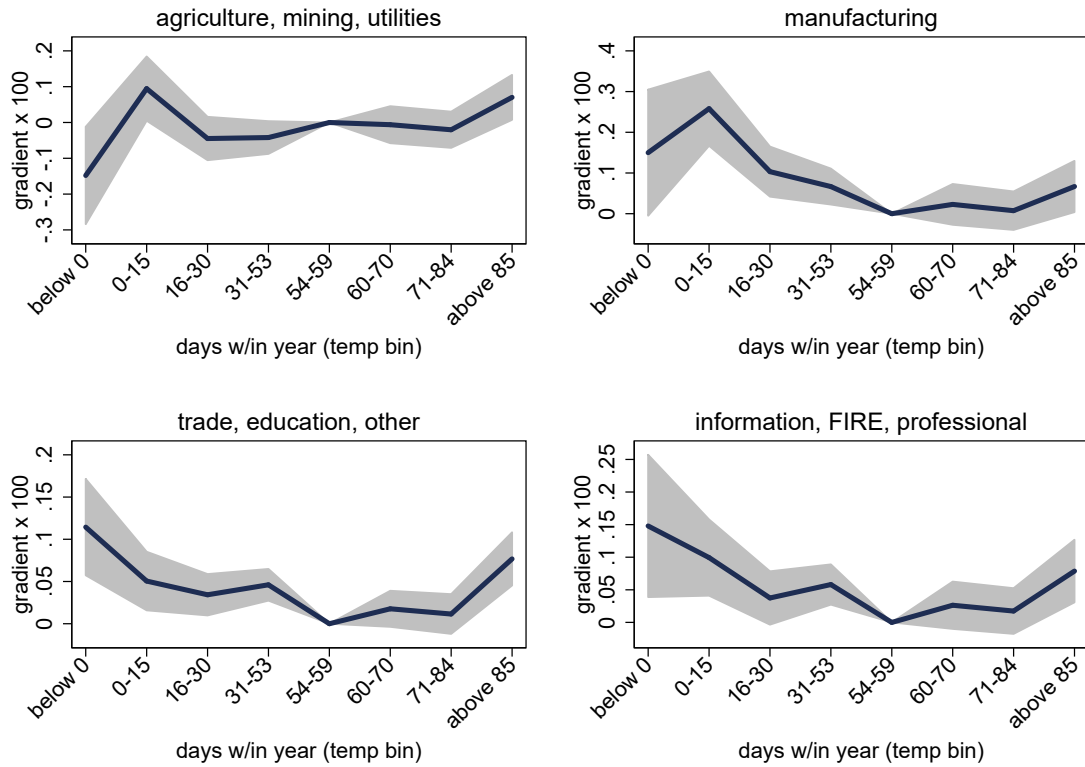


Figure 5: Semiparametric Response of Industry Earnings to Temperature, 1990-2014

Notes.—Sources: PRISM and Quarterly Census of Employment and Wages from 1990 to 2014. The figure reports the coefficients associated regressions of logged three-digit industry-by-county annual wages (deflated using the 2010 personal consumption expenditure index) on bins for the number of days in a year that fall within the corresponding bin (e.g., number of days in a year below zero degrees Fahrenheit), precipitation, and their lags, conditional on county, three-digit NAICS, and year fixed effects. Standard errors are clustered at the county-level. All observations are weighted equally.

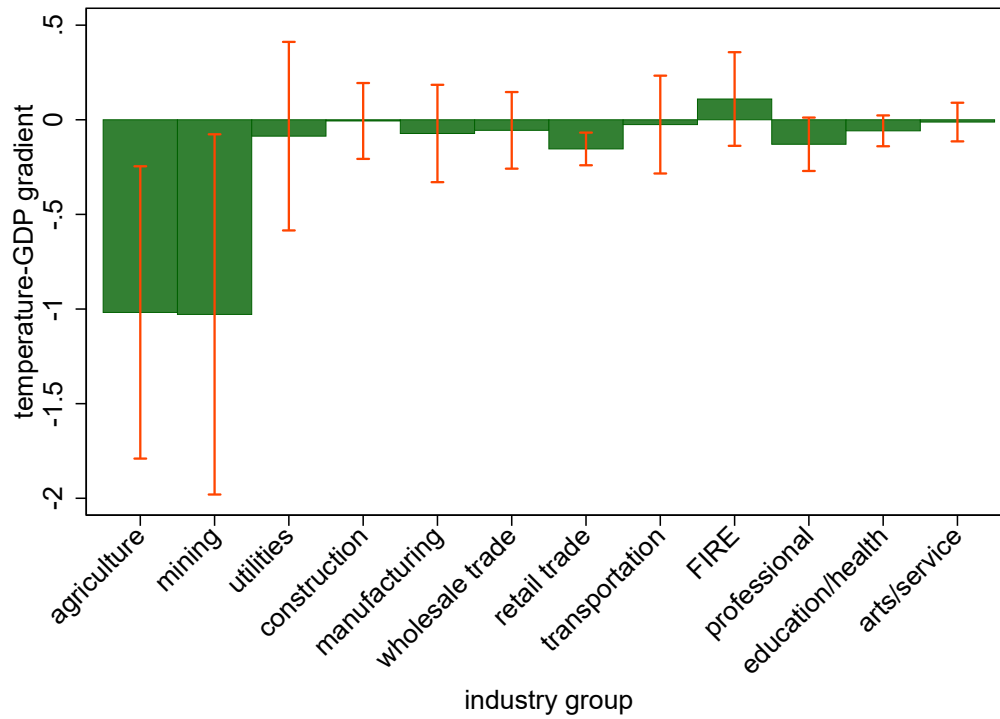


Figure 6: The Effects of Temperature on Metropolitan-by-Industry Gross Domestic Product

Notes.—Sources: BEA and NOAA, 2001-2015. The figure reports the coefficients associated with regressions of logged metropolitan-by-industry GDP on logged average temperature, conditional on metropolitan and year fixed effects. Standard errors are clustered at the metropolitan level.

Table 1: Long-run Differences and Evidence of Adaptation to Temperature

Dep. var. =	10-year growth rate in county average family income							
	All	All	All	All	All	All	LowAgMining	HiAgMining
10- Δ temperature	-2.76*** [.21]	-.87*** [.14]	-4.09*** [.25]	-3.00*** [.34]	-.78*** [.18]	-.85*** [.24]	.30 [.25]	-1.44*** [.26]
20- Δ temperature			-.57** [.23]	-.91** [.41]	1.22*** [.15]	.39 [.27]	1.33*** [.20]	1.13*** [.21]
interaction			141.22*** [9.25]	107.31*** [9.31]	38.03*** [6.19]	36.08*** [8.44]	21.77*** [6.21]	55.23*** [9.35]
10- Δ precipitation	-.10*** [.02]	.04*** [.01]	-.13*** [.02]	-.02 [.04]	.02 [.01]	.00 [.02]	.05*** [.02]	-.04** [.02]
10- Δ population	.17*** [.01]	.12*** [.03]	.16*** [.01]	.06*** [.02]	.11*** [.03]	.07** [.03]	-.00 [.03]	.23*** [.05]
10- Δ marriage	1.68*** [.11]	.44*** [.05]	1.67*** [.10]	1.67*** [.09]	.46*** [.05]	.57*** [.09]	.48*** [.08]	.35*** [.06]
10- Δ unemployment	-.02*** [.00]	-.03*** [.00]	-.02*** [.00]	-.06*** [.01]	-.03*** [.00]	-.04*** [.00]	-.04*** [.01]	-.03*** [.01]
10- Δ college	.32*** [.03]	.06*** [.01]	.30*** [.03]	.45*** [.02]	.06*** [.01]	.14*** [.02]	.14*** [.02]	.04** [.02]
10- Δ white	.25*** [.05]	.51*** [.04]	.23*** [.05]	-.13** [.06]	.47*** [.04]	.31*** [.05]	.59*** [.07]	.38*** [.05]
R-squared	.83	.94	.84	.91	.94	.97	.96	.93
Sample Size	12381	12381	12381	12381	12381	12381	5894	6487
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	No	No	No	No	Yes	No	No
Year FE	No	Yes	No	No	Yes	Yes	Yes	Yes
County FE	No	Yes	No	No	Yes	Yes	Yes	Yes

Notes.—Sources: NOAA and Census Bureau, 1960-2010. The table reports the coefficients associated with regressions of 10-year growth rates in family income on 10-year growth rates in average temperature, 20-year growth rates in average temperature, their interactions, conditional on 10-year differences in the control variables. Controls include: precipitation, semiparametric bins on the age distribution, race, male, marital status, college attainment, population, and the unemployment rate. Weights refers to the use of population weights. LowAgMining and HiAgMining refers to whether the county has at least 7% of its labor force working in the agriculture or mining sectors. Standard errors are clustered at the county-level.

Table 2: Model Fit: Industry shares (%)

Industry	Data	Model
Agriculture	2.9318	2.5936
Manufacturing	30.6759	33.0660
Business	33.0485	31.4581
Services	33.3438	32.8814

Notes.—“Data” refers to our data; “Model” refers to implied average choice probabilities using the estimates of the individual preference model.

Table 3: Model Fit: State shares (%)

State	Data	Model	State	Data	Model
AL	1.5859	1.5127	MT	0.2873	0.2589
AZ	1.5260	1.6435	NE	0.6592	0.5923
AR	0.8758	0.7709	NV	0.6196	0.7034
CA	9.9445	10.2835	NH	0.4913	0.4874
CO	1.6638	1.6680	NJ	3.1781	3.4080
CT	1.3603	1.4514	NM	0.5268	0.4905
DE	0.2949	0.2871	NY	6.8754	7.0920
DC	0.3066	0.2990	NC	2.9773	2.7670
FL	5.0567	5.0828	ND	0.2175	0.1995
GA	2.9633	2.8790	OH	4.6460	4.6140
ID	0.4057	0.3885	OK	1.1568	1.0632
IL	4.8725	5.0023	OR	1.1487	1.1126
IN	2.5036	2.4698	PA	4.8027	4.8315
IA	1.1595	1.0985	RI	0.3872	0.3667
KS	1.0325	0.9696	SC	1.4310	1.3024
KY	1.4341	1.3343	SD	0.2454	0.2063
LA	1.5111	1.4609	TN	2.0848	1.9283
ME	0.4566	0.4139	TX	7.3558	7.4962
MD	2.2019	2.3225	UT	0.7295	0.7339
MA	2.4536	2.5199	VT	0.2233	0.1964
MI	3.7324	3.8669	VA	2.7413	2.7672
MN	1.8826	1.9074	WA	2.0132	2.0772
MS	0.9001	0.7904	WV	0.6376	0.5890
MO	2.1222	1.9967	WI	2.1181	2.0931
			WY	0.1999	0.2028

Notes.—“Data” refers to our data; “Model” refers to implied average choice probabilities using the estimates of the individual preference model.

Table 4: Structural Wage Estimates

Variable	(1)	(2)
log GDP	0.158*** (0.002)	0.219*** (0.002)
log employment (agriculture)	0.023*** (0.001)	0.034*** (0.002)
log employment (manufacturing)	0.017*** (0.000)	0.000 (0.001)
log employment (business)	0.035*** (0.000)	0.071*** (0.001)
log employment (services)	0.060*** (0.001)	-0.043*** (0.001)
Average temperature	0.035*** (0.001)	0.021*** (0.001)
Avg temperature squared / 100	-0.024*** (0.001)	-0.014*** (0.001)
Std Dev temperature	0.025*** (0.001)	0.019*** (0.001)
ρ	0.842 (0.002)	0.781 (0.002)
θ agriculture	1.287 (0.074)	1.269 (0.042)
θ manufacturing	1.280 (0.073)	1.226 (0.041)
θ business	1.301 (0.074)	1.317 (0.042)
θ services	1.260 (0.072)	1.225 (0.040)
N	7,400,291	7,400,291
Demographic characteristics	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	
State fixed effects	Yes	
State-Industry fixed effects		Yes

Notes.—Sources: 2% sample of the 1970 Census (Form 1 State and Form 2 State samples), 5% samples of 1980, 1990, and 2000 Censuses, and 2010–2014 1% samples from the American Community Survey. “Demographic characteristics” includes dummies for highest degree attained, race dummies, gender dummy, and a cubic in age. All individuals are household heads.

Table 5: Household Preference Estimates

Variable	(1)
$\log(wage)$	1.0671
$\log(rent)$	-0.1003
Avg temperature	-0.0389
Avg temperature \times college	0.0228
Avg temperature \times non-white	0.0063
Avg temperature \times $age \geq 40$	-0.0056
Avg temperature \times female	0.0243
(Avg temperature) ²	0.0004
(Avg temperature) ² \times college	-0.0002
(Avg temperature) ² \times non-white	-0.0001
(Avg temperature) ² \times $age \geq 40$	0.0000
(Avg temperature) ² \times female	-0.0002
SD(temperature)	0.0337
SD(temperature) \times college	-0.0107
SD(temperature) \times non-white	-0.0152
SD(temperature) \times $age \geq 40$	-0.0024
SD(temperature) \times female	-0.0190
Born in state	4.5447
Born in state \times college	-0.8003
Born in state \times non-white	-0.1589
Born in state \times $age \geq 40$	-0.1353
Born in state \times female	-0.0354
Born in division	0.0550
Born in division \times college	-0.0651
Born in division \times non-white	0.1681
Born in division \times $age \geq 40$	-0.0189
Born in division \times female	-0.0390
industry FE	Yes
industry-demographic interactions	Yes
state FE	Yes
state-demographic interactions	Yes
<i>N</i>	222,083

Notes.—Sources: NOAA and Census Bureau, 1970-2014. Demographics include college degree dummy, non-white dummy, $age \geq 40$ dummy, and gender dummy.

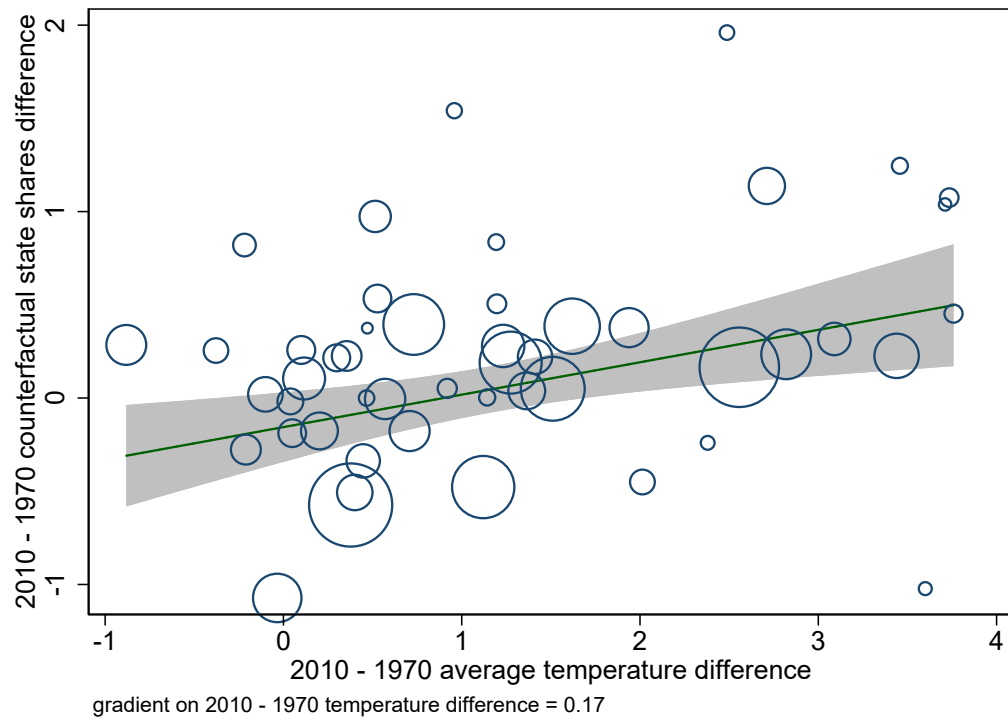


Figure 7: 2010 - 1970 Actual Temperature with Counterfactual Population Change

Notes.—The figure plots the 2010 - 1970 difference in average state temperature with the counterfactual 2010 - 1970 change in the state population share.

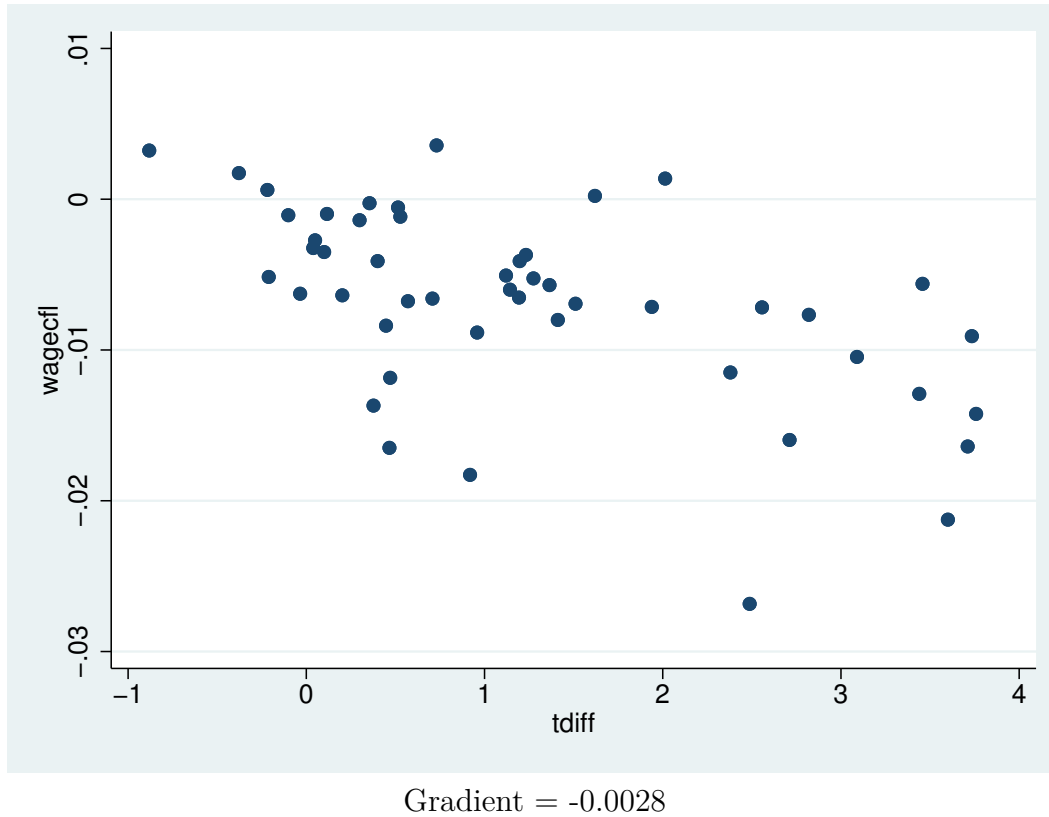


Figure 8: 2010 - 1970 Actual Temperature with Counterfactual Wage Change

Notes.—The figure plots the 2010 - 1970 difference in average state temperature with the counterfactual 2010 - 1970 change in the state wages.

Table 6: 1970 temperature counterfactual wages by industry

Industry	Δw
Agriculture	-0.0064
Manufacturing	-0.0053
Business	-0.0063
Services	-0.0061

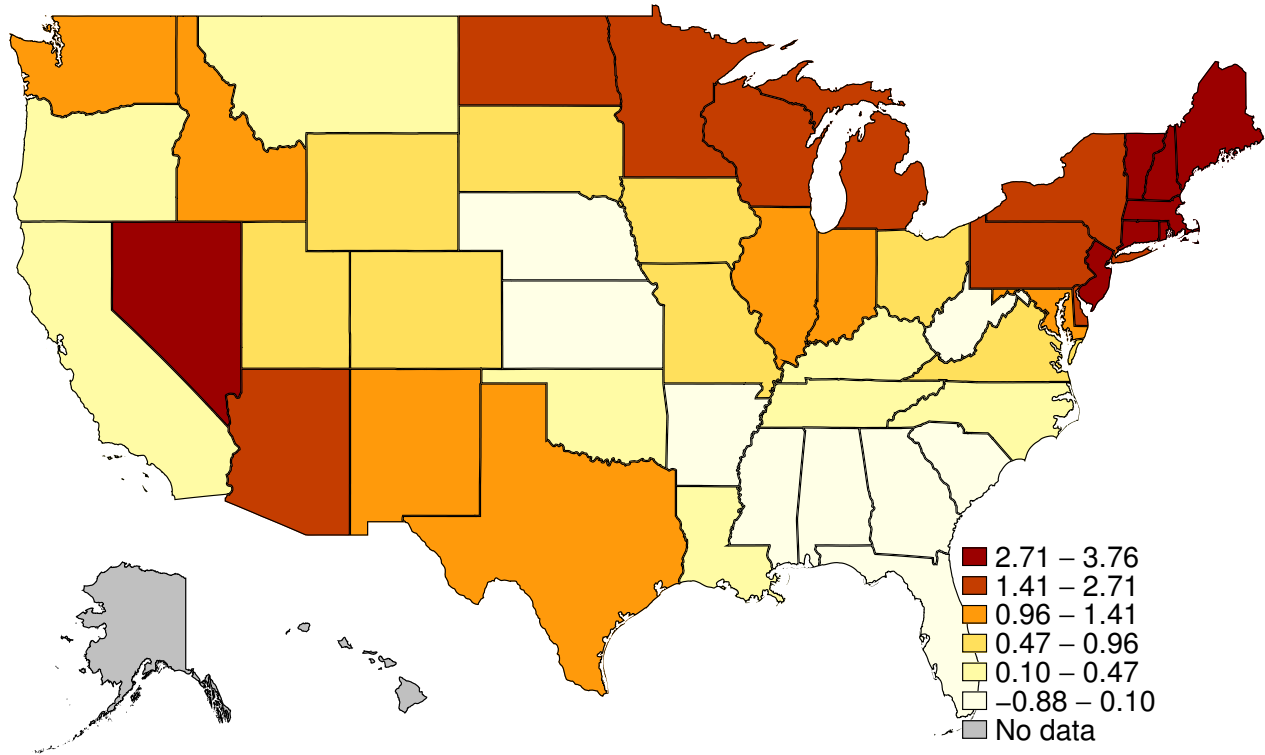


Figure 9: 1970–2010 change (°F) in temperature by state

Notes.—The figure plots the 1970–2010 change in temperature by state.

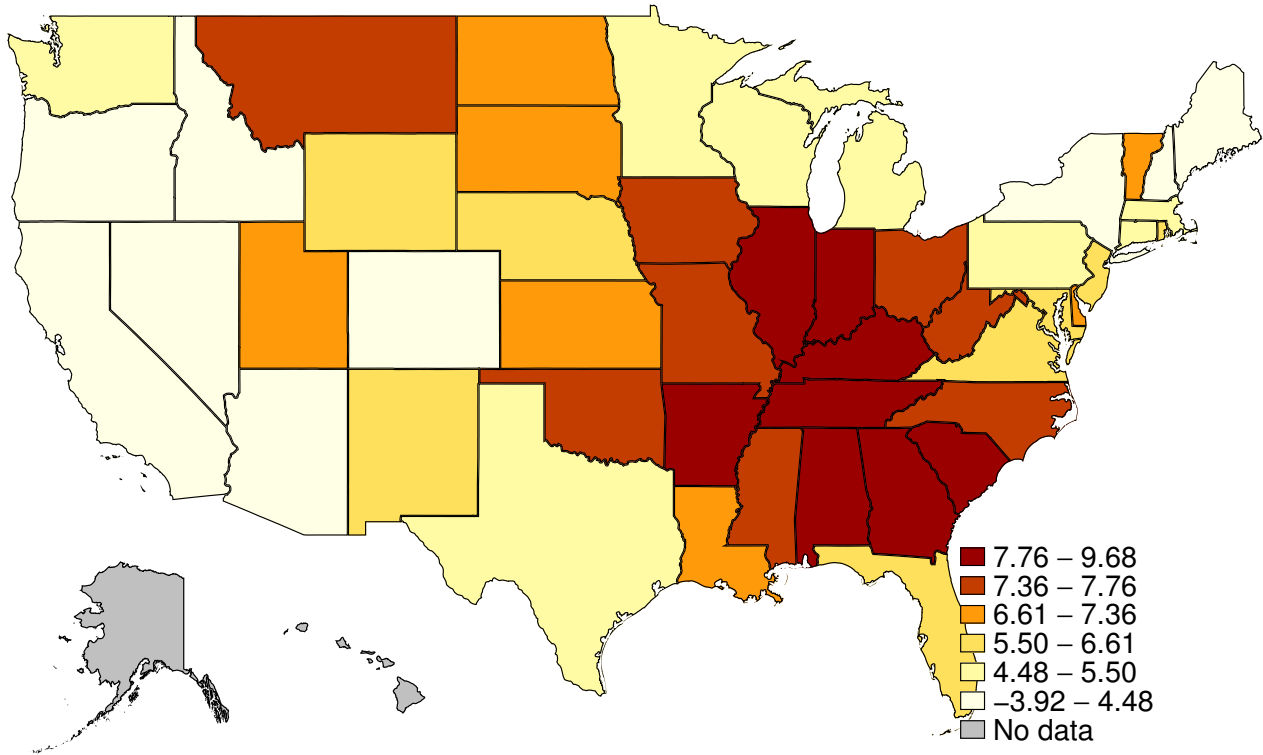


Figure 10: 2010–2099 projected change in temperature (°F) by state

Notes.—The figure plots the 2010–2099 projected change in temperature by state.

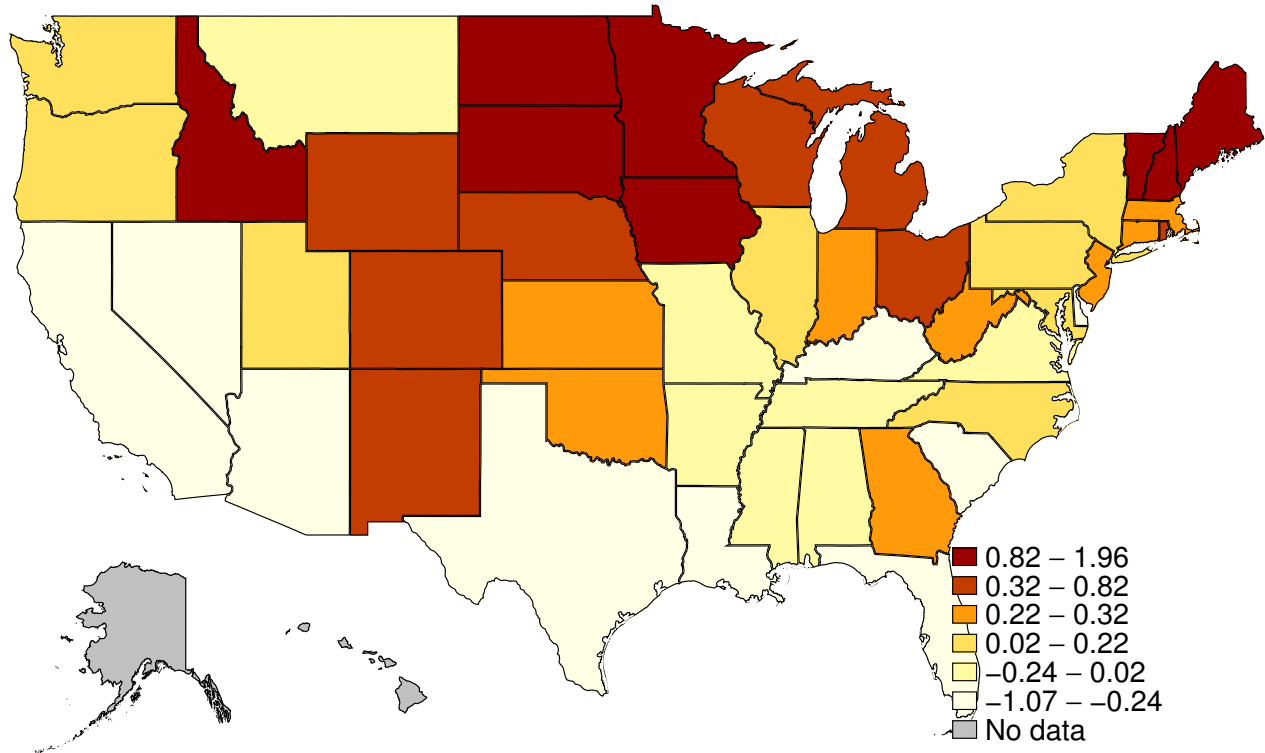


Figure 11: Percent change in state shares if temperature distribution were same as 1970

Notes.—The figure plots the percentage difference in the probability of living in a given state in the 1970 temperature counterfactual compared to the baseline.

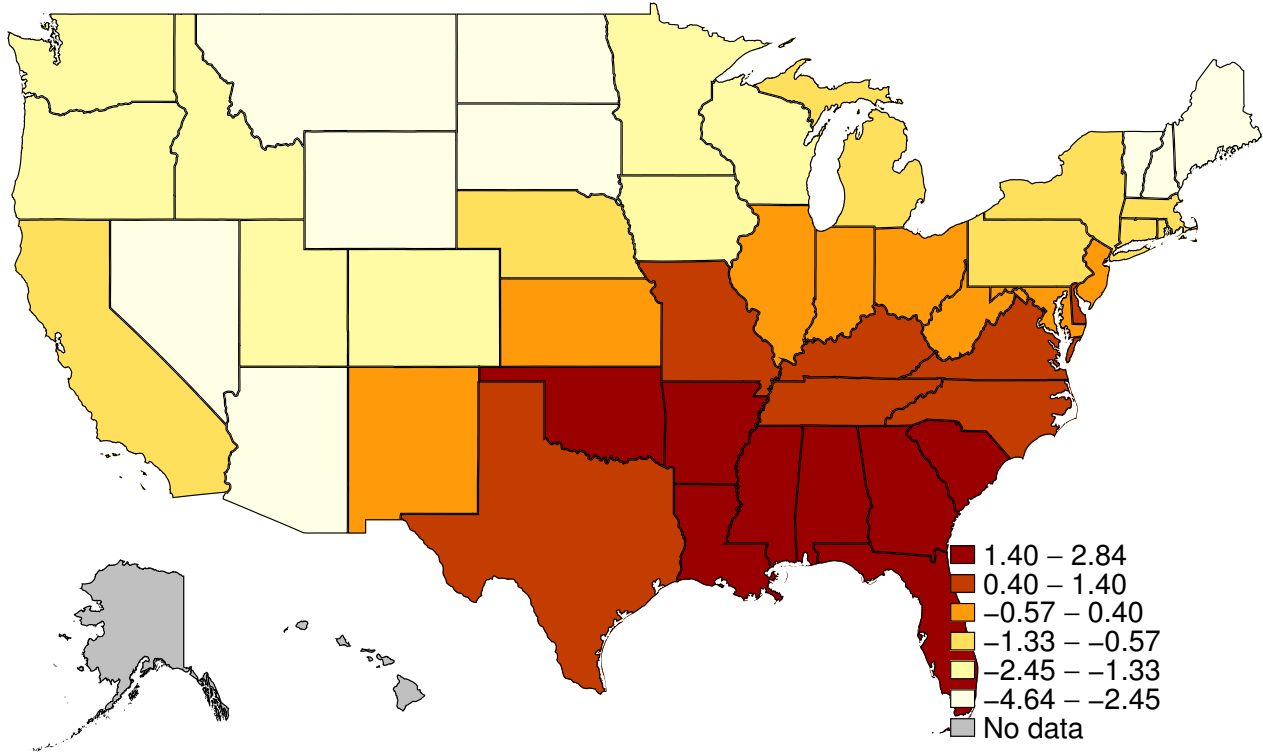


Figure 12: Percent change in state shares if temperature distribution were same as 2099 projection

Notes.—The figure plots the percentage difference in the probability of living in a given state in the 2099 temperature counterfactual compared to the baseline. We hold standard deviation of temperature fixed at the baseline (status quo) since there is not a future projection for this measure.

8. Online Appendix (Not for Print)

8.1. A Stylized Model for Demand

This section begins by outlining a stylized model that focuses purely on the potential effects of temperature on the allocation of time as motivating evidence for plausible demand-side mechanisms. Suppose an individual has preferences over consumption (c), leisure ($l = 1 - n$), and temperature (T) through the following equation²⁰

$$u(c, l; T) = \frac{c^{1-\nu}}{1-\nu} + \chi \frac{(l^\alpha T^{1-\alpha})^{1-\gamma}}{1-\gamma} \quad (27)$$

²⁰The approach here involves modeling temperature as an input in preferences. The Appendix develops a stylized model with temperature indirectly affecting productivity through the presence of moral hazard in the work place. Since temperature may decrease individual-level productivity, this raises the desire for employees to shirk since labor services are not perfectly observed. While this alternative formulation is reasonable and promising, it is analytically intractable, and thus is omitted for the sake of a simple stylized model.

subject to a budget constraint equal to $c = w(1 - l)$. ν governs the intertemporal elasticity of substitution, χ governs the relative disutility of working, $\alpha \in (0, 1)$ governs the relative elasticity of temperature and leisure, and γ governs the elasticity of labor supply. While the individual can choose consumption and leisure, temperature is taken as exogenous. The first-order conditions produce the following equilibrium condition

$$w = c^\nu \chi \alpha T^{1-\alpha} (l^\alpha T^{1-\alpha})^{-\gamma} l^{\alpha-1} = c \chi \alpha T^{(1-\alpha)(1-\gamma)} l^{\alpha(1-\gamma)-1} \quad (28)$$

Equation 28 is nothing more than the standard intratemporal Euler with non-separable interactions between labor supply and temperature. Taking logs of Equation 28 produces

$$\ln w = \beta_0 + \nu \ln c + [\alpha(1 - \gamma) - 1] \ln l + (1 - \alpha)(1 - \gamma) \ln T \quad (29)$$

where $\beta_0 = \ln \chi + \ln \alpha$. The income elasticity of temperature is, therefore, given by

$$\partial \ln w / \partial \ln T = (1 - \alpha)(1 - \gamma) \quad (30)$$

The introduction of temperature in Equation 27 is grounded in the observation that higher levels of temperature make leisure activities, such as time out doors, less desirable (Graff Zivin and Neidell, 2014). Solving for the optimal allocation of leisure from Equation 28 produces

$$l^* = \left[\frac{w T^{(1-\alpha)(1-\gamma)}}{\chi \alpha c^\nu} \right]^{\frac{1}{\alpha(1-\gamma)-1}} \quad (31)$$

which shows that the optimal allocation of leisure is decreasing in temperature

$$\frac{\partial l}{\partial T} = - \left[\frac{1}{\alpha(1 - \gamma) - 1} \right] \left[\frac{w T^{(1-\alpha)(1-\gamma)}}{\chi \alpha c^\nu} \right]^{\frac{2-\alpha(1-\gamma)}{\alpha(1-\gamma)-1}} (1 - \alpha)(1 - \gamma) w T^{(1-\alpha)(1-\gamma)-1} / (\chi \alpha) < 0 \quad (32)$$

when $\gamma > 1$ with an elasticity of leisure and temperature given by

$$\frac{\partial \ln l}{\partial \ln T} = - \frac{(1 - \gamma)(1 - \alpha)}{\alpha(1 - \gamma) - 1} \quad (33)$$

While there is still a debate between the elasticity of labor supply (e.g., see Chetty (2012)

and Keane and Rogerson (2012) for competing views), an elasticity greater than unity means that an increase in temperature is associated with a decline in the hourly wage. The key empirical question is the magnitude of the coefficient on $\ln T$ in Equation 29: how does temperature affect the hourly wage? Whether or not the coefficient on $\ln T$ is small depends crucially on the extent to which individuals adapt to weather fluctuations by undertaking defensive investments (e.g., in the case of tropical cyclones, building sand walls (Hsiang and Narita, 2012) or buy consumer durables (e.g., in the case of heat, using air conditioning (Barreca et al., 2016) as forms of adaptation. These regressions are also conceptually related to a much older hedonic pricing literature that examined how risk is priced into different jobs (Aldy and Viscusi, 2008; Viscusi, 1979).²¹ If random temperature fluctuations reflect truly idiosyncratic risk, then areas that are very hot or very cold must compensate employees more.

8.2. Supplement to Short Run Invariance to Temperature

8.2.1. Replication Exercises of Hsiang and Deryugina

8.3. Replication of Deryugina and Hsiang (2014)

Before turning to the main results, it is useful to begin by replicating an important, salient, and recent contribution from Deryugina and Hsiang (2017). Using per capita income between roughly 1970 and 2011 at the county level, they document a negative gradient on temperature: an additional 1.8F increase in daily temperature is associated with a 1.7% decline in per capita income (productivity). For comparability, we follow their data construction and specification for the baseline results and pointing out points of deviation when presenting different results.

The top-right plot in Figure 3 replicates their main results by estimating the relationship between logged per capita income and the flexible function of temperature across different parts of the distribution. It shows that there is a statistically significant negative gradient between the two at the top of the temperature distribution, whereas there is a null relationship below 70 degrees. The bottom-right plot in Figure 3 also documents the strong negative relationship at the top of the temperature distribution when the outcome variable is logged farm earnings.

²¹Cropper and Arriaga-Salinas (1980), Cropper (1988), and Smith (1983) showed that linking the job with the site characteristics (e.g., air quality) was important for identification since sites differ for many unobserved reasons. This is addressed through measures of individual skill content, occupation and industry fixed effects, and MSA fixed effects.

However, several modifications of the specification lead to different results. For example, the top-left plot in Figure 3 takes out the lagged dependent variable (per capita income), which removes the negative relationship. Importantly, the decline in the temperature gradient is not coming from the lack of a dynamic relationship—lagged values of the temperature bins are still included in the regression. Instead, the difference comes exclusively from the inclusion of the lagged outcome variable. Interestingly, however, including it in the case of farm earnings as the outcome variable does not alter the results. We are still looking into potential counter-explanations for our contrasting results, but we believe there are two possible reasons.

The first is that there is the well-known Nickell (1981) bias. However, given that the sample series covers such a wide range of years, it is unlikely the main culprit. In other (omitted) diagnostics where we vary the length of the sample horizon, the bias does not seem to change considerably. The second is that lagged per capita income is likely correlated with many other factors, in particular mobility, that are also correlated with temperature. While these endogeneity concerns would be present even without the lagged variable inserted as a control, introducing a lag can amplify these concerns. For example, Reed (2013) shows that lagging highly persistent variables can introduce significant bias and create an appearance of an effect when none exists in reality. Bias is often accelerated when the sample size grows. Bellemare et al. (2016) further highlights that the inclusion of lagged values introduces a “no dynamics among unobservables” assumption that is unlikely to hold in reality.

[INSERT FIGURE 3 HERE]

Why, then, are the results with farm income as the outcome variable relatively invariant to the inclusion of lagged farm income as a control? While per capita income is likely to be correlated with shocks affecting migration probabilities and other correlates of quality of life, farm income is less so because of the low employment share in agriculture. In this sense, to the extent there are unobserved factors bundled in the ϵ in Equation 1 that are correlated with temperature, these factors will be amplified when including lagged per capita income since these unobserved factors are likely to be even more heavily correlated with per capita income.

We now explore several additional specifications in Table 7: (i) weighting by population, and (ii) endogeneity arising from the inclusion of lagged income. Column 1 presents the baseline results, which includes lagged values of the semiparametric temperature spline and precipitation. These coefficients are unweighted. Column 2 now weights by population, showing that there is

no significant gradient at the top of the distribution for these areas. Columns 3 and 4 restrict the sample to counties with over 350 and 360 days of observations, respectively, which does not produce any meaningful differences relative to the benchmark. Column 5 now includes population growth as an additional control, which does not alter the coefficients by much.

Column 6 removes the lags on temperature and precipitation, which reduces the magnitude of the coefficients at the top of the temperature distribution by only a few percentage points. Columns 7 and 8 both include lagged per capita income as a control on the right hand side of the equation. However, one concern, especially when $N > T$, is that bias can emerge in dynamic panel data models (Nickell, 1981). Therefore, column 8 instruments for lagged per capita income using third and fourth period lags (Arellano and Bond, 1991). However, the results are only marginally affected.

Table 7: Temperature and Productivity Robustness Exercises

Dep. var. =	ln(per capita income)							
	base	weighted	>350days	365days	popgrowth	nolags	dynamic	dynamic
days $t < 0$, F	-.0009*** [.0002]	-.0009** [.0004]	-.0009*** [.0002]	-.0009*** [.0002]	-.0008*** [.0002]	-.0007*** [.0002]	.0002** [.0001]	.0008*** [.0001]
days $0 < t < 15$, F	.0006*** [.0001]	.0003 [.0003]	.0006*** [.0001]	.0005*** [.0001]	.0006*** [.0001]	.0007*** [.0001]	.0003*** [.0001]	.0003*** [.0001]
days $16 < t < 30$, F	-.0006*** [.0001]	-.0006*** [.0002]	-.0006*** [.0001]	-.0007*** [.0001]	-.0006*** [.0001]	-.0006*** [.0001]	-.0003*** [.0000]	-.0002*** [.0000]
days $31 < t < 53$, F	-.0002*** [.0001]	-.0002 [.0001]	-.0002*** [.0001]	-.0002*** [.0001]	-.0002*** [.0001]	-.0002*** [.0001]	-.0000 [.0000]	.0000 [.0000]
days $60 < t < 70$, F	-.0005*** [.0001]	-.0003*** [.0001]	-.0006*** [.0001]	-.0005*** [.0001]	-.0005*** [.0001]	-.0005*** [.0001]	-.0002*** [.0000]	-.0001*** [.0000]
days $71 < t < 84$, F	-.0006*** [.0001]	-.0003 [.0002]	-.0006*** [.0001]	-.0007*** [.0001]	-.0006*** [.0001]	-.0005*** [.0001]	-.0004*** [.0000]	-.0003*** [.0000]
days $t > 85$, F	-.0004*** [.0001]	-.0000 [.0002]	-.0004*** [.0001]	-.0004*** [.0001]	-.0004*** [.0001]	-.0002*** [.0001]	-.0006*** [.0000]	-.0006*** [.0000]
population growth					.3528*** [.0394]			
$\ln(\text{pc income})^{t-1}$.7805*** [.0072]	.8619*** [.0066]
R-squared	.88	.94	.88	.89	.88	.89	.95	.95
Sample Size	95569	95569	94075	77161	95569	105159	95566	76792
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.—Sources: Bureau of Economic Analysis and PRISM, 1970-2014. The table reports the coefficients associated with regressions of logged county per capita income on a semiparametric measure of temperature that counts the number of days within a year-county between a given temperature threshold, conditional on controls.

We now turn towards actual evidence that the introduction of the lagged outcome variable

(Maximum Daily) Temperature and Per Capita Income / Farm Income

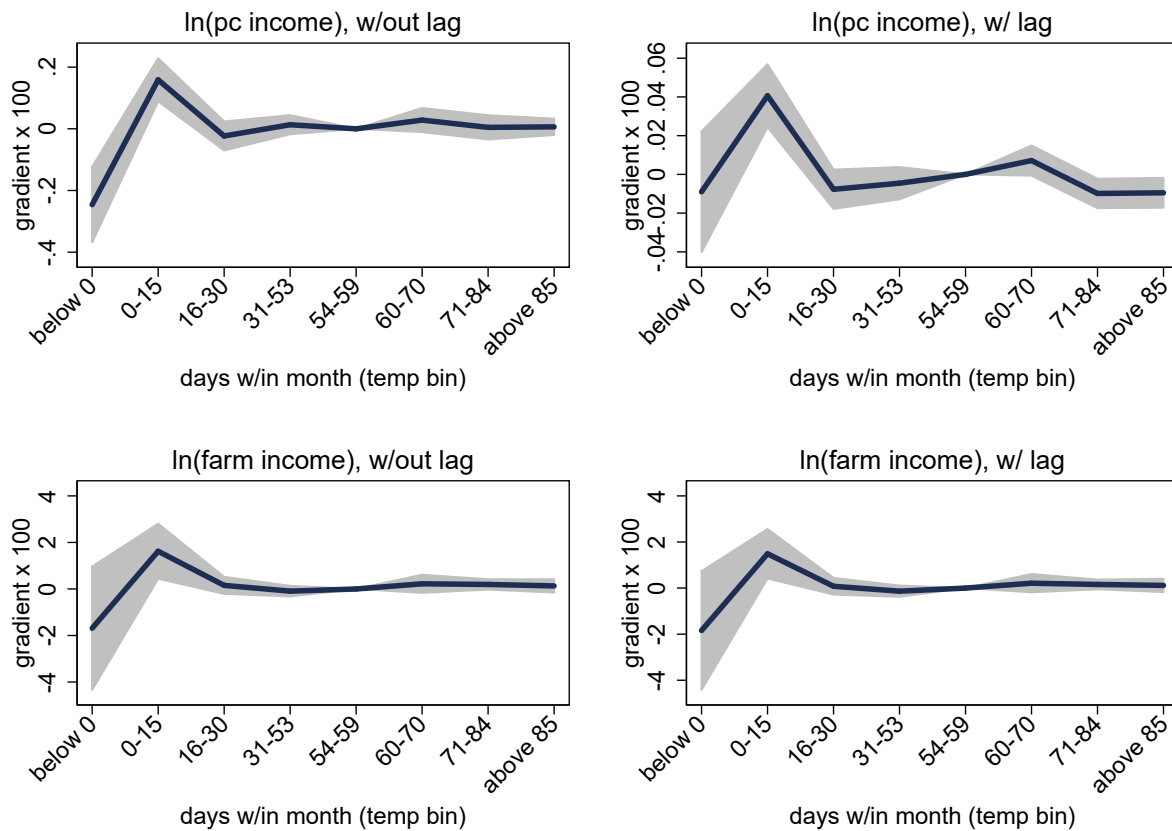


Figure 13: Notes.—Sources: PRISM and BEA regional data, 1970-2014. The figure plots the coefficients associated with regressions of logged county per capita income and logged county farm earnings on counts of the days in different temperature bins (based on maximum daily), conditional on county and year fixed effects and county precipitation all at the county-by-year level. The difference between the specifications is that two contain lagged values of the outcome variable as additional controls to allow for dynamic effects. Observations are weighted by county population. The sample is restricted to counties with at least 340 days of temperature records observed.

creates a new source of endogeneity. The main concern is that unobserved shocks to per capita income that are correlated with temperature shocks will be amplified when a lagged value of the outcome variable are included. For example, if migration across counties is influenced by economic development, and economic development is correlated with temperature, then the lagged dependent variable accelerates the rate at which bias takes place.

Table 8 tests this hypothesis by using the population growth rate—which behaves as a proxy for migration—regressed on not only the growth rate of average temperatures (or maximum daily), but also the growth rate of per capita income and farm earnings. While increases in the growth rates of both temperature and per capita income are associated with statistically significant declines in county population growth rates, increases in the growth rate of farm income are not. These results are consistent with the hypothesis that changes in migration are likely correlated with both per capita income and temperature shocks, but not with farm earnings shocks.

Table 8: Testing for Bias with Lagged Dependent Variables

Dep. var. =	county population growth rate	
	(1)	(2)
$\Delta \ln(\text{avg temperature})$	-.0037*** [.0013]	-.0024* [.0012]
$\Delta \ln(\text{per capita income})$	-.0266*** [.0016]	
$\Delta \ln(\text{farm income})$		-.0000 [.0000]
R-squared	.01	.00
Sample Size	95699	92956

Notes.—Sources: Bureau of Economic Analysis and PRISM, 1970-2014. The table reports the coefficients associated with regressions of the county population growth rate on the growth in average temperature and the growth in per capita income or farm income. Both per capita income and farm income are deflated using the 2010 personal consumption expenditure index. Standard errors are clustered at the county-level.

8.3.1. Individual Level Regressions

The main text presented results using the annual CPS between 1963 and 2015 to assess the impact of temperature on earnings. Figure 14 now examines the impact of temperature on weekly hours worked. Like before, there is no statistically significant association between temperature and hours for any of the four sub-groups (college, non-college, manufacturing, and services). Figure 15 also plots the semiparametric response between temperature and earnings using the monthly

CPS between 1994 and 2014; the results are unchanged. If anything, hours appears to rise at the top of the temperature distribution.

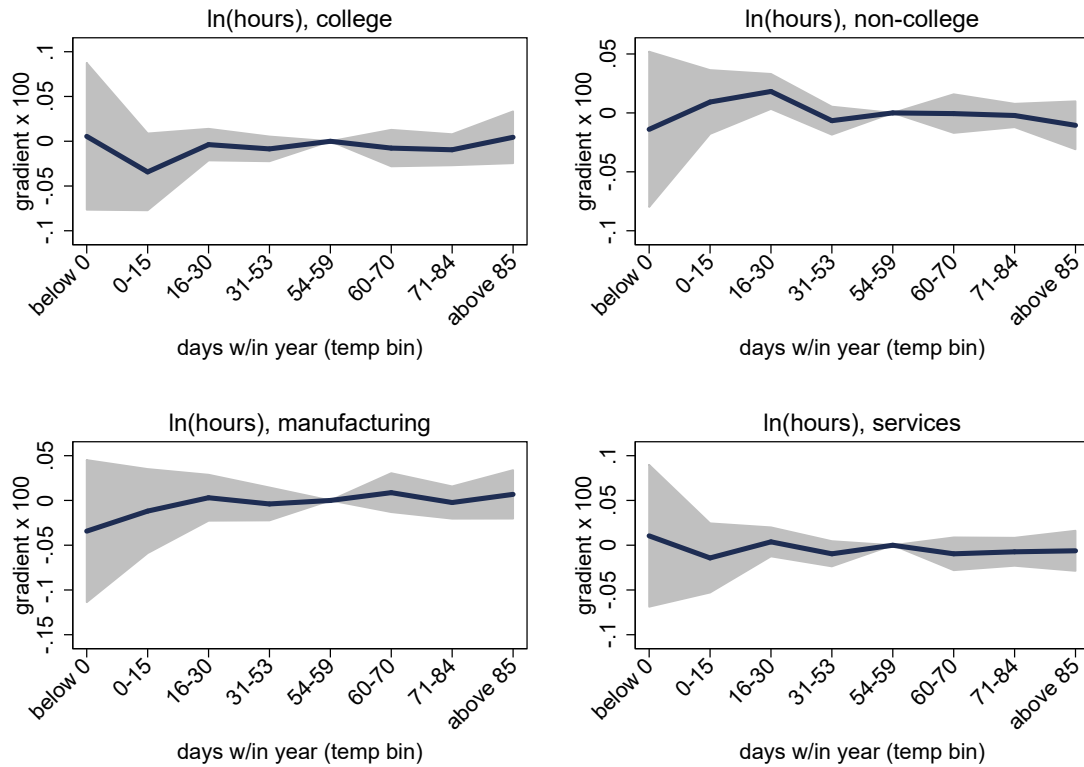


Figure 14: Semiparametric Response of Hours to Temperature, 1963-2015

Notes.—Sources: NOAA, Current Population Survey (CPS) from 1963-2015. The figure reports the coefficients associated regressions of logged weekly hours worked (deflated using the 2010 personal consumption expenditure index) on bins for the number of days in a year that fall within the corresponding bin (e.g., number of days in a year below zero degrees Fahrenheit), which is unique at the metropolitan level. Controls include: a quadratic in both educational attainment and age, number of children, race, gender, marital status, and race. Standard errors are clustered at the metropolitan level (2013 OMB codes) and observations are weighted by the survey sample weights.

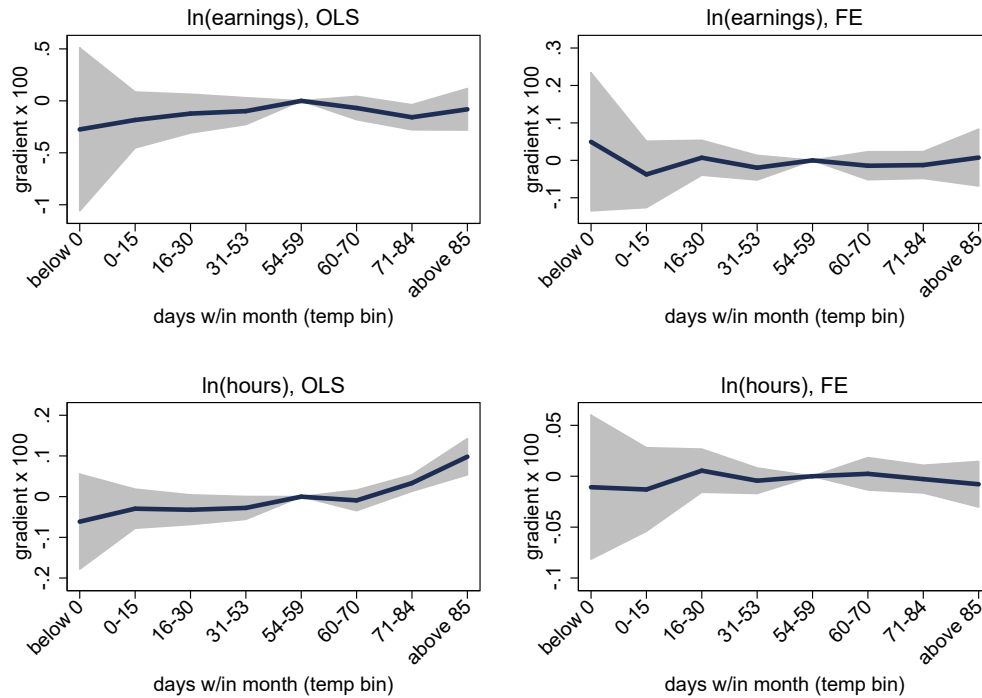


Figure 15: Semiparametric Response of Earnings / Hours to Temperature, 1994-2014

Notes.—Sources: NOAA, Current Population Survey (CPS) monthly from 1994-2014. The figure reports the coefficients associated with least squares and fixed effects regressions of logged weekly earnings (deflated using the 2010 personal consumption expenditure index) and separately of logged weekly hours worked on bins for the number of days in a month that fall within the corresponding bin (e.g., number of days in a month below zero degrees Fahrenheit), which is unique at the metropolitan level. Controls include: a quadratic in both educational attainment and age, number of children, race, gender, marital status, and race. Standard errors are clustered at the metropolitan level (2013 OMB codes) and observations are weighted by the survey sample weights.

While the semiparametric results do not suggest that there is an association, we now consider simpler results involving a regression of logged earnings and hours worked on logged average and maximum metropolitan temperature. Table 9 documents these. While there is a very significant negative correlation in the cross-section—for example, a 1% rise in maximum (mean) annual temperature is associated with a 0.37% (0.17%) decline in annual earnings—the magnitude and precision drop significantly once individual controls are included. The negative correlation vanishes once metropolitan and year fixed effects are introduced. In fact, column 5 suggests that, if anything, there is a positive association! Although not reported, we also examined the potential for alternative functional forms, including non-linearities through the inclusion of a polynomial for temperature and linear (rather than log) terms. However, these specifications affected neither the magnitude nor the precision.²²

²²For example, when temperature is measured in logs, the coefficients on the direct and non-linear terms (for a quadratic specification) are 0.075 (p -value = 0.969) and -0.010 (p -value = 0.966). When temperature is measured in levels, the coefficients are 0.00025 (p -value = 0.979) and 0.00000979 (p -value = 0.999).

Table 9: Temperature and Income & Labor Supply using the Current Population Survey, 1963-2015

Dep. var. =	ln(annual earnings)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
ln(mean temperature)		-.17*** [.04]		-.09** [.04]		-.01 [.06]
ln(max temperature)	-.37*** [.10]		-.19** [.08]		.14** [.06]	
R-squared	.00	.00	.30	.30	.31	.31
Sample Size	1464264	1464264	1353166	1353166	1353166	1353166
Dep. var. =	ln(weekly hours worked)					
Panel B						
ln(mean temperature)		.04*** [.01]		.05*** [.01]		.02 [.02]
ln(max temperature)	.11*** [.01]		.13*** [.01]		.04* [.02]	
R-squared	.00	.00	.06	.06	.06	.06
Sample Size	1464264	1464264	1353166	1353166	1353166	1353166
Controls	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes
Metro FE	No	No	No	No	Yes	Yes

Notes.—Sources: NOAA, Current Population Survey (CPS) from 1963-2015. The table reports the coefficients associated with regressions of logged annual earnings (deflated using the 2010 personal consumption expenditure index) on logged temperature, which is proxied using both the average across months in the same year and the maximum across months. Controls include: a quadratic in both educational attainment and age, number of children, race, gender, marital status, and race. Standard errors are clustered at the metropolitan level (2013 OMB codes) and observations are weighted by the survey sample weights.

One concern with these results, however, is that the gradient between temperature and income might have longer-lasting dynamic effects. To examine the potential for dynamic effects, we estimate regressions of the form

$$y_{ijt} = \beta X_{it} + \sum_{l=0}^{10} \psi^l T_{j,t+l} + \phi_j + \lambda_t + \epsilon_{ijt} \quad (34)$$

where y denotes logged annual earnings, X denotes the usual vector of controls, $\sum_l \psi^l$ denotes the cumulative impulse response associated with a rise in logged average temperatures, and ϕ and λ are fixed effects on metropolitan area and year. Figure 16 plots the estimated ψ^l 's associated with Equation 34 using 10 forward variables. While the OLS estimates are not identified due to non-random sorting, it is interesting to point out that they suggest an initial rise in income in response to a temperature shock, which slowly decline in magnitude and turns negative around roughly the $t+7$ -th forward variable. However, the more plausibly exogenous fixed effects estimates display no trend and hover around zero.

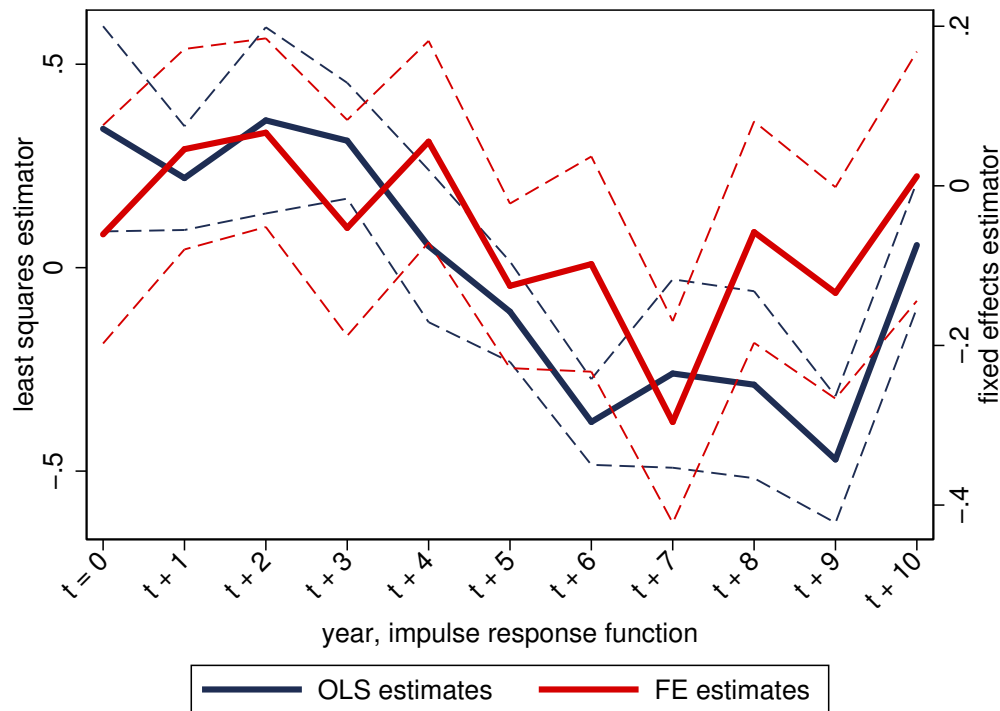


Figure 16: Examining Dynamic Effects via an Impulse Response Function

Notes.—Sources: NOAA, Current Population Survey (CPS) from 1963-2015. The table reports the coefficients associated with regressions of logged annual earnings (deflated using the 2010 personal consumption expenditure index) on logged average temperature and 10 one-year forward variables. Controls include: a quadratic in both educational attainment and age, number of children, race, gender, marital status, and race. Standard errors are clustered at the metropolitan level (2013 OMB codes) and observations are weighted by the survey sample weights.

8.3.2. Industry-level Regressions

This section explores a large series of robustness exercises using industry-by-location-level data to assess the relationship between temperature and earnings. First, Figure 17 considers a broader measure of employee earnings based on their total pay, rather than annual wages. While wages already include bonuses, stock options, severance pay, and other gratuities (<https://www.bls.gov/cew/cewfaq.htm>), total pay includes several additional components of compensation. Evidently, there is no qualitative change in the main result that there is no association between earnings and temperature. If anything, there appears to be an uptick in earnings at the top of the temperature distribution.

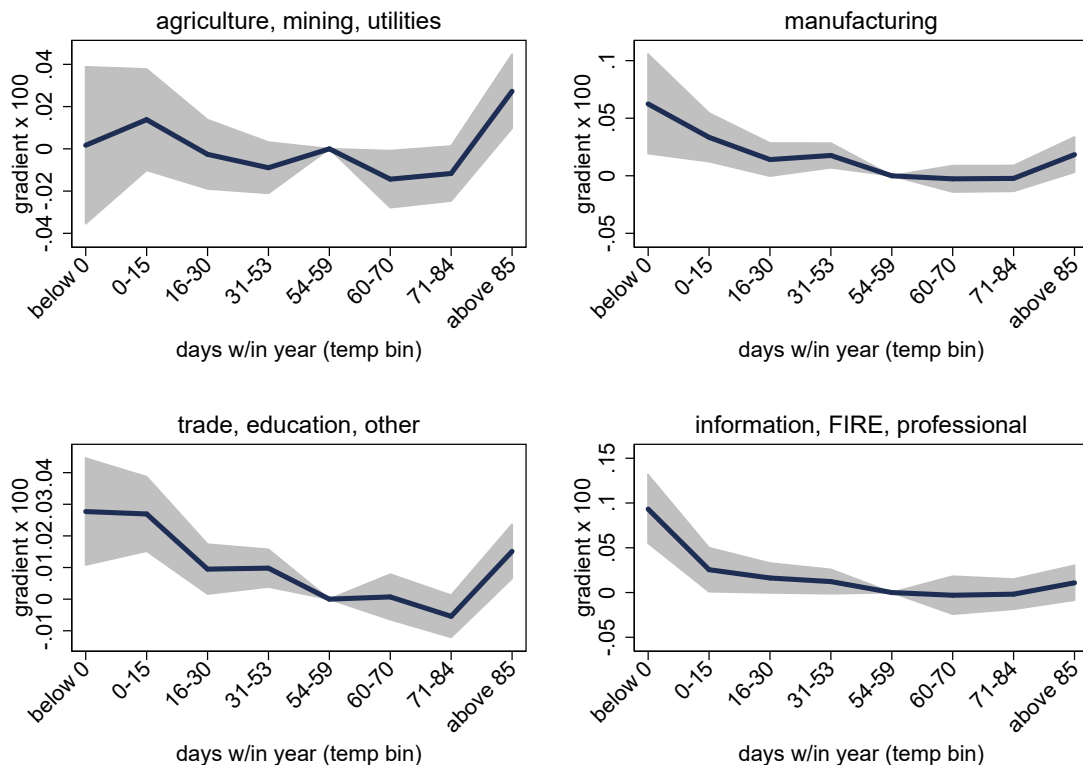


Figure 17: Semiparametric Response of Industry Total Pay to Temperature, 1990-2014

Notes.—Sources: PRISM and Quarterly Census of Employment and Wages from 1990 to 2014. The figure reports the coefficients associated regressions of logged three-digit industry-by-county annual total pay (deflated using the 2010 personal consumption expenditure index) on bins for the number of days in a year that fall within the corresponding bin (e.g., number of days in a year below zero degrees Fahrenheit), precipitation, and their lags, conditional on county, three-digit NAICS, and year fixed effects. Standard errors are clustered at the county-level. All observations are weighted equally.

Second, Figure 18 explores the same specification as the result in the main section with one minor exception—lagged logged annual wages is included as a control. Unlike the results with the BEA county data, the gradient does not turn negative even at the top of the temperature

distribution. The argument presented in the main text in the context of the BEA data was that unobserved shocks to per capita income are likely to be amplified when its lag is included as a right hand side variable. However, since here the disaggregation is greater (at a three-digit industry-level within a county), the concern for omitted variables bias declines, especially after the inclusion of industry fixed effects. There does appear to be a negative gradient when working at the data at a county-level, or when not including industry fixed effects.

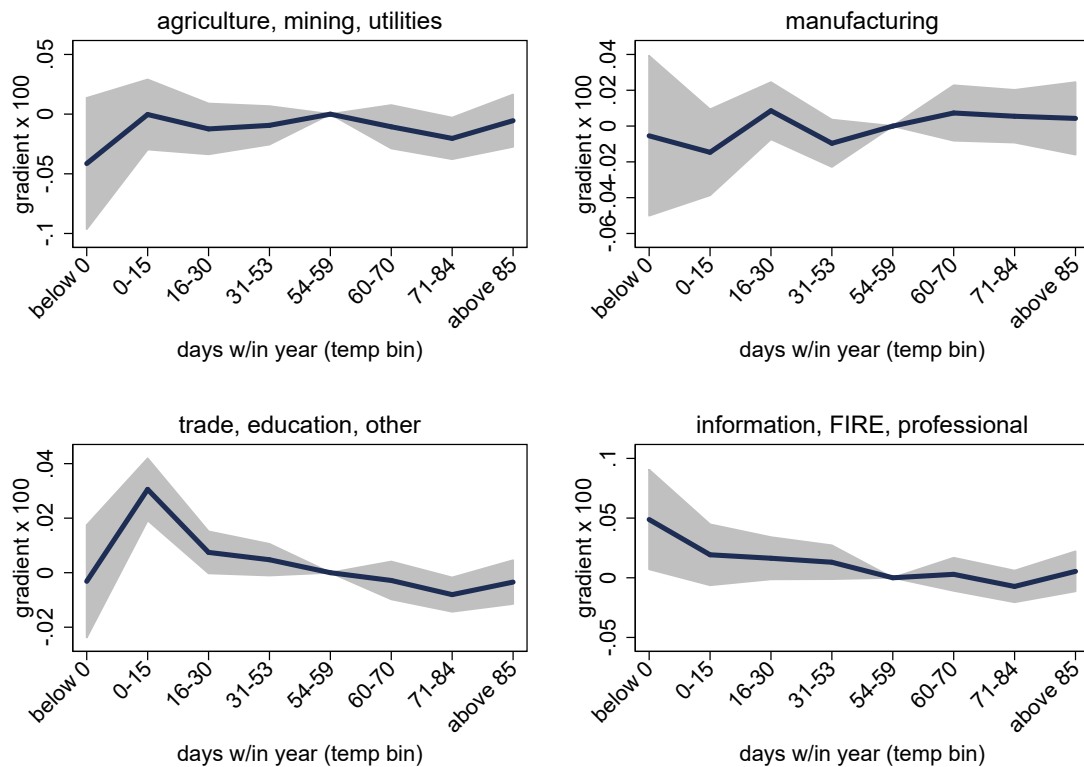


Figure 18: Semiparametric Response of Industry Wages to Temperature w/ Lag, 1990-2014

Notes.—Sources: PRISM and Quarterly Census of Employment and Wages from 1990 to 2014. The figure reports the coefficients associated regressions of logged three-digit industry-by-county annual total pay (deflated using the 2010 personal consumption expenditure index) on bins for the number of days in a year that fall within the corresponding bin (e.g., number of days in a year below zero degrees Fahrenheit), precipitation, and their lags, conditional on county, three-digit NAICS, and year fixed effects. Standard errors are clustered at the county-level. All observations are weighted equally.

Third, Figure 19 presents results using metropolitan level data—that is, the number of days within a year for a given metropolitan area between a certain temperature range. These results also suggest that there is no relationship between wages and temperature throughout the distribution. The results are also strengthened if controls, such as logged employment and establishments, are inserted to mitigate concerns about omitted variables bias. The results also hold if a lagged outcome variable is included. Figure 20 presents analogous results using metropolitan GDP as a

direct measure of productivity.

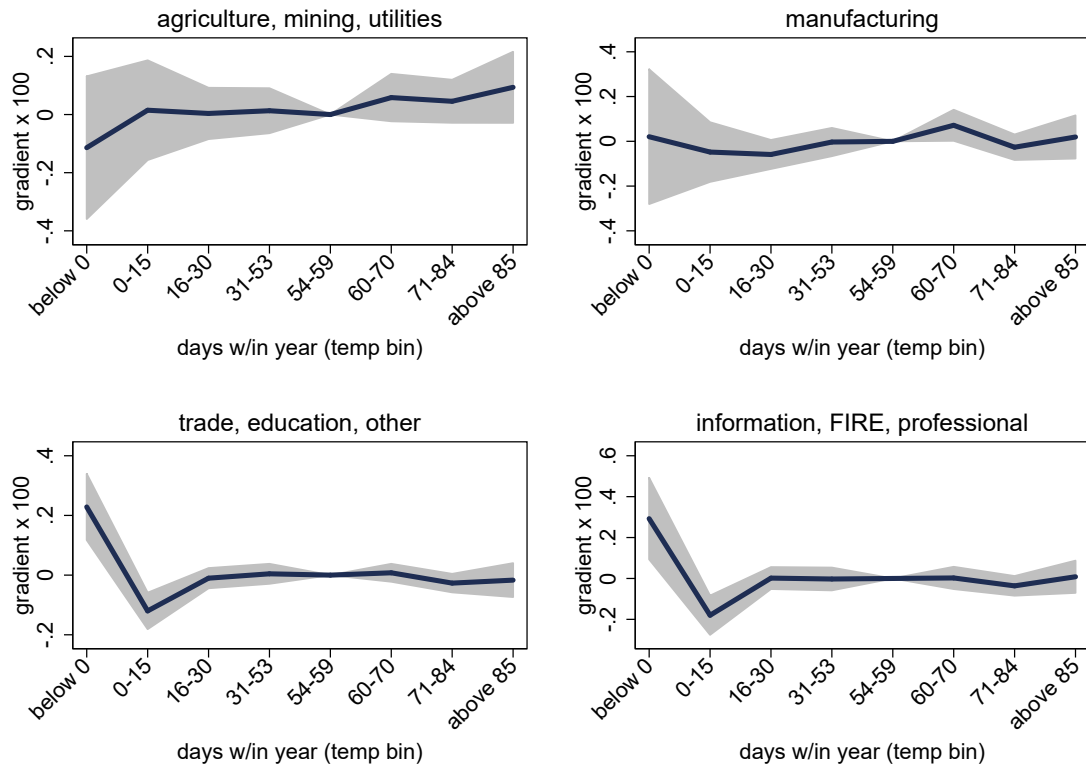


Figure 19: Semiparametric Response of Industry Wages to Temperature, 1990-2014

Notes.—Sources: NOAA and Quarterly Census of Employment and Wages from 1990 to 2014. The figure reports the coefficients associated regressions of logged three-digit industry-by-metro annual wages (deflated using the 2010 personal consumption expenditure index) on bins for the number of days in a year that fall within the corresponding bin (e.g., number of days in a year below zero degrees Fahrenheit), and their lags, conditional on county, three-digit NAICS, and year fixed effects. Standard errors are clustered at the metropolitan-level. All observations are weighted equally.

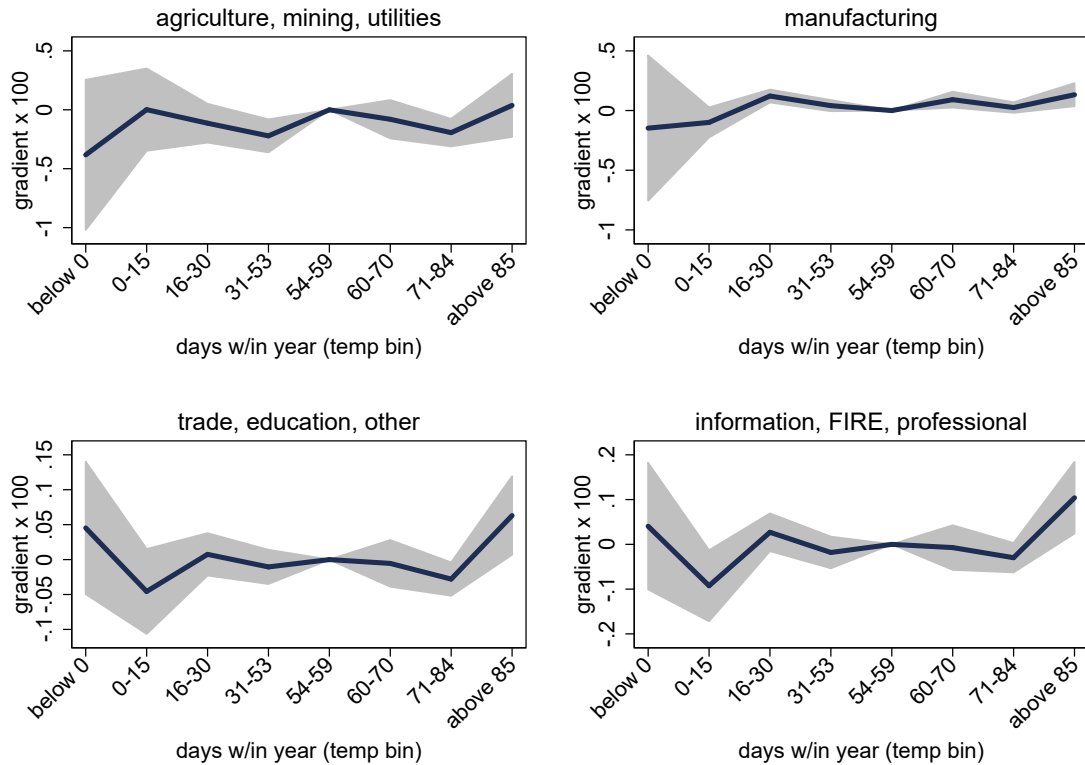


Figure 20: Semiparametric Response of Metro GDP to Temperature, 2001-2015

Notes.—Sources: NOAA and BEA GDP data from 2001 to 2015. The figure reports the coefficients associated regressions of logged three-digit industry-by-metro annual gross domestic product (deflated using the 2010 personal consumption expenditure index) on bins for the number of days in a year that fall within the corresponding bin (e.g., number of days in a year below zero degrees Fahrenheit), and their lags, conditional on county, three-digit NAICS, and year fixed effects. Standard errors are clustered at the metropolitan-level. All observations are weighted equally.

Using the LEHD data, increases in the average maximum monthly temperature are uncorrelated with in both the least squares and fixed effects regressions. Applying the semiparametric estimator also produces a precise zero estimate for days above 31 degrees Fahrenheit, meaning that the only negative point estimates are those arising from cold days. Using the QCEW also produces similar results with the semiparametric estimator, the standard measure of logged temperature, and the dynamic impulse response function (using up to 10 forward quarter variables). Lastly, using the County Business Patterns (CBP), we conduct similar regressions using logged wage bills (ratio of payroll expenditures to employment) as the outcome variable and estimate industry-specific temperature gradients. Figure 21 documents these results. The data suggests that there is no statistically significant association except slightly for the agricultural sector, which has a large confidence interval.

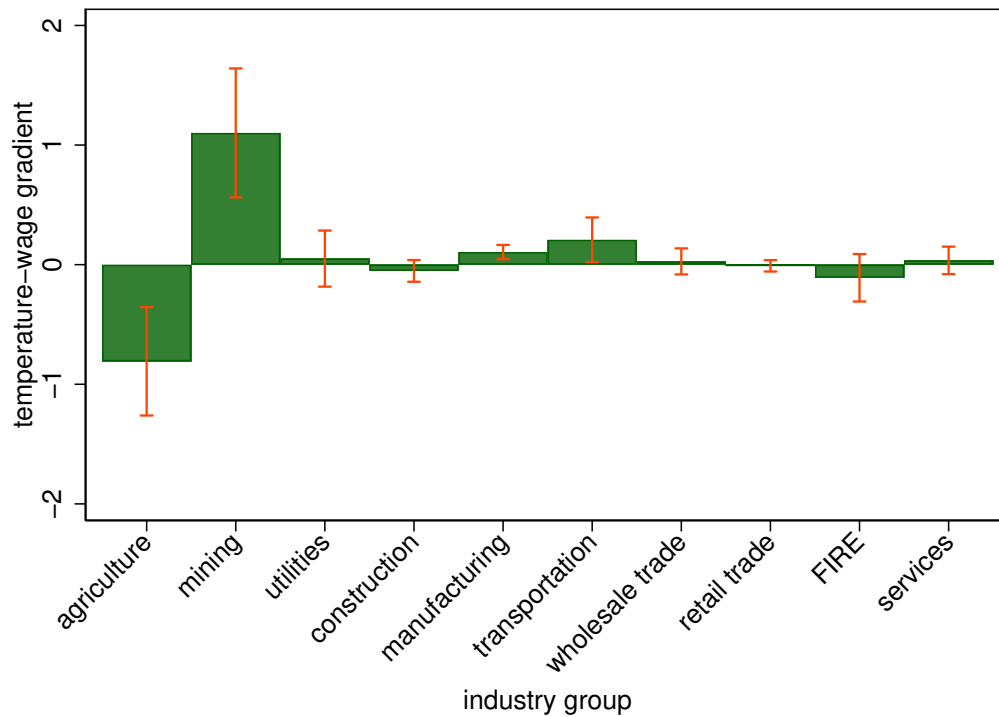


Figure 21: The Effects of Temperature on County-by-Industry Wage Bills

Notes.—Sources: County Business Patterns and PRISM. The figure reports the coefficients associated with regressions of logged wage bills (the ratio of payroll to employment) on logged maximum temperature (the average across the maximum of all months in a year), conditional on county and year fixed effects. Standard errors are clustered at the county level and observations are weighted by the long-run average industry-by-county employment.

8.4. Supplement to Computational Algorithm

The methodological approach is based on [Berry et al. \(2004\)](#) and [Bayer et al. \(2007\)](#) who provide a strategy for integrating micro-data into discrete-continuous choice models.

8.4.1. Step 1a: Household Preferences with Homogeneous Logit

Before turning to the more nuanced version of the estimation, it is useful to start with a basic homogeneous logit regression where there is no heterogeneity in tastes. Consider our utility function

$$w_{jt}^k = \alpha w_{jt}^k - \zeta r_{jt} + \psi D_{jt} + \eta T_{jt} + \sum_{m=1}^M \eta_m d_{jt}^m T_{jt} + \varepsilon_{jt} = x_{jt} \beta + \xi_{jt} \quad (35)$$

where w_{jt}^k denotes a location's logged wage bill in industry k , r_{jt} denotes a location's logged median housing values, D_{jt} denotes a vector of controlling covariates, and T_{jt} denotes average temperature and $d_{jt}^m T_{jt}$ denotes the spline on temperature; x is simply short-hand for all these. Denote the following “mean” utility components for each location

$$\delta_{jt} = \alpha w_{jt}^k + \zeta r_{jt} + \beta D_{jt} + \eta T_{jt} + \sum_{m=1}^M \eta_m d_{jt}^m T_{jt} \quad (36)$$

where in practice $\zeta < 0$ will be estimated (since higher rents reduce individual utility). Given a “guess” on each of the parameters, denoted

$$\theta_1 = (\alpha, \zeta, \beta, \eta, \eta_1, \dots, \eta_M) \quad (37)$$

then we can recover predicted population shares for each location by industry by exploiting the fact that ε is distributed extreme value type I such that the population shares are given by

$$s_{jt}^k = \frac{\exp(\delta_{jt}^k)}{\sum_{n=0}^J \exp(\delta_{nt}^k)}, \quad s_{0t}^k = \frac{1}{\sum_{n=0}^J \exp(\delta_{nt}^k)} \quad (38)$$

where $\delta_{0t} = 0$ is a normalization. Practically, that means dividing the population shares by the outside option for some $j = \hat{j}$

$$s_{jt}^k / s_{0t}^k = \exp(\delta_{jt}^k) \quad (39)$$

Taking logarithms, that reduces down to

$$\ln(s_{jt}^k) - \ln(s_{0t}^k) = \delta_{jt}^k = \alpha w_{jt}^k + \zeta r_{jt} + \beta D_{jt} + \eta T_{jt} + \sum_{m=1}^M \eta_m d_{jt}^m T_{jt} + \xi_{jt} \quad (40)$$

Under the assumption of exogeneity for wages and housing prices, then this can be estimated using least squares. However, allowing for endogeneity and given a set of instruments, denoted Z , then the system can be solved in two steps. First, compute $\hat{\delta}_{jt}^k = \ln(s_{jt}^k) - \ln(s_{0t}^k)$ and let $\theta = (\alpha, \zeta, \beta, \eta, \eta_1, \dots, \eta_M)$ and denote

$$\xi_{jt}(\theta) = \hat{\delta}_{jt}^k - x_{jt}\beta \quad (41)$$

Second, use the method of moments condition that $E[\xi(\theta) \times Z] = 0$ by minimizing

$$\min_{\theta} \xi(\theta)' Z W Z' \xi(\theta) \quad (42)$$

8.4.2. Step 1b: BLP

Building on the homogeneous logit example, this procedure allows for individual taste heterogeneity

$$u_{ijkt} = x_{jkt}\beta_i + \xi_{jt} + \varepsilon_{jt} \quad (43)$$

where x denotes a vector of the relevant covariates (e.g., wages and rents) and β_i denote the random coefficients (equal to the dimension of the observable characteristics) and are related to the individual characteristics based on

$$\underbrace{\beta_i}_{N \times 1} = \underbrace{\beta}_{N \times 1} + \underbrace{\Gamma'}_{L \times K} \underbrace{D_i}_{L \times 1} + \omega_i \quad (44)$$

with $\omega_i | D_i \sim \mathcal{N}(0, \Sigma)$ and z_i denote the L different individual characteristics (normalized to

have a mean zero such that β 's can be interpreted as average marginal utilities). The ingenuity behind BLP is that it does not require micro-data, rather using the employment shares (conventionally market shares) for each discrete alternative, together with the marginal distributions of individual characteristics, to back out individual heterogeneity.

1. Following convention, decompose the following components of utility

$$u_{ijt} = \underbrace{x_{jkt}\beta + \xi_{jt}}_{\delta_{jkt}} + \underbrace{x_{jt}(\Gamma' D_i + \omega_i)}_{v_{ijkt}} + \varepsilon_{ijkt} \quad (45)$$

Under homogeneous logit where $\Gamma = 0$ and $\Sigma = 0$, then given a guess on the parameter vector, the employment shares can be computed as

$$s_{jkt}(\delta_{jkt}; \Gamma = 0, \Sigma = 0) = \frac{\exp(\delta_{jkt})}{\sum_{l=0}^J \exp(\delta_{lkt})} \quad (46)$$

2. Draw repeatedly from the distributions of D_i , ω_i , and ε_{ijkt} to calculate the employment shares for each discrete alternative, denoting the vector $s(\delta; \Gamma, \Sigma)$ with dimension $JT \times 1$.
3. Fix only Γ and Σ . For every δ_{jkt} , there is an implied employment share. The goal now is to find the vector of δ_{jkt} such that the implied employment shares are equal to the observed employment shares for every j , k , and t . To do this, guess a starting value for δ_{jkt}^0 and solve for the fixed point on

$$\delta_{jkt}^{n+1} = \delta_{jkt}^n + \ln s_{jkt} - \ln s_{jkt}(\delta_{jkt}^n; \Gamma, \Sigma) \quad (47)$$

which will converge to a function $\delta(s; \Gamma, \Sigma)$ because it is a contraction mapping. It follows that the residual represents the unobserved location heterogeneity

$$\hat{\xi}_{jt} = \delta_{jkt}(s_{jkt}; \Gamma, \Sigma) - x_{jkt}\beta \quad (48)$$

4. Since $\hat{\xi}_{jt} \rightarrow \xi_{jt}$ eventually, then generalized method of moments can be used to recover the coefficients by introducing a vector of instruments and solving the following

$$\min_{\theta} \xi(\theta)' ZWZ' \xi(\theta) \quad (49)$$

8.4.3. Step 2: Production Elasticities

In equilibrium, Equation 12 must hold. These elasticities can, therefore, be estimated externally from the data. Unfortunately, output data is not available for counties and is only available from 1998 onwards for metropolitan areas. To resolve this problem, we first cross-walk counties and metropolitan areas into commuting zones (CZs). We subsequently implement a random forest algorithm to predict GDP in commuting zones based on a function of observables obtained from the Census, i.e., $Y_j = g(X_j, \theta)$, using data from the 2000 and 2010 Decennial Censuses. Table XX presents validation exercises to illustrate that the GDP predictions for these counties are reliable.

[TABLE XX]

Based on these predictions, we now estimate Equation 12 separately for each k . Table XX presents the elasticities under three specifications: least squares, first-differences, and instrumental variables.

[TABLE XX]

8.4.4. Step 3: Firm Demand and Supply

8.5. Supplement to Quantitative Analysis

8.5.1. Defense of Instruments

We now present evidence that there is sufficient variation in our instruments. We first begin with the wage instrument, which exploits variation in the employment share of workers in different industries and how they respond to national wage shocks. Figure 22 plots these distributions for 1980 and 2010, displaying the variation that exists across counties and within-counties, particularly

for the manufacturing and business sectors. We subsequently plot a similar plot distribution of households in different types of homes in Figure 23.

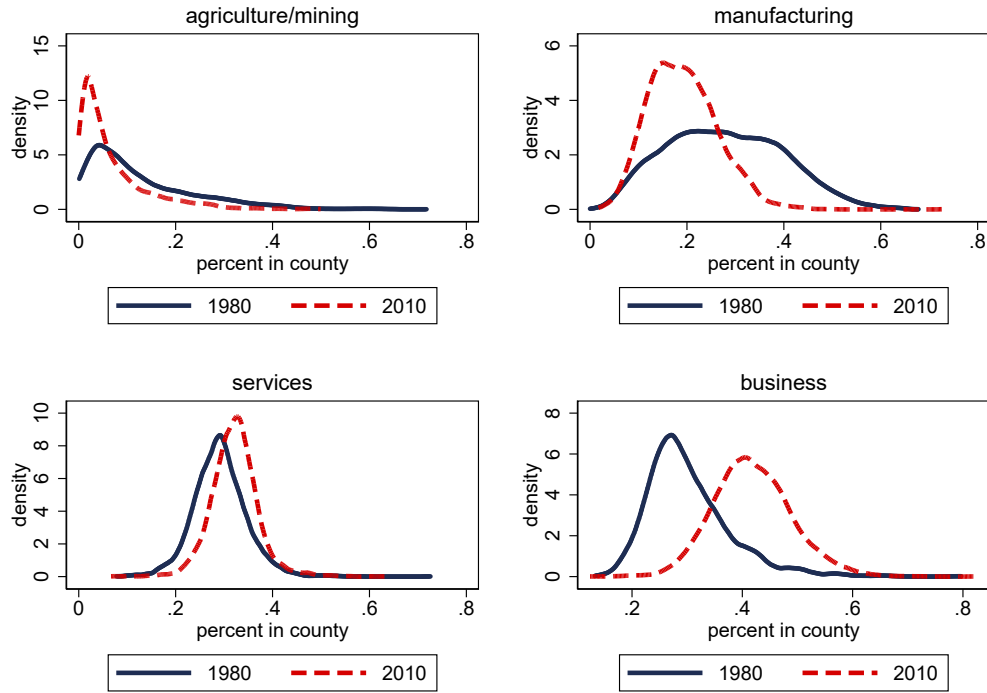


Figure 22: Distribution of the Share of Workers in Different Industries

Notes.—Sources: Census Bureau (SocialExplorer). The figure plots the distribution of the share of workers in different industries across all counties in the United States using data from 1980 and 2010.

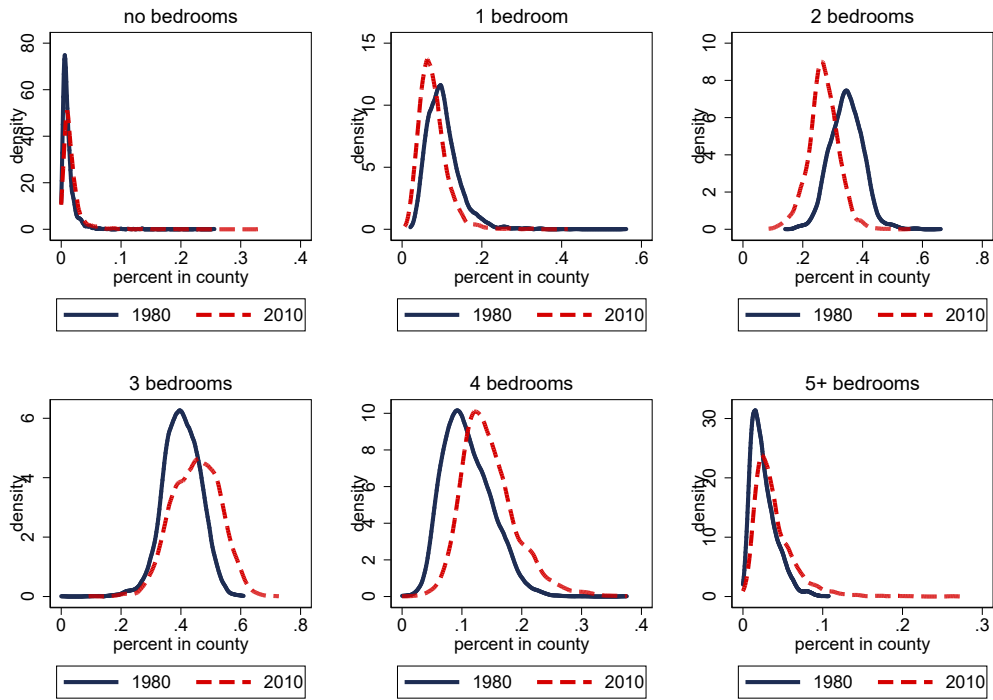


Figure 23: Distribution of the Share of Households in Different Homes

Notes.—Sources: Census Bureau (SocialExplorer). The figure plots the distribution of the share of households living in different types of residences across all counties in the United States using data from 1980 and 2010.

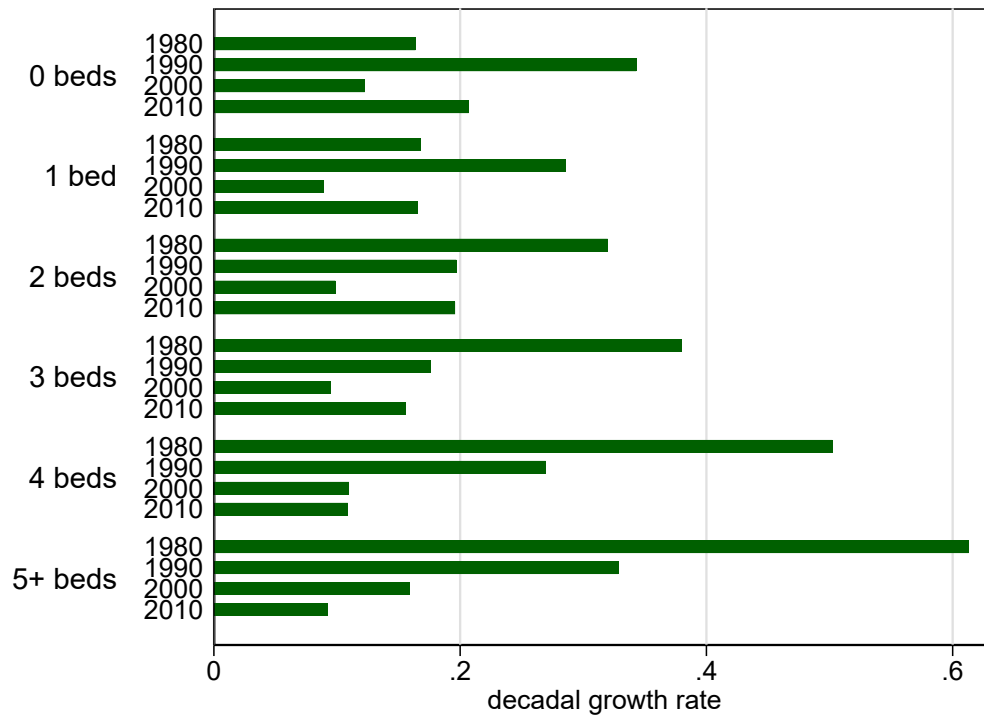


Figure 24: Housing Price Growth Across Bedroom Types, 1980-2010

Notes.—Sources: Census Bureau. The figure plots the growth rate in housing prices (including renters and owners) from one decade to the next for different types of homes. Nominal self-reported property values are deflated using the 2010 personal consumption expenditure index.

Table 10: Industry definitions from 3-digit NAICS codes

Industry Name	3-digit NAICS codes	Major NAICS industries
Agriculture	10–50	Agriculture, Mining
Manufacturing	60–392	Construction, Manufacturing
High-skill services (i.e. business)	700–712, 812–932	FIRE, Science, Education, Health care
Low-skill services (i.e. services)	400–691, 721–810	Wholesale/Retail trade