

# Will We Adapt? Temperature, Labor and Adaptation to Climate Change

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## Abstract

We explore heat-related labor impacts both for their own interest and to understand the role of adaptation in responding to climate change. Focusing on non-agricultural sectors in the United States, we find that hot temperatures exert a causal negative impact on county-level payroll – reducing payroll by several percentage points in a 2°C hotter year – with larger impacts in highly exposed industries such as construction and manufacturing. We assess differences in implied adaptation investments across regions with varying incentives for long-run adaptation, and find evidence consistent with hotter climates being better adapted to heat.

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# 1 Introduction

Will economic agents adapt to future climate change, reducing the realized economic costs of a hotter world? Or will adaptation to climate change be slow, costly, and constrained by practical limits? The central objective of this paper is to shed light on the potential for future adaptation by studying historical responses of workers and firms across locations with different incentives for adaptation investment.

Motivated in part by a desire to inform economic policy aimed at reducing the welfare impacts of climate change, many recent studies use short-run weather-economy estimates to project potential climate impacts.<sup>1</sup> Due to the gradual and long-term nature of climate change, however, it is unclear to what extent such estimates can be used to inform policy. In particular, incorporating the potential for adaptation over time is a critical factor that may substantially affect social cost of carbon estimates and thus the implied optimality of various policies aimed at reducing greenhouse gas emissions. Given the extent of warming over the next thirty years that is ‘locked-in’ due to past emissions, understanding the process of adaptation is also important in its own right – irrespective of its implications for present or future climate mitigation policy.

So far, evidence for long-run adaptation to changes in climate are mixed, with some analyses suggesting substantial scope for effective adaptation (Mendelsohn et al., 1994; Butler and Huybers, 2013; Barreca et al., 2016; Bleakley and Hong, 2017) and others finding the opposite (Annan and Schlenker, 2015; Burke and Emerick, 2016). The existing literature on adaptation has focused primarily on agriculture and human health. This despite the fact that, as a proportion of total climate damages, labor productivity impacts may be considerable (Burke et al., 2015; Heal and Park, 2016). This paper focuses on labor-related production impacts of hot days and potential investments in adaptive capital that may reduce these impacts in the long run. In contrast to much of the existing literature, which simulates adaptation costs based on engineering estimates of particular technologies or case studies of specific communities, our approach utilizes a revealed preference approach, and does so in a setting where liquidity and income constraints are relatively less likely to bind.<sup>2</sup>

We examine a historical panel of weather, payroll, and air conditioning data from the United States (1986-2011) to assess differences in adaptation investments across regions

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<sup>1</sup>A wave of recent empirical work documents a casual relationship between short-run fluctuations in temperature and production-related outcomes, including labor supply, labor productivity, and local economic output. See Dell et al. (2014) and Heal and Park (2016) for reviews. A non-exhaustive set of examples include Cachon et al. (2012), Graff Zivin and Neidell (2014), Sudarshan and Tewari (2013), Deryugina and Hsiang (2014), Burke et al. (2015). These studies find statistically significant and economically meaningful short-run impacts of hot temperature in both developed and developing economy settings, consistent with the earlier physiological and ergonomic literature (Seppanen et al., 2006).

<sup>2</sup>See Kahn (2016) for a review of the economic literature on the adaptation to climate change. See Gertler et al. (2016) for an illustration of potential liquidity constraints to adaptation uptake in developing countries. Unlike engineering estimates such as Kjellstrom and Crowe (2011), we estimate the extent of potential future adaptation using observed economic data which reflect real economic incentives and are net of avoidance behaviors (Graff Zivin and Neidell, 2013).

with varying incentives for long-run adaptation. By comparing the marginal impact of short-run (annual) heat exposure across regions that have experienced different long-term (decadal) climates, we generate a revealed preference estimate of the potential for long-run adaptation to heat exposure: given current adaptation costs and vis-a-vis the suite of adaptation options for which benefits are privately internalized.

Leveraging quasi-random variation in the number of hot days within a given county over many years, we find evidence consistent with hotter climates being better adapted to hot weather. Counties that expect more hot days (e.g. days with maximum temperatures above 95°F) on average experience reduced labor-related production impacts per hot day compared to their cooler counterparts. However, we also find that hot days reduce payroll even in some of the hottest regions of the United States, suggesting potential limits to adaptation without further innovation.

The empirical analysis proceeds in four steps. First, we estimate the causal impact of extreme heat on local non-agricultural production.<sup>3</sup> Using panel estimation models that control for county population trends and correlated output shocks at the state and national level, we find that the average U.S. county experiences a -0.04% reduction in payroll per capita during a year with one additional day with maximum temperatures above 95°F. The estimation strategy relies on the assumption that year-to-year fluctuations in the number of hot days are uncorrelated with unobserved determinants of per capita payroll.

Second, to further isolate production impacts of heat exposure – that is, impacts operating through supply-side labor inputs as opposed to demand-side factors or correlated ecological shocks – we study the impacts in sectors where production is more or less likely to be exposed to the elements. Industries classified by the National Institute for Occupational Safety and Health (NIOSH) as highly exposed – namely, construction, transportation, utilities, manufacturing, and mining – experience markedly higher impacts compared to relatively insulated ones such as education or financial services. The impacts are roughly 9 times as large in exposed sectors and suggest that, on any given workday, temperatures above 95°F reduce the corresponding day’s labor product by roughly 50% in exposed sectors, consistent with both time-use and task productivity studies (Graff Zivin and Neidell, 2014; Seppanen et al., 2006).

Third, we compare the marginal impact of an additional hot (95°F+) day on output across counties with different average climates to estimate the scope for long-run adaptation. The intuition here is as follows. To the extent that producers have an incentive to protect labor inputs from heat-related production impacts – or that laborers and the self-employed are able to protect themselves – we would expect investment in long-run adaptive capital (e.g. air conditioning, workplace norms) to occur to the point where the expected payoffs over time equal the net present costs of investment.<sup>4</sup> In this case, the re-

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<sup>3</sup>Unless otherwise specified for the remainder of the paper payroll refers to local non-agricultural payroll.

<sup>4</sup>As discussed in section 2, and suggested by some recent studies (Annan and Schlenker, 2015; Park, 2016), there may be important market or institutional failures that drive a wedge between the socially efficient adaptation frontier and realized – privately optimal – adaptations. Behavioral failures are also

alized marginal impact of an additional hot day in a place like Houston, which experiences 23 days above 95°F per year on average, would be different from the marginal impact in a place like Boston, which experiences only 1 such day per year: due to the fact that the expected benefits of air conditioning or other fixed cost adaptive investments in Boston are lower on average. Since Bostonians and Houstonians have faced different private incentives regarding adaptation to their historical climates but likely have access to a similar suite of adaptation technologies, one might obtain valuable information regarding the potential scope for adaptation to future climate change by studying the differences in marginal impacts between them.

We find that very hot places (e.g. Houston, Orlando, Phoenix) seem to be significantly better adapted to heat stress than cooler areas (e.g. Boston, Minneapolis, Seattle). Regions in the 1<sup>st</sup> and 4<sup>th</sup> quartile of the 95°F+ day distribution – which on average feature 1 and 30 such days per year – experience short-run impacts of -0.208 percentage points and -0.05 percentage points per 95°F+ day respectively. The short run impact of an additional hot day falls monotonically as one moves to hotter regions within the U.S., suggesting that optimizing agents do in fact respond to persistent temperature extremes, and that adaptation can reduce realized production impacts of hot temperatures, though likely at some non-trivial cost.

Fourth, we explore the role of air conditioning in mitigating these adverse impacts using a newly constructed panel of residential AC penetration at the county-year level.<sup>5</sup> We find that a significant proportion of the differences in marginal impacts can be explained by the spread of air conditioning, consistent with recent findings in the context of adaptation to heat-related health impacts (Barecca et al, 2016). Because changes in AC penetration are not experimental, we cannot rule out the possibility that the effects documented here are driven by correlated changes in other unobserved variables. Indeed, our analyses suggest that other non-AC adaptations may be important in reducing labor-related production impacts as well, including, for instance, increased flexibility in work hours.

Finally, we use down-scaled climate change projections to provide a preliminary assessment of the potential biases arising from omitting adaptation when estimating future climate damages. We use the CMIP5 multi-model ensemble to project the number of days over 95°F that each US county in our sample is expected to experience annually between 2040 and 2050. We compare estimates of lost payroll implied by the above regression

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possible, if agents are myopic or there are salience effects in recognizing the extent of heat-related productivity impacts. These would further increase the size of the wedge between observed adaptive investments and socially efficient adaptation. For the purposes of this analysis, we make the simplifying assumption that the size of this wedge is not systematically different across climate zones within the U.S. Testing this assumption – and exploring such market and institutional failures – remains an important area for future research.

<sup>5</sup>Given the focus on production impacts, commercial and/or industrial AC data may be a more suitable measure. High quality, spatially dis-aggregated data on commercial AC was not to our knowledge publicly available. In results available upon request, we attempt to replicate the residential AC analysis with EIA CBECs data. However, the data that is available shows a tight correlation between residential and commercial AC penetration across regions, suggesting that residential AC penetration may provide a good proxy for average AC penetration in production-related sectors for a given region.

models under various stylized adaptation scenarios. For instance, lost payroll under a “no adaptation” scenario, where local economies fail to adapt to new, hotter climates, is at least 50% higher in 2040-2050 compared a scenario in which local economies adapt to their new (hotter) climates in a way that is similar to the adaptation undertaken by those experiencing those climates today. Any endogenous technical change – which our method does not capture – will likely raise this figure considerably, as would extending the projections beyond 2050. Conversely, to the extent that individuals and firms are already sorted based on heterogeneous preferences or production characteristics relevant to determining heat-sensitivity of output, realized future adaptation may be lower than these estimates suggest.

These findings contribute to a growing literature on adaptation to environmental change (Mendelsohn et al., 1994; Hornbeck, 2012; Burke and Emerick, 2016). The method explored here – of leveraging the spatial gradient in temperature sensitivity and the degree of climate adaptation that this implies – builds upon work by Butler and Huybers (2013) in agriculture, Barreca et al. (2016) in health, and Auffhammer (2017) in energy use. One objective of these studies has been to allow researchers to eventually link the econometrically well-identified studies of weather-driven output shocks to the historically more simulation-based estimates of the social costs of carbon (Nordhaus and Yang, 1996; Hope, 2006; Stern, 2007), an objective that this paper shares. It is to our knowledge the first study to explore adaptation in labor-related settings using observed as opposed to simulated economic data.

Our results also build on a growing empirical literature on the economic impacts of climate change, reviewed by Tol (2009), as well as the growing literature on the welfare impacts of climate change arising from direct heat exposure (Dell et al., 2014; Heal and Park, 2016). The estimates of temperature-driven economic impacts are broadly consistent with prior results, including Hsiang et al. (2013), Dell et al. (2012), and Deryugina and Hsiang (2014), though this paper focuses more explicitly on the various adjustments relevant to the labor dimension. Our findings also imply that even the world’s wealthiest economies are subject to non-trivial heat-related output losses – impacts which may be exacerbated by future climate change. The magnitude of these losses may be larger in the developing world, given the higher density of workers in highly exposed sectors as well as lower rates of electrification and air conditioning.

The results reported here, while suggestive, also highlight the many gaps that remain in the literature. More careful research is needed to determine the extent to which realized welfare impacts are a function of local labor market structure and existing public policies. For instance, the magnitude of production impacts may depend on whether laborers are paid their true marginal product, or by some proxy contractual arrangement such as by the hour or on a salaried basis. Whether or not public policies such as minimum wages (Graff-Zivin and Neidell, 2012) or temperature-dependent compensation programs – e.g. Chinese high temperature subsidies (Zhao et al., 2016)– increase or decrease the distance

between realized and socially optimal adaptation is an important unresolved question.<sup>6</sup> More generally, while much of the existing literature has abstracted away from market failures in adaptation investment, such market imperfections may be important both for estimating the extent of future (privately optimal) adaptation as well as for assessing the case for public intervention in local adaptation investment. This may be particularly important in light of the distributional impacts of increased warming from climate change (Park et al., 2015; Hsiang et al., 2017).

The rest of the paper is organized as follows. Section 2 summarizes the related empirical literature and presents a simple conceptual framework that guides the empirical analysis. Section 3 describes the data and summary statistics. Section 4 presents the empirical strategy and Section 5 presents the main empirical findings. Section 6 discusses and concludes.

## 2 Background and Conceptual Framework

### 2.1 The Welfare Impacts of Heat Exposure

Recent empirical studies find strong evidence for a causal impact of short-run heat exposure on economically relevant outcomes. These include impacts on human health, labor productivity, labor supply, and human capital. In seminal work, (Deschênes and Greenstone, 2011) find that an additional day with mean temperatures above 90°F leads to a 0.11% increase in annual mortality in the United States, controlling for location-specific characteristics and the potential for harvesting. Graff Zivin and Neidell (2014) document substantial contractions in labor supply on hot days in those U.S. industries with high exposure to extreme temperature and weather shocks. They find that, for highly exposed occupations (e.g. construction), days with temperature above 100°F (37°C) lead to 23% lower labor supply than temperatures between 77°-80°F (25°-27°C).<sup>7</sup> These studies – and the longstanding experimental literature on temperature and task productivity (Seppanen et al., 2006) – form the basis for exploring adaptation to heat stress in the context of non-agricultural production activities.

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<sup>6</sup>The welfare incidence of hot temperature – between owners of capital and owners of labor, or across segments of the income distribution – is a largely unexplored area that may have important implications for designing economic policy.

<sup>7</sup>In the context of labor productivity, Cachon et al. (2012) document significant negative impacts of extreme heat on automobile plant output, controlling for plant-specific productivity and seasonality in production. They find that a week with six or more days with maximum temperatures above 90°F reduces output that week by 8% on average. Sudarshan and Tewari (2013) find similar plant-level productivity declines among Indian manufacturers, even when controlling for region, firm, and individual-specific factors. Deryugina and Hsiang (2014) find substantial impacts of hot days on county-level income in the United States.

## 2.2 Adaptation and Economic Policy

How quickly and effectively economic agents can adjust to changes in their environment is a question of central relevance for economic theory as well as economic policy (Samuelson, 1948; Mendelsohn et al., 1994; Davis and Weinstein, 2002; Kahn, 2005; Burke and Emerick, 2016).<sup>8</sup> Despite a rapidly evolving literature using weather variation to identify causal impacts, it remains unclear whether these short-run *weather-sensitivity* parameters are reflective of long-run *climate sensitivity* of economic activity, much less social welfare, mainly due to the possibility of adaptation.

How might estimating adaptation be important for climate policy? Generally speaking, one can imagine four stylized possibilities. First, adaptive investments may be effective at reducing climate impacts and occur quickly at low cost, in which case using short-run weather sensitivities to estimate long-run climate damages would overstate the urgency of public policy in addressing climate change. Alternatively, adaptive investments may occur slowly, prove to be prohibitively costly, or exhibit market failures such as collective action or principal-agent problems. In this world, economic damages under climate change would likely be large and persistent, implying a more substantial role for public policy in addressing future climate threats. A third possibility is that, regardless of the potential effectiveness of some adaptive investments, the set of affordable adaptation options actually shrinks in the long run, due to the depletion of finite resource stocks such as fossil aquifers or ecological buffer capacity, or because of general equilibrium effects which amplify the aggregate welfare costs of impacts in any given sector. Finally, induced innovation might lead to an expansion of the set of feasible adaptive technologies over time, increasing the potential for adaptation and reducing the realized damages of climate change, but with significant lags in timing of uptake.

Many recent weather-economy studies combine historical short-run damage coefficients with climate model projections to estimate the expected costs of long-run future climate change. These approaches, while providing valuable information to integrated assessment models aimed at estimating the social cost of carbon, are subject to important limitations. Suppose the temperature-output response functions with and without long-run adaptation are as depicted in Figure 1a. If what one is interested in from a policy standpoint is the true long-run social costs of climate change,  $(V_0 - V_1)$ , then estimating this using short run panel impacts,  $(V_0 - V_2)$ , might overstate damages by  $(V_1 - V_2)$ , which is the extent of adaptation that occurs over the long run.

More generally, the realized welfare costs of climate change will be highly sensitive to the potential (1) magnitude, (2) mechanisms (and associated market/behavioral failures), and (3) adjustment costs of adaptation in the long-run. This paper attempts to shed light on the first two of these policy-relevant parameters, for which there are few empirical

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<sup>8</sup>At the most general level, economists have debated this issue theoretically since at least Samuelson (1948), who suggested the LeChatelier principle: that longer time horizons will allow for greater margins of adjustment to any given shock or change in the economic environment.

estimates currently available.

### 2.3 Evidence for Adaptation

The economic literature on adaptation to climate change has to date focused primarily on agricultural yield (Mendelsohn et al., 1994, 2000; Schlenker et al., 2006; Butler and Huybers, 2013; Burke and Emerick, 2016), human health (Barreca et al., 2016), and energy demand (Auffhammer, 2017). The evidence is mixed, with some studies suggesting substantial scope for adaptation to hot temperature, and others finding weak or inconclusive evidence that individuals adapt to changes in climate.

Barreca et al. (2016) find evidence for adaptation in the context of health responses to temperature shocks. They find that the mortality impacts of heat stress in the United States, which are most acute when daily mean temperatures reach above 90°F, declined rapidly over the twentieth century: by roughly 75 percent, most of it occurring after 1960. Using state-level air conditioning penetration data, they find that the vast majority of this decline can be explained by adoption of air conditioning as opposed to electrification or the number of physicians in the state. In contrast, Burke and Emerick (2016) find little evidence for adaptation to heat exposure over time by American farmers. Similarly, Burke et al. (2015) suggest that both rich and poor economies have exhibited little to no changes in the heat-sensitivity of output over the past several decades.

This paper addresses the prospect of privately optimal adaptation to the impacts of heat stress on labor inputs. The intention is to include all economic sectors that are subject to temperature-related production impacts arising from thermal stress of the human body — including labor supply, task productivity, and direct disutility — but that are not directly affected by the well-documented relationship between temperature and agricultural yield.

### 2.4 Adaptation to Heat-Related Labor Impacts

Adaptation to heat exposure in labor-related settings may involve a wide range of mechanisms, depending in large part on the appropriability of the benefits of investment as well as the relevant time-frame (Table 1b provides a non-exhaustive heuristic of adaptation mechanisms by type). For instance, in the short run, workers may adjust labor supply, either on the intensive margin — choosing to work fewer hours overall, during a different time of day, or on a different day of the week — or on the extensive margin, choosing to exit the labor force temporarily (e.g. dropping out of seasonal construction labor markets during a very hot year). Individuals may also adjust exertion levels (labor effort) — especially if remuneration is by the hour or effort is imperfectly observable — or engage in other forms of defensive behavior such as wearing lighter clothing.

In the longer run, persistent temperature shocks may lead workers to change occupations, migrate to a more hospitable climate, or exit the labor force completely. Similarly, flow expenditures on heating and cooling may in most cases be easily adjusted in the short

run, but changes in the stock of heating and cooling equipment – for instance, upgrading an air conditioner from window unit to central AC, or retrofitting a home with better insulation – may require longer time horizons.

An important assumption made by some climate adaptation studies has been that adaptation, unlike mitigation, does not exhibit obvious market failures, leading to the implication that observed adaptation patterns identify the outer envelope of potential adaptation to climate (Deryugina and Hsiang, 2014). It is possible however that adaptation to heat exposure involves non-trivial market imperfections, particularly in labor or human capital-related settings. For instance, there may be important principal-agent problems in the context of workplace temperature amenities if it is unclear to the principal whether thermal comfort comprises a consumption or a production amenity. Similarly, it is possible that, in the context of imperfectly competitive local labor markets, firms have an incentive to maximize profit at the cost of worker health – if part of the benefits of air conditioning or other adaptive investments consist of health benefits to workers.<sup>9</sup> It is also possible that weak or corrupt institutions drive an additional wedge between observed levels of adaptation and the optimal adaptation frontier, as is suggested by studies in the context of natural disasters (Kahn, 2005), agriculture (Annan and Schlenker, 2015), and human capital (Park, 2016).<sup>10</sup>

Any combination of these market imperfections would imply that observed levels of adaptation do not represent the efficient adaptation frontier, even in contexts where liquidity constraints – as in Gertler et al. (2016) – do not bind. Applied microeconomic research on these topics represent important areas for future research. For the purposes of our analysis, and given the lack of empirical evidence to date, we make what we believe to be a conservative assumption that there is some set of privately optimal adaptation technologies and that the set of technologies available does not differ systematically across regions within the United States according to long-run climate.

The empirical strategy employed in this paper thus takes a revealed preference approach to inferring the extent of adaptation to climate stress. Specifically, comparing the realized impacts of temperature stress on output net of short run adaptations *within each region* with the impacts of temperature stress given different levels of long run adaptation *across regions* allows an analysis of the potential for adaptation in the long run, subject to the assumptions noted above.

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<sup>9</sup>If the health effects of heat exposure are imperfectly observable (to both employer and employee) or show up with sufficiently long lags, even competitive labor markets may under-provide workplace cooling.

<sup>10</sup>Induced innovation may also be an important component of adaptation: for instance, R&D in low-cost, energy efficient cooling devices may have the potential to substantially reduce the production costs associated with hotter climates. If there are R&D spillovers which are not completely internalized by any given firm, the market may under-provide investment in new adaptation technologies.

## 2.5 Production Impacts of Heat Stress

To motivate the empirical strategy, we outline a partial equilibrium model of local adaptive investment in response to the production impacts of heat stress.

Define production-relevant temperature stress,  $T^E$ , as a measure of extreme heat. For instance, this could be the number of hot days per year, or a cumulative measure such as the concept of killing degree days in the agricultural literature.  $T^E$  is a random variable, the historical distribution of which reflects average climate in that area.

Consider the production function  $Y(A, L)$ , which take as inputs labor productivity  $A$ , and effective labor supply  $L$ , where labor supply includes both dimensions of hours and effort. Recent empirical work suggests that both  $A$  and  $L$  depend on experienced temperature. While the focus here is on labor, it is worth noting that a possible adaptive response to heat stress may be to adjust capital-labor ratios of production, depending on which factor is more temperature sensitive. Let us make the simplifying assumption that extreme heat does not significantly affect the productivity of non-labor inputs (e.g. the productivity of capital).<sup>11</sup> We will also assume for the time being that the price of output is not affected by temperature in the short run, though it is certainly possible for demand-side responses to affect prices in some sectors, as discussed in greater detail below.

Allowing labor supply and productivity to depend on temperature means that output is a function of experienced temperature:

$$Y(A, L) = Y(A(T^E), L(T^E))$$

We abstract away from principal-agent problems or labor market frictions, such that the revenue impact of a productivity shock is completely internalized. One way to conceptualize this is to assume that laborers are proportional shareholders in the firm. Workers maximize utility,  $U(Y, L, T^E)$ , which is increasing in total output (i.e. income, which we assume is spent on a composite consumption good) and decreasing in labor supply, labor effort, and temperature stress, which causes direct disutility ( $\frac{\partial U}{\partial T^E} \leq 0$ ). Any such market frictions would mean that our estimates understate the potential for socially-optimal adaptation.

The task productivity literature suggests that physical and cognitive task productivity falls with extreme temperature — both heat and cold. Here, we focus on the hot end of the temperature-task productivity relationship, such that  $\frac{\partial A}{\partial T^E} \leq 0$ .<sup>12</sup> Existing studies also suggest that labor supply, defined here as a combination of labor hours and labor effort, reacts negatively to extreme temperature, in part due to direct disutility, in part due to lower productivity:  $\frac{\partial L}{\partial T^E} \leq 0$ . While we have abstracted away from the labor-leisure tradeoff, it is possible to show that, absent strong income effects, temperature

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<sup>11</sup>It is possible that the effectiveness of physical capital may be sensitive to extreme heat. For instance, heat rates at power plant are affected by ambient temperature, and electronics are known to malfunction at high temperatures. Whether extreme heat has a first-order effect on capital product is a question that remains yet unresolved.

<sup>12</sup>The empirical analysis presented below suggests that the labor productivity impacts of extreme cold are relatively small, at least in developed economies such as the United States.

deviations from the thermoregulatory optimum will affect labor hours and labor effort in the same direction (Heal and Park, 2013), such that heat shocks will reduce effective labor product, net of optimizing responses of workers who may reallocate labor effort and hours accordingly.

Provided that  $\frac{\partial A}{\partial T^E} \leq 0$  and/or  $\frac{\partial L}{\partial T^E} \leq 0$ , extreme heat will have a non-positive impact on total output:

$$\frac{dY(A(T^E), L(T^E))}{dT^E} \leq 0$$

Importantly, given utility-maximizing workers who have some flexibility in their choice of work hours or effort, realized output fluctuations in response to temperature shocks will be net of adjustments on the labor supply and labor effort margins.

### 2.5.1 Long-Run Adaptive investments

Suppose firms can undertake structural adaptive investments,  $\alpha$ , which can mitigate the negative impact of extreme heat stress by reducing the temperature sensitivity of workers' task productivity,  $\frac{\partial^2 A}{\partial T^E \partial \alpha} > 0$ , and/or reducing the temperature sensitivity of labor supply:  $\frac{\partial^2 L}{\partial T^E \partial \alpha} > 0$ .

In principle, firms might be able to engage in adaptive investments in either the short or long run, as discussed above. Here, we focus on the decision to invest in long-run adaptive capital, which may take the form of structural investments such as centralized cooling systems or cultural capital in the form of procedural norms.<sup>13</sup>

Firms will choose to invest in adaptive capital such that the expected marginal benefit associated with additional adaptive investment (in terms of heat-related damages avoided) is equal to the marginal cost.<sup>14</sup> In a stable climate, one would expect such long-run investments to be a function of the expected (historical) climate,  $\alpha_t(E(T^E))$ . A proxy for expected benefits would be provided by the average historical incidence of heat events that affect production adversely,  $E(T_t^E) \equiv \bar{T}_t^E \approx \frac{\sum_{\tau=1}^{t-1} T_\tau^E}{(t-1)-\tau}$ .<sup>15</sup> For the time being, we abstract away from forward-looking investments by firms who anticipate the production impacts of a shifting climate distribution.<sup>16</sup>

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<sup>13</sup>In effect, we are defining  $\alpha$  such that it corresponds to a fixed cost investment in time  $t$  that reduces the future stream of variable costs associated with cooling in periods  $t+1$  and beyond. In other words, we assume that these adaptive investments are sufficiently lump sum so as not to be adjustable in response to acute heat stress (a few hot days or an unusually hot summer), but rather have been chosen prior to the realization of current extreme heat  $T_t^E$ .

<sup>14</sup>Absent market failures, one would expect firms and workers to engage in the most cost-effective adaptation technologies first, moving up the "adaptation cost curve" as the marginal benefit (in terms of avoided production impacts) increases, either due to intensification of warming or higher marginal value of production.

<sup>15</sup>We use  $\tau = 1$  to denote the starting date when determining the average number of temperature events to recognize that expectations over climate need not consider all of history but might reflect something like a 20-year moving average.

<sup>16</sup>This is not a trivial assumption. As Severen et al. (2016) and Lemoine (2017) suggest, firms that anticipate future warming will respond not only to past realizations of weather, but also to future climate projections. Given the historical nature of our empirical analysis, which uses data from 1986 to 2011, we abstract away from this forward-looking dimension.

The production function can be written as:

$$Y_t(A, L) = Y_t(A(T_t^E, \alpha_t(\overline{T}_t^E)), L(T_t^E, \alpha_t(\overline{T}_t^E))),$$

where

$$\frac{\partial A}{\partial T^E} < 0, \frac{\partial^2 A}{\partial T^E \partial \alpha} > 0; \frac{\partial A}{\partial T^E}(T^E, \alpha)$$

and

$$\frac{\partial L}{\partial T^E} < 0, \frac{\partial^2 L}{\partial T^E \partial \alpha} > 0; \frac{\partial L}{\partial T^E}(T^E, \alpha).$$

Output is a function of labor productivity, labor supply, and adaptive capital. Labor productivity and supply at any given point in time will depend not only on the contemporaneous temperature,  $T_t$ , but also the history of temperature shocks in that location –  $\overline{T}_t^E$ , that is, the local climate – due to the fact that adaptive capital stock will have been chosen to maximize profits subject to the conditions mentioned above.

### 2.5.2 Application to empirical strategy

The overall effect of adaptive investments will be to reduce the short-run temperature-sensitivity of total output ( $Y$ ):  $\frac{\partial^2 Y_t}{\partial T_t \partial \alpha} \geq 0$ . To the extent that workers are paid their marginal product, and given our assumptions regarding the (lack of) temperature-sensitivity of capital above, this would be reflected in a similar reduction in the short-run temperature sensitivity of payroll per worker ( $y$ ):  $\frac{\partial^2 y_t}{\partial T_t \partial \alpha} \geq 0$ .

Thus, in the long run, one would expect firms in hotter climates (H) to exhibit higher levels of adaptive investment than cooler ones (C),  $\alpha_H > \alpha_C$ , provided that  $\overline{T}_H^E > \overline{T}_C^E$ . This paper aims to estimate the production impacts of extreme heat,  $\frac{\partial y_t}{\partial T_t^E}$ , in addition to the expected extent of long run adaptation,  $\alpha_H - \alpha_C$ , by using differences in realized production impacts across various climate regions,  $\frac{\partial y_C}{\partial T_C^E} - \frac{\partial y_H}{\partial T_H^E}$ , as well as across regions with different levels of air conditioning penetration, which may be one component of  $\alpha$ .

## 3 Data and Summary Statistics

### 3.1 County-Level Payroll Data

We use payroll data from the County Business Patterns database from 1986-2011, which records annual and 1st quarter payroll for roughly 3,000 US counties by two-digit NAICS classification. Payroll includes all forms of compensation, including salaries, wages, commissions, dismissal pay, bonuses, vacation allowances, sick-leave pay, and employee contributions to qualified pension plans paid during the year to all employees.<sup>17</sup>

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<sup>17</sup>For corporations, payroll includes amounts paid to officers and executives; for unincorporated businesses, it does not include profit or other compensation of proprietors or partners. Payroll is reported before deductions for social security, income tax, insurance, union dues, etc.

The choice of payroll as the dependent variable of interest – rather than, for instance, total profits or total income – is motivated by two factors. First, changes in per capita payroll provide close proxies to changes in total and marginal labor product, separately from changes in capital expenditures. Importantly, payroll is less likely to include capital income or direct expenditure on heating and cooling, which may be the case for total income. This means that one is in principle able to more closely approximate labor impacts, and to estimate the implied marginal benefits of adaptation separately from the short-run marginal costs.<sup>18</sup> Second, payroll data from the CBP allows us to isolate production impacts in non-agricultural sectors, as well as to distinguish between sectors that are likely to be more or less exposed to temperature stress.

## 3.2 Daily Weather Data

County-level payroll data is matched with daily weather data from the PRISM model, which provides temperature and precipitation readings for a 2km x 2km grid of the contiguous United States. Daily max, min, and average temperatures as well as daily precipitation are area-weighted to the county level, and variables containing the number of days with daily maximum temperatures in a series of 10°F bins are constructed by county and year.

Past literature has documented a persistent, non-linear relationship between temperature and economic outcomes, particularly in the context of extreme heat exposure (Schlenker et al., 2006; Hsiang, 2010; Deschênes and Greenstone, 2011; Burke et al., 2015; Barreca et al., 2016). Where data has been available, this relationship has been captured using the concept of temperature days: for instance, growing or killing degree days in the case of agriculture, which measure the amount of time a crop is exposed to temperatures between a given lower and upper bound, with daily exposures summed over the growing season to ascertain annual growing degree days. We use a flexible, degree-day binning approach that estimates the marginal impact of additional days at any part of the temperature-day distribution, compared to an omitted optimal category.

## 3.3 Air Conditioning Data

Air conditioning penetration by county and year is constructed using county level residential AC information from the 1980 decennial census combined with data on changes in residential AC penetration over time by census region from the Energy Information Agencies Residential Energy Consumption (REC) surveys. We use the reported penetration rates in 1980 as a basis and then extrapolate based on the region-level growth rate of cen-

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<sup>18</sup>For instance, if firms pay wages as a function of hours worked and units of production, fluctuations in payroll arising from temperature shocks would reflect changes in labor supply and labor productivity. If, in addition, firms respond by running existing air conditioning equipment at a higher utilization rate, this added cost would be reflected in lower profits or net income, thus conflating some portion of realized output shocks with short-run flow expenditures on adaptive capital. Payroll, which more closely approximates marginal product of labor than capital, is thus more likely to provide information on differences in long-run adaptation, absent data on technology-specific adaptation costs.

tral, window and total AC penetration recorded by RECS, which provide penetration rates by region from 1980 to 2009 with a two or three-year frequency. We linearly interpolate growth rates for the missing years and assign counties their corresponding regional growth rate. Using this growth rate and the observed penetration rate in 1980 we create a measure of penetration in every county in each year from 1980 to 2011. We top-code penetration at 100%. Our primary specification uses the penetration rate of total AC but we conduct the same exercise for central and window AC and estimate all models with all three measures of AC penetration. The results across all three measures are qualitatively similar.

Given the focus on production impacts operating through labor inputs, the ideal measure of AC would include commercial and/or industrial AC penetration. Such data was not available. However, available evidence suggests that commercial and residential AC penetration rates are highly correlated within regions. For instance, according to the EIA, 74% of commercial buildings in the Northeast region had some form of AC as of 2009, while approximately 80% of residential buildings did. In the East-South-Central region, the commercial and residential penetration rates were 90% and 95% respectively. Based on this observation, and the assumption that local determinants of residential and commercial AC are likely to have shared components (Biddle, 2008), we take residential AC as a proxy for total AC at the county level.

### 3.4 Summary Statistics

Over the period 1986 to 2011, a county in the middle of the United States climate distribution experienced an average annual temperature of 54.6°F and approximately 5 days with temperatures above 95°F per year. This masks tremendous variation across regions. Much of the Northeast and coastal regions of the West seldom experience more than a few days above 95°F. Seattle and San Francisco experienced fewer than one such day per year on average over the period. In contrast, parts of the South and Southwest regularly get more than 30 such days per year.<sup>19</sup> Figure 2 depicts the average incidence of 95°F+ days and mean daily temperature across the country by county. Figures 3a and 3b depict changes in 95°F days year-to-year for a few representative counties, illustrating the primary source of identifying variation.<sup>20</sup>

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<sup>19</sup>Running simple OLS regressions in the cross-section suggests a strong correlation between productivity and average climate. Pooling all years in the sample, a region with one more heat day (95°F and above) per year on average features 0.01% lower non-agricultural payroll per capita, controlling for precipitation. This is consistent with the cross-sectional gradient documented by Acemoglu and Dell (2010), who find a within-country slope of roughly -1% per degree F increase in average annual temperature across municipalities in North and South America. While this relationship may be driven by climate *per se*, it may also be driven by unobserved omitted variables such as institutional quality or human capital, motivating the panel estimation strategy described below.

<sup>20</sup>It is important to note that realized temperatures can vary considerably even within small geographic locales (e.g. counties) depending on elevation, distance to bodies of water, vegetation, and surface albedo. For instance, within Los Angeles County, the temperature on a given summer day may be 30°F lower in Santa Monica, which is on the coast, than it is in Pasadena, which is farther inland. To the extent that our measures of local temperature are measured with (classical) error, we would expect the estimates of the impact of heat exposure on production to be downward attenuated.

Figures 4 and 5 depict imputed average AC penetration rates across the country in the years 1990, 2000, and 2010 respectively, excluding Alaska and Hawaii. As of 1986, the average residential AC penetration rate across all counties was 58%. By 2010, it had risen to 75%. Once again, there is considerable variation across regions, both in initial levels of AC penetration and rates of uptake over time. For instance, AC penetration in New York City rose rapidly during the period 1986 to 2011, increasing from 55% to 89%. In Marin County, CA, AC uptake was much slower, from 12% to 21% over the same period (Figure 6a). Houston, TX, on the other hand, had close to universal AC since 1986.

## 4 Empirical Strategy

### 4.1 Regression Framework

The analyses presented below are based on estimating variants of the following equation:

$$\ln(y_{ist}) = \sum_k \beta_k TMAX_{itk} + \pi_1 PREC_{it} + \gamma_i + \eta_t + f_{i,s}(YEAR_t) + \epsilon_{ist} \quad (1)$$

where  $y_{ist}$  is annual payroll per capita in county  $i$ , state  $s$ , and year  $t$ .  $PREC_{it}$  represents average daily precipitation in each county, measured in tenths of an inch per day. The variables  $\gamma_i$  and  $\eta_t$  denote county- and year-fixed effects respectively.  $\gamma_i$  controls for time-invariant unobserved factors that may determine the relative productivity of county  $i$  (e.g. human capital).  $\eta_t$  accounts for correlated shocks that are common across the United States (e.g. recession years).  $f_{i,s}(YEAR_t)$  represents non-linear time trends that are allowed to vary by county or state, and control for smooth changes in payroll over time as well as the potential for correlation between secular regional productivity trends not accounted for by annual population and year fixed effects.

The variables  $TMAX_{itk}$  represent our measures of temperature, which are constructed to capture exposure to the full distribution of temperatures in a given year. The  $TMAX_{itk}$  variables are defined as the number of days in a county-year in which the daily maximum temperature is in the  $k^{th}$  of 9 temperature bins ranging from 0°-10°F to 95°F and above. In practice, the 70°F-79°F bin is the excluded group, so the coefficients on the other bins are interpreted as the effect of exchanging a day in the 70°F-79°F range with a day in other bins. The primary functional form restriction imposed by this model is that the impact of the daily max temperature on annual payroll is constant within 10°F bin intervals.

We use the number of days above 95°F as the primary indicator of extreme heat. This is motivated by previous studies, which find strong impacts of heat stress on human behavior and task productivity beginning around 85°F, as well as the observation that most productive activity occurs during the daytime, motivating a choice of daily max as opposed to min or mean temperature as the primary measure (Deschênes and Greenstone, 2011;

Graff Zivin and Neidell, 2014; Barreca et al., 2016).<sup>21</sup> Not specifying additional bins above or below this threshold represents an effort to remain as non-parametric as possible while also obtaining estimates that are precise enough to permit meaningful interpretation.<sup>22</sup> In all versions of equation 1, the  $\beta_k$  parameters are identified from inter-annual variation in temperature realizations.

## 4.2 Estimating Labor-Related Temperature Impacts

To isolate the impact of temperature on non-agricultural sectors, we subtract agricultural payroll from total annual payroll for each county-year, and run a version of equation 1 that uses log non-agricultural payroll as the dependent variable.

To further isolate the impact on labor inputs, we examine impacts by sector, where  $j$  denotes NAICS sector classification:

$$\ln(y_{ijst}) = \sum_k \beta_k TMAX_{itk} + \pi_1 PREC_{it} + \gamma_i + \eta_t + f_{ij,sj}(YEAR_t) + \epsilon_{ijst} \quad (2)$$

Determining ex ante which industries are more or less susceptible to temperature stress in an empirically executable way is not an exact science, in part because CBP payroll data is categorized by two-digit NAICS parent codes as opposed to specific occupations. Each parent category (e.g. Construction, Retail, Transportation) includes many specific occupations that may feature vastly different working environments. For instance “Transportation” includes “Rail-Track Laying and Maintenance Equipment Operators”, who are likely to work outdoors, as well as “Air Traffic Controllers” who are less likely to work outdoors.

As a conservative categorization scheme, we follow the National Institute for Occupational Safety and Health’s (NIOSH) classification of “highly exposed” industries: namely, construction, manufacturing, utilities, transportation and mining.<sup>23</sup> We classify the rest – retail, wholesale, health, education, and finance-insurance-real estate – as “not exposed”.<sup>24</sup>

It is worth noting that it is possible for demand-side factors to affect our estimation. For instance, hot days may induce greater demand for certain products that are complementary

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<sup>21</sup>The kink point is lower in lab studies (Seppanen et al., 2006). This could be due to the fact that most lab experiments impose something akin to a no-adaptation constraint, since participants are required to concentrate on challenging tasks under temperature stress without the ability to rest between sessions, adjust physical surroundings, or adapt production techniques.

<sup>22</sup>In analyses available upon request, we use alternative measures of temperature shocks, including days with daily max temperatures above 90 and 100°F. By and large, the results are consistent across different measures of temperature, though they are sharpest using the 95°F maximum temperature threshold.

<sup>23</sup>“Highly exposed” industries include industries where the work is primarily performed outdoors — agriculture, forestry, fishing, and hunting; construction; mining; and transportation and utilities — as well as manufacturing, where facilities are typically not climate-controlled and the production process often generates considerable heat.

<sup>24</sup>To the extent that the comparison of interest is between highly exposed and non-exposed occupations and this classification only crudely approximates the true subset of exposed occupations, we would expect the analysis to provide an underestimate of the difference, as we would be measuring impacts for air traffic controllers alongside railway repair workers within the same “highly exposed” category, and similarly for occupations that may be more likely to work outdoors in the “non-exposed” category.

to consumption activities during warm weather (e.g. ice cream). They may also lead to avoidance behavior or adverse health outcomes that directly affect demand for services and thus annual payroll (e.g. emergency room visits to hospitals). If sector-specific product demand is affected positively by temperature, our estimates are likely to be downward biased. If demand is negatively affected, they may be upward biased. We attempt to account for some of these factors by examining specific sectors that are likely to be more or less affected by intra-annual demand-side factors. To our knowledge, there is as yet little empirical work exploring demand-side responses to short-run temperature fluctuations, which will be important to consider in performing full welfare accounting.

### 4.3 Estimating Adaptation

To measure adaptation, we first classify counties according to their average historical climate. The relevant definition of average climate will depend, in part, on the aspects of the climate distribution that affect the relevant investment decisions noted in section 2. To the extent that output impacts are driven by extreme heat – as opposed to impacts from shifts in average annual temperatures, which may reflect warmer winters – one might expect the relevant metric to be the expected number of extreme heat days over time.

In practice, we use various moments of the long-run climate distribution to define “climate”. The preferred specification categorizes counties by the average number of days with maximum temperatures above 95°F, though the results are qualitatively similar in specifications that use a lower temperature threshold (e.g. 80°F, 90°F) or average annual temperatures. All specifications use averages over the period 1986-2011 for consistency.

We measure the extent of potential long-run adaptation in two ways. First, we run equation 2 separately by quartile of the historical climate distribution. Second, we augment equation 2 by adding interactions of the temperature variables with county-specific measures of long-run climate:

$$\ln(y_{istj}) = \sum_k \beta_k TMAX_{itk} + \sum_k \theta_k^{CL} TMAX_{itk} \times T\bar{MAX}_{i,k=9} + \omega T\bar{MAX}_{i,k=9} + \pi_1 PREC_{it} + \gamma_i + \eta_t + f_{s,i}(YEAR_t) + \epsilon_{istj} \quad (3)$$

The coefficients  $\theta_k^{CL}$  on the interaction term measure whether the effect of an additional day in a given temperature range is affected by the average historical incidence of hot days, relative to the effect of the average historical incidence on a day in the omitted bin. According to the model presented in section 2, we would expect places that experience greater heat exposure on average to be better adapted to heat stress, and thus experience lower marginal impacts per hot day. This would result in a positive interaction term for days above 95°F. We also present results from running equation 2 separately by climate bin.

#### 4.4 Exploring the Role of Air Conditioning

To assess the role of air conditioning in reducing the impact of extreme heat on production, we augment equation 2 with measures of air conditioning penetration. We interact interpolated AC penetration at the county-year level with the temperature variables to estimate the role that AC may have played as a modifier on the effect of hot days on production:<sup>25</sup>

$$\ln(y_{istj}) = \sum_k \beta_k TMAX_{itk} + \sum_k \theta_k^{AC} TMAX_{itk} \times AC_{it} + \lambda AC_{it} + \pi_1 PREC_{it} + \gamma_i + \eta_t + f_{s,i}(YEAR_t) + \epsilon_{istj} \quad (4)$$

The interaction term measures whether the effect of an additional day in a given temperature range is affected by the average AC penetration rate in that county-year, relative to the effect of the average historical incidence on a day in the omitted bin. The hypothesis is that the coefficients on the interaction terms ( $\theta_k^{AC}$ ) will be positive for hot days ( $k=9$ ), suggesting that investment in AC mitigates the marginal impact of hot days on production. The interpretation assumption being made in using residential AC is that the determinants of a total AC both across and within counties are similar to the determinants of residential AC over the period 1986-2011.

### 5 Results

#### 5.1 The Production Impacts of Heat Exposure

Figure 6b provides a binned scatterplot that motivates the analyses that follow. It shows the relationship between log payroll per capita and the number of hot days by percentile of the hot day distribution, controlling for average differences across counties and years, as well as the other weather controls and time trends noted in equation 1. It suggests a strong negative relationship between hot days during the year and payroll that year.

Table 1 presents the results from running versions of equation 1 with state- and county-specific time trends. The dependent variable in this case is non-agricultural payroll per capita. Robust standard errors are clustered at the state by year level to allow for spatial correlation of error terms within a given state and year. The estimates suggest that an additional hot day causes a -0.04% ( $se=0.002$ ) decline in payroll per capita on average. This means that a year with 10 more hot days results in approximately -0.4% lower payroll per capita for the mean U.S. county, or that, in any given year, hot days (of which there are on average 10) reduce total per capita payroll by approximately -0.4% from what would otherwise have been the case if not county experienced a day with temperatures above 95°F.

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<sup>25</sup>We also do the same for average AC for the entire period (1986-2012), as a check against results being driven by the AC interpolation scheme.

## 5.2 Exposed versus Non-Exposed Industries

Figures 7a and 7b illustrate the relationship between residualized payroll and hot days for highly exposed and non-exposed industries respectively. They suggest more acute impacts in sectors where workers are exposed to the elements. An additional hot day causes a statistically significant -0.23% (se=0.006) decline in payroll per capita in highly exposed industries, as opposed to an insignificant -0.011% (se=0.002) decline in non-exposed industries. This corresponds to a more than 5-fold difference between exposed and non-exposed sectors. The magnitude in exposed sectors is large: a year with 10 additional 95°F+ days reduces labor product by approximately 2%. Including the impact of hot days below this threshold (e.g. including days with max temperatures between 80°F and 95°F), the implication is that, for a county in the middle of the summer temperature distribution, a +2°C (+3.6°F) hotter year results in a -10.4% decline in payroll in these sectors.<sup>26</sup>

These results are consistent with a story of reduced labor product due to reductions in cognitive capacity and physical functioning from thermal stress of the human body, as well as shocks arising from reduced concentration and increased mistakes, reduced labor effort, and reduced labor supply.<sup>27</sup>

Figures 8a, 8b, 9a, and 9b present analagous binned scatterplots for construction, transportation, education, and healthcare sectors respectively. As might be expected, construction payroll declines in years with more hot days. This may be driven by the effects of hot temperature on labor supply, labor effort, or labor productivity (e.g. higher error rates on hot days). Unless construction demand is higher when there are more extremely hot days (controlling for cold days and precipitation), it seems unlikely that the observed effect is being driven by demand-side factors. The extent to which the observed effects on payroll are a function of reductions in hours, effort, or productivity will depend in part on the prevailing contractual structure, as suggested by Heal and Park (2016) and Kahn (2016), and documented in the context of air pollution and agricultural workers (Graff-Zivin and Neidell, 2012). Transportation payroll also shows substantial declines in years with more hot days. Here, it is less clear whether the effect is due to reduced transportation demand (e.g. fewer cab or train trips demanded) or reduced productivity/supply of labor inputs (e.g. productivity of road and railway maintenance workers).

Payroll in the education sector is unaffected by hot temperature, which is consistent with a higher concentration of unionized and salaried workers. Healthcare payroll seems to increase slightly during years with more hot days, consistent with – though by no means

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<sup>26</sup>For a county in the 3rd (middle) quintile of the US extreme heat day distribution, a +1°F warmer year corresponds to 5 additional days between 80°F and 90°F, and 13 additional days above 90°F.

<sup>27</sup>Note that while there may be some bias due to selection in the location of highly exposed industries in the cross section (industries that are highly exposed may choose to locate in locations that are typically colder) our panel approach mitigates this bias. To the extent that some highly exposed industries produce non-traded goods (e.g. construction), work must take place in places that are both hot and cold. While construction workers in hot places may choose to work differently than those in colder places – earlier in the morning for example – it is as yet unfeasible for construction to be completely out-sourced to cooler locations.

definitive proof of – increased demand for healthcare services due to more hospitalizations and emergency room visits (Schwartz et al., 2004). In results available upon request, we find that agricultural payroll is slightly positively related to the number of hot days as well, which may be due to Federal Crop Insurance payments (Annan and Schlenker, 2015) or demand-side factors.

### 5.3 Evidence for Long-Run Adaptation: Comparing Across Climatic Regions

Results from running equation 2 by quartile of the average hot day distribution are reported in Table 3. A county in the bottom quartile of the extreme heat day distribution (e.g. San Francisco, Seattle) exhibits a short-run weather sensitivity of approximately -0.21 percentage points ( $se = 0.0010$ ) per extreme heat day ( $95^{\circ}F+$ ). A relatively hot county at the top quartile of the US average temperature distribution (e.g. Houston, Orlando) has a short-run weather sensitivity of -0.052 percentage points ( $se = 0.0188$ ) per extreme heat day: roughly a quarter the impact. As columns (1) through (4) suggest, the marginal impact of a hot day seems to decline monotonically as one moves to climates that experience more hot days on average. For highly exposed sectors (bottom panel), the effect sizes are larger in all climate bins, but show a similar pattern of declining marginal impacts as one moves to hotter parts of the country.

The impact of an additional hot day is roughly 75% smaller in counties in the top quartile of historical extreme heat incidence, compared to counties in the bottom quartile, suggesting substantial scope for adaptation given appropriate investments.<sup>28</sup> Whether because of AC or other adaptations, private or public, the same  $95^{\circ}F+$  day seems to have a very different short run impact in Houston than it might in Boston. While the reduction in temperature sensitivity associated with moving from less to more heat-prone areas is large, it is worth noting that, even in these presumably very well-adapted areas, extreme heat days have statistically significant and economically meaningful impacts on output. These estimates suggest that, at least for highly exposed industries such as manufacturing, construction, or transportation, even those counties in the top quartile of extreme heat exposure suffer routine heat-related output impacts of up to -5.2% per year, given the high incidence of hot days. This is despite near universal air conditioning in many parts of the US South and Southwest.

### 5.4 The Role of Residential Air Conditioning

Nearly all households in Houston had AC as of 2009, of which 80% were central AC units. In contrast, only 20% of Massachusetts households had central AC, and 21% did not have air conditioning units altogether. For average Texas households, 18% of total energy usage is devoted to cooling, compared to 1% for Massachusetts households. Such differences in

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<sup>28</sup>Running the analysis by quintiles yields similar results. Both specifications suggest monotonically declining temperature sensitivities as one moves to regions with greater degrees of perennial heat stress.

AC represent but one of a potentially very large number of adaptations that local workers, consumers, and firms have evolved over the years in response to different climates. It is worth noting that, while average AC penetration and incidence of hot days is highly positively correlated, the relationship is far from uniform, especially in hotter regions. This is consistent with some hot but poor regions such as Grady, GA having experienced slow AC uptake relative to what climatic averages might suggest. It is also worth noting that, aside from a few recent examples noted above (Davis and Gertler, 2015; Barreca et al., 2016), air conditioning as an adaptation strategy has received limited attention in both the academic and policy literature.<sup>29</sup>

Table 4 presents the results from running augmented versions of equation 2 that interact temperature and AC penetration rates. Columns (1) and (2) present interaction terms between hot temperature and AC penetration by county. The coefficients on the interaction terms between hot temperature and AC penetration are positive, suggesting that having more AC helps protect against the production impacts of hot days. The interaction term between AC and cold days is not significant, further suggesting that the effect is operating through the protecting impact of air conditioning against heat. Because AC penetration is not experimental, however, it is impossible to infer from these estimates that adaptation is a function of AC *per se*. Further, Column (3) provides results of a regression with interactions of 95°F+ days with both AC penetration and the average number of hot days in that county. Both interaction terms are significant and positive, suggesting that, even controlling for AC penetration, the marginal effect of a 95°F+ day is lower in areas that, on average, experience more days above 95°F. That suggests that there are adaptive strategies, or technologies, being employed above and beyond adoption of AC. We take these results as consistent with a model of firm and worker behavior in which some combination of average climate, changes in production technologies, and changes in worker tastes over time leads to differential uptake of AC and other fixed cost adaptation investments, all of which have the realized effect of reducing the short-run production impacts of hot weather.

## 6 Future Projections

Here we provide an illustration of the important role that adaptation can play in assessing optimal climate policy. Our goal is to demonstrate the sensitivity of long-run damage projections to adaptation assumptions, rather than to generate specific parameter estimates.<sup>30</sup>

Our projections of future temperatures come from the CMIP5 multi-model ensemble projections of future climate change. We download data from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (USDOL, 2013). We model temperatures on

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<sup>29</sup>For instance, chapter 17 of the 5th IPCC report, which summarizes the economics of adaptation, does not mention air conditioning as an adaptation strategy.

<sup>30</sup>It is impossible to claim that the estimates that we provide can be thought of either as upper or lower bounds. Induced innovation and future technical change would mean that using such approaches might understate potential adaptation, while market and behavioral failures in local adaptation investment might suggest the opposite.

the Representative Concentration Pathway (RCP) 4.5 emissions path. The RCP 4.5 path assumes that emissions will peak around 2040, which requires carbon policies similar or slightly more aggressive than those outlined in the Paris agreement, and results in a global mean temperature increase of 1.4°C by 2065. We use a downscaled model of climate and hydrology at the scale of the continental United States.

Using these climate projections, we construct the same set of climatic variables for each county that we use in the historical analysis. This provides us with a count of the days in each temperature bin, including the number of days above 95°F, and the total annual precipitation in the county. To construct projected payroll, we take a county-specific linear projection of historic payroll out to 2050. This linear projection is based on observed payroll in our data from 1986 to 2011 and accounts for the existing trend in the number of days above 95°F in a given county over the period from 1986 to 2011. In addition to the linear projection we take logarithmic and quadratic projections. The results are qualitatively similar.

Based on our projected temperature data, in 2050 the median county in the U.S. is expected to experience 66 days with maximum temperature above 95°F (compared to 5 over 1986-2011). The average annual temperature in that median county is projected at 60.1°F (compared to 54.6°F in our sample). This corresponds to shifting the distribution of counties across the 1986-2011 climate quartiles from a uniform distribution to one with 86% of counties in the warmest quartile and just under 2% in the coldest.

## 6.1 Naive Impacts

We estimate future damages from climate change, without adaptation, relative to a counterfactual in which counties continue to experience the same average number of 95°F+ days they do from 1986-2011.

We calculate this relative loss by county as:

$$RelativeLoss_{it} = \beta_{95} \times (\widehat{DaysAbove95}_{it} - \overline{DaysAbove95}_i) \quad (5)$$

where  $i$  and  $t$  again indicate county and years. Here  $\widehat{DaysAbove95}_{it}$  indicates the projected number of days over 95°F from our projected climate data and  $\overline{DaysAbove95}_i$  indicates the average number of days over 95°F in a given county from 1986 to 2011. In both calculations  $\beta_{95}$  is the estimated impact of a day above 95°F from equation 1. We calculate monetary losses in each year by multiplying our projected payroll by the product of estimated percentage loss in payroll and number of hot days.

## 6.2 Adaption Inclusive Impacts

To estimate potential adaptation we recalculate equations 5 replacing  $\beta_{95}$  with  $\beta_{95j}$  where  $j$  indicates the climate quartile specific impact estimated in the quartile specific versions of equation 2. We assign counties to a quartile based on the average number of days they will

experience over 95°F between 2040 and 2050. As in the naive case we use our adaptation inclusive estimates to calculate annual monetary losses as the product of our estimated impact, frequency of hot days and projected payrolls.

We find that not accounting for adaptation leads to estimates of the damages of extremely hot days from 2040 to 2050 that are roughly 50% higher on average. The 50% difference we find in the impact when accounting for adaptation translates to an overestimate of the annual average monetary impacts of productivity losses of \$18 billion (in 2015 dollars) from 2040 to 2050, though the absolute damages are sensitive to secular payroll projection assumptions as well as whether one includes impacts from days between 80°F and 95°F, which are more numerous.

## 7 Discussion and Conclusion

This paper uses county-level payroll and daily weather data to identify the impact of hot temperature on labor and the potential for adaptive investments by workers and firms in the long run. We find substantial causal impacts of hot days on payroll, with larger impacts in exposed sectors such as construction, transportation, and manufacturing. For the US as a whole, an additional day with daily max temperatures above 95°F results in a -0.22% reduction in the level of per capita payroll in exposed sectors that year. Given well-documented short-run wage rigidities, it seems likely that these effects are related to reductions in labor supply, effort, and productivity.

These effects are non-trivially large, especially in exposed industries such as construction and manufacturing. To illustrate: a year in which annual temperatures are +3.6°F (+2°C) warmer than average is associated with 25 additional days above 95° for the median U.S. county, implying a -4.56% reduction in per capita payroll for highly exposed sectors. We estimate that approximately 25-40 million individuals work in highly exposed industries in the United States. This figure is likely much larger for the world as a whole, given the size of the exposed workforce in many large developing economies including China and India. The construction sector alone accounts for over 13% of world GDP. This study thus lends evidence in support of adding labor productivity impacts into integrated assessment models of climate change, which typically assume total damages on the order of a few percentage points of GDP by 2100.

We characterize implied climate adaptation by comparing estimates of the short-run heat-shock sensitivity of local output across regions that experience varying amounts of hot days in expectation. We find substantial geographic variation in these short-run impacts, suggesting that adaptation depends in part on the incentives that firms and individuals face for making fixed cost adaptation investments. For instance, a county in the hottest quartile of the US climate distribution (measured by historical incidence of 95°F days) experiences 75% smaller payroll impacts per hot day than a county in the coldest quartile. While there are as yet many policy relevant unknowns that require further research (e.g. the potential

for induced innovation or market failures in adaptation uptake), these estimates illustrate the importance of taking potential adaptation into account, especially when projecting damages far into the future. At the same time, it is important to note that adaptation may come at substantial costs, which are not captured by this method. Better understanding the magnitude of adaptation costs as well as the extent of potential market and behavioral failures is an important and policy-relevant area for future research.

The central methodological message of this paper is that it may be possible to extract policy-relevant information regarding the potential extent of future adaptation by comparing short run temperature-sensitivities of local economies that have already adapted to varying levels of average heat exposure. Cross-sectional gradients in realized output sensitivities should reflect net-of-private-adaptation values across different climates, an intuition that parallels work by Mendelsohn et al. (1994) and others using the Ricardian method in agricultural contexts, but also addresses critiques regarding causal inference often associated with cross-sectional approaches. Unlike simulation studies which trace the hypothetical costs and benefits of adaptation strategies through particular mechanisms, this analysis empirically estimates the temperature sensitivity of local output and how this sensitivity varies with average local climate using revealed economic behavior.

This paper raises important questions for future research. For instance, how rational or forward-looking are agents in making adaptive investments? In choosing the HVAC system for a manufacturing plant in Boston, a fully rational investor might make her decision based on some weighted average of existing climate projections published by the IPCC. Given limited bandwidth or lack of information, she may alternatively make a decision based on an intuitive sense of historical climate averages. Depending on the geographic mobility of labor inputs and firms, it is possible that worker- and firm-location decisions may increasingly reflect future climate expectations. Whether and to what extent such decisions vary systematically based on education or income may be relevant in assessing the distributional consequences of climate mitigation policy, as well as the potential for welfare-enhancing climate adaptation interventions.

Another set of policy-relevant questions involves the welfare economics of adaptation investment. How much of the relevant adaptive investments will be in the form of private goods, such as home air conditioning, versus local or global public goods, such as workplace norms, electric infrastructure (e.g. peak grid capacity), or new cooling technologies? Assessing these and other potential market failures in the context of labor market responses to climate shocks presents an important area of future research.

The production impacts documented here imply that it may be possible to uncover adaptation cost functions using observed – as opposed to simulated – data, with some assumptions about production technologies. Though the present analysis does not allow for detailed estimation of the costs associated with such long run adaptations, similar analyses using richer data and/or structural estimation techniques may be able to estimate the implied adaptation costs which rationalize observed gradients in short-run weather

impacts.

Finally, it is unclear whether the heat-related impacts and scope for adaptation documented here are reflective of what one might expect in other countries, particularly in the developing world. The substantial heterogeneity in temperature sensitivities within the United States, combined with previous (larger) estimates of labor productivity, mortality, and agricultural output declines due to heat stress in developing countries (Burgess et al., 2014; Sudarshan and Tewari, 2013) suggests that the long-run impacts of climate change may be more severe for the developing world than previously estimated. It is well-documented that rates of air-conditioning have historically tended to follow income growth quite closely, and have neared saturation in warmer parts of the US (Biddle, 2008; Gertler et al., 2016). Given much lower AC penetration in much of the developing world as well as parts of Europe and East Asia, these estimates suggest substantial labor productivity impacts from climate change in the medium to long run, even with rapid uptake of AC.

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## Tables and Figures

Table 1: Measuring the Impact of Short-Run Heat Exposure on Annual Payroll.

|                               | (1)                        | (2)                        | (3)                        |
|-------------------------------|----------------------------|----------------------------|----------------------------|
| Above 95°F                    | -0.000419*<br>(0.000248)   | -0.000505**<br>(0.000245)  | -0.000418*<br>(0.000247)   |
| 90° to 95°F                   | -0.000410***<br>(0.000150) | -0.000575***<br>(0.000152) | -0.000405***<br>(0.000150) |
| 80° to 90°F                   | -0.000120<br>(0.000128)    | -0.000205*<br>(0.000114)   | -0.000119<br>(0.000128)    |
| 60° to 70°F                   | -0.000169<br>(0.000150)    | -0.000143<br>(0.000138)    | -0.000167<br>(0.000149)    |
| 50° to 60°F                   | 0.0000862<br>(0.000166)    | 0.000000205<br>(0.000157)  | 0.0000881<br>(0.000166)    |
| 40° to 50°F                   | -0.000146<br>(0.000207)    | -0.0000413<br>(0.000201)   | -0.000143<br>(0.000207)    |
| 30° to 40°F                   | 0.0000605<br>(0.000229)    | -0.0000810<br>(0.000218)   | 0.0000621<br>(0.000228)    |
| 20° to 30°F                   | -0.000153<br>(0.000275)    | -0.0000548<br>(0.000268)   | -0.000147<br>(0.000275)    |
| 10° to 20°F                   | 0.000623<br>(0.000401)     | 0.000417<br>(0.000376)     | 0.000623<br>(0.000401)     |
| 0° to 10°F                    | 0.000118<br>(0.000666)     | -0.000294<br>(0.000626)    | 0.000115<br>(0.000666)     |
| Avg Precip                    | -0.00314<br>(0.00236)      | -0.00498**<br>(0.00226)    | -0.00313<br>(0.00236)      |
| N                             | 79907                      | 79907                      | 79907                      |
| r <sup>2</sup>                | 0.991                      | 0.995                      | 0.991                      |
| Fixed Effects                 |                            |                            |                            |
| County                        | X                          | X                          | X                          |
| Year                          | X                          | X                          | X                          |
| State-specific linear trends  | X                          |                            |                            |
| County-specific linear trends |                            | X                          |                            |
| State-specific cubic trends   |                            |                            | X                          |

Robust standard errors in parentheses

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

Notes: The dependent variable is log non-agricultural payroll per capita. Robust standard errors are clustered at the state-by-year level. The number of days with temperatures in the 70° to 79° bin is the omitted category. All other temperature bins are suppressed in output.

Table 2: Measuring the Impact of Short-Run Heat Exposure on Annual Payroll in Highly Exposed Industries.

|                              | (1)                        | (2)                       | (3)                        |
|------------------------------|----------------------------|---------------------------|----------------------------|
| Above 95°F                   | -0.00233***<br>(0.000614)  | -0.00209***<br>(0.000624) | -0.00233***<br>(0.000613)  |
| 90° to 95°F                  | -0.00189***<br>(0.000387)  | -0.00182***<br>(0.000394) | -0.00188***<br>(0.000387)  |
| 80° to 90°F                  | -0.000756***<br>(0.000289) | -0.000664**<br>(0.000287) | -0.000756***<br>(0.000289) |
| 60° to 70°F                  | -0.000658*<br>(0.000347)   | -0.000639*<br>(0.000341)  | -0.000654*<br>(0.000347)   |
| 50° to 60°F                  | -0.000624<br>(0.000408)    | -0.000586<br>(0.000390)   | -0.000621<br>(0.000407)    |
| 40° to 50°F                  | -0.00135***<br>(0.000479)  | -0.00121**<br>(0.000477)  | -0.00134***<br>(0.000478)  |
| 30° to 40°F                  | -0.000946*<br>(0.000546)   | -0.00106**<br>(0.000529)  | -0.000940*<br>(0.000546)   |
| 20° to 30°F                  | -0.00122*<br>(0.000682)    | -0.00132**<br>(0.000647)  | -0.00121*<br>(0.000682)    |
| 10° to 20°F                  | -0.000206<br>(0.000942)    | -0.000737<br>(0.000909)   | -0.000203<br>(0.000943)    |
| 0° to 10°F                   | 0.00137<br>(0.00174)       | 0.000412<br>(0.00171)     | 0.00136<br>(0.00174)       |
| Avg Precip                   | -0.0178***<br>(0.00608)    | -0.0162***<br>(0.00601)   | -0.0178***<br>(0.00608)    |
| N                            | 78035                      | 78035                     | 78035                      |
| r2                           | 0.853                      | 0.899                     | 0.853                      |
| Fixed Effects                |                            |                           |                            |
| County                       | X                          | X                         | X                          |
| Year                         | X                          | X                         | X                          |
| State-specific linear trends | X                          |                           |                            |
| County-specific trends       |                            | X                         |                            |
| State-specific cubic trends  |                            |                           | X                          |

Robust standard errors in parentheses

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

Notes: The dependent variable is log non-agricultural payroll per capita. Robust standard errors are clustered at the state-by-year level. The number of days with temperatures in the 70° to 79° bin is the omitted category. All other temperature bins are suppressed in output.

Table 3: Production Impacts by Quartile of Climate Distribution.

| Panel A: All payroll                          |                         |                          |                           |                            |
|---|-------------------------|--------------------------|---------------------------|----------------------------|
|   | (1)                     | (2)                      | (3)                       | (4)                        |
| Above 95°F                                    | -0.00208**<br>(0.00102) | -0.00108**<br>(0.000497) | -0.000597**<br>(0.000238) | -0.000521***<br>(0.000188) |
| N   | 20285                   | 19700                    | 20006                     | 19916                      |
| r <sup>2</sup>                                | 0.993                   | 0.993                    | 0.991                     | 0.987                      |
| Standard errors in parentheses                |                         |                          |                           |                            |
| * $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$ |                         |                          |                           |                            |
| Panel B: Highly Exposed Payroll               |                         |                          |                           |                            |
|   | (1)                     | (2)                      | (3)                       | (4)                        |
| Above 95°F                                    | -0.00640*<br>(0.00353)  | -0.00597***<br>(0.00131) | -0.00239***<br>(0.000659) | -0.00162***<br>(0.000463)  |
| N   | 19970                   | 19386                    | 19532                     | 19147                      |
| r <sup>2</sup>                                | 0.885                   | 0.890                    | 0.850                     | 0.785                      |
| Standard errors in parentheses                |                         |                          |                           |                            |
| * $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$ |                         |                          |                           |                            |

Notes: The dependent variable in panel A is log payroll per capita. In panel B it is log payroll per capita in highly exposed industries. All regressions include the parsimonious bins for the number of days in 20°F bins from 0°F to 70°F, county and year fixed effects which are suppressed in the output, as well as state-specific cubic time trends in payroll. Robust standard errors are clustered at the state-by-year level. The number of days with temperatures in the 70°F to 95°F bin is the omitted category.

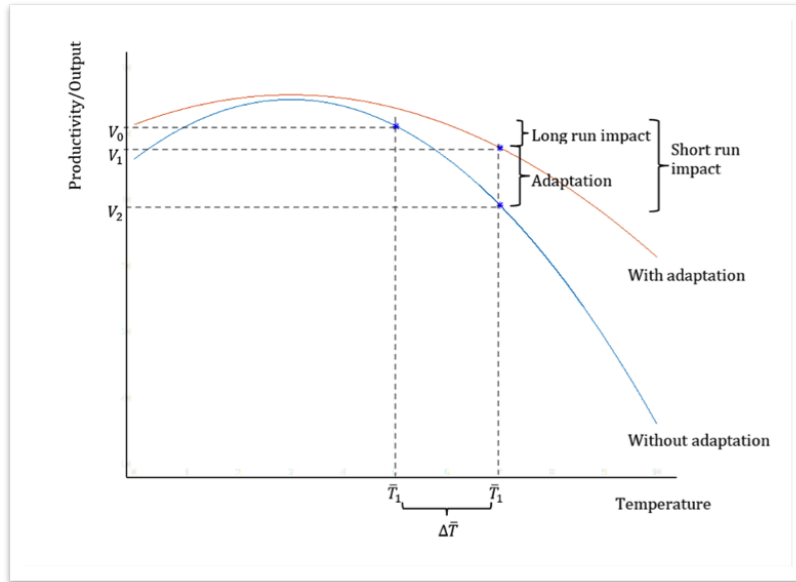
Table 4: Measuring Adaptation with Air Conditioning in Highly Exposed Industries

|  | (2)                         | (3)                         | (4)                         |
|--|-----------------------------|-----------------------------|-----------------------------|
| Above 95°F                                       | -0.00755***<br>(0.00190)    | -0.00755***<br>(0.00190)    | -0.00836***<br>(0.00200)    |
| Above 95°F $\times$ Avg Hot Days per Year (95°+) |                             |                             | 0.0000506*<br>(0.0000305)   |
| Above 95°F $\times$ Total AC(%)                  | 0.0000720***<br>(0.0000223) | 0.0000719***<br>(0.0000223) | 0.0000624***<br>(0.0000207) |
| Total AC(%)                                      | 0.00710***<br>(0.000949)    | 0.00713***<br>(0.000948)    | 0.00724***<br>(0.000937)    |
| Days 0° to 19° $\times$ Total AC(%)              |                             | -0.00000557<br>(0.0000159)  | -0.00000790<br>(0.0000156)  |
| N  | 78035                       | 78035                       | 78035                       |
| r <sup>2</sup>                                   | 0.853                       | 0.853                       | 0.853                       |

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Notes: The dependent variable is log payroll per capita in highly exposed industries. All regressions include the parsimonious bins for the number of days in 20°F bins from 0°F to 70°F, county and year fixed effects which are suppressed in the output, as well as state-specific cubic time trends in payroll. Robust standard errors are clustered at the state-by-year level.

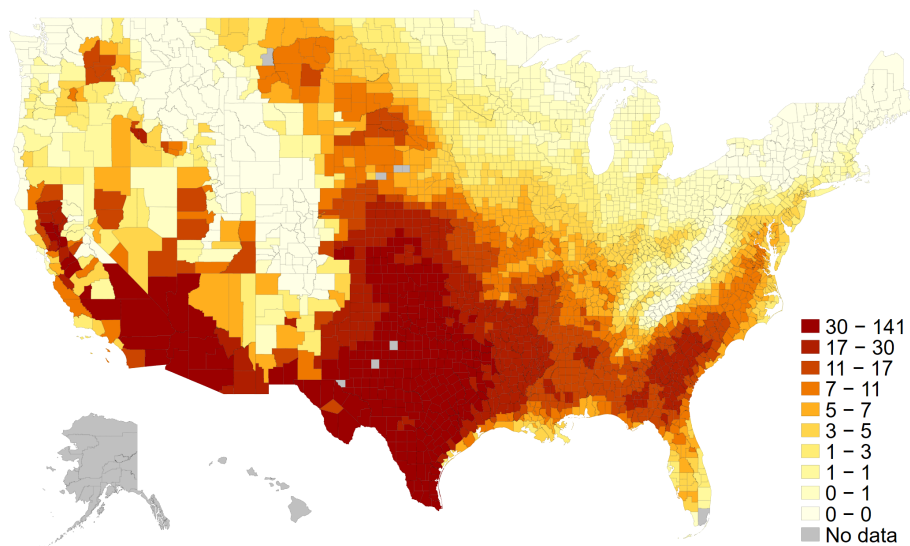


(a) Stylized representation of the potential bias in estimating climate damages without taking future adaptation into account, assuming that adaptation can reduce impacts in the longer term.

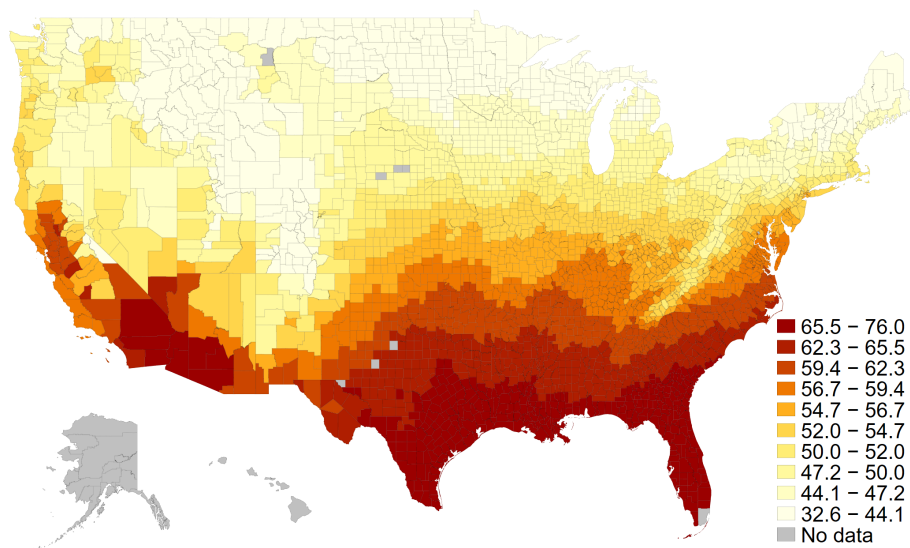
| Short Run                                   |  | Long Run   |                                      |
|---|--|--|--------------------------------------|
| Adjust labor effort                         | Cooling flow expenditures (e.g. turn on ceiling fan) | Cooling equipment stock expenditures (e.g. install air conditioning) | R&D                                  |
| Adjust timing of labor supply (within-day)  |  |  | Investments in public health systems |
| Adjust timing of labor supply (across days) |  | Changes in wardrobe  | Informational interventions          |
|   |  | Occupational choice  | Labor migration                      |
|   |  | Energy Infrastructure  | Firm relocation                      |
|   |  | Labor force participation (extensive margin)                         | Genetic adaptation                   |

(b) Possible adaptation mechanisms in response to temperature stress

Figure 1: Adaptation intuition and mechanisms



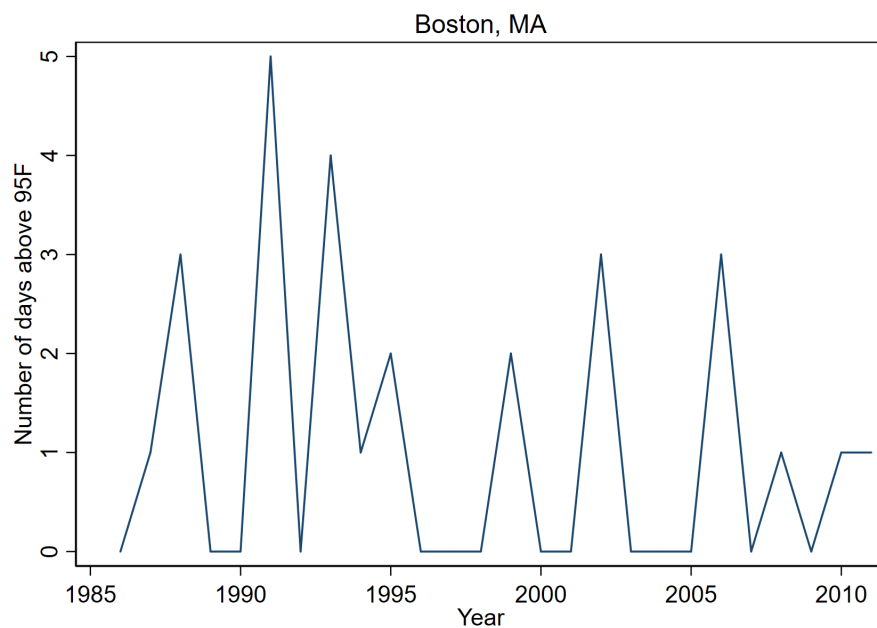
(a) Average Incidence of hot days (95°F+) per year



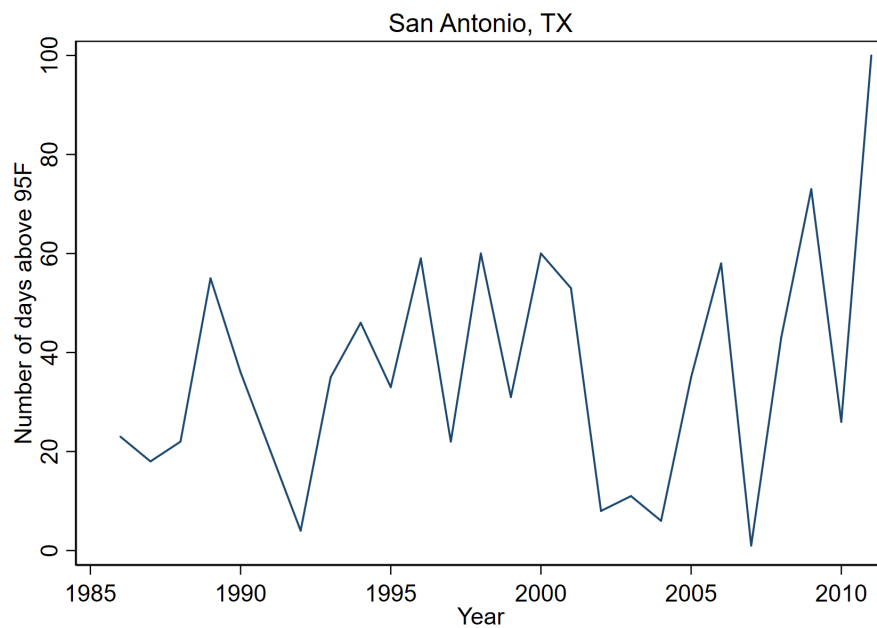
(b) Average daily mean temperature (°F)

Figure 2: Average long-run temperatures by county.

Notes: Top panel shows number of days with daily max temperature above 95°F over the period 1986-2011. Bottom panel shows average daily mean temperatures over the same period.



(a) Hot days per year in Suffolk County, MA.



(b) Hot days per year in Bander County, TX.

Figure 3: Main identifying temperature variation

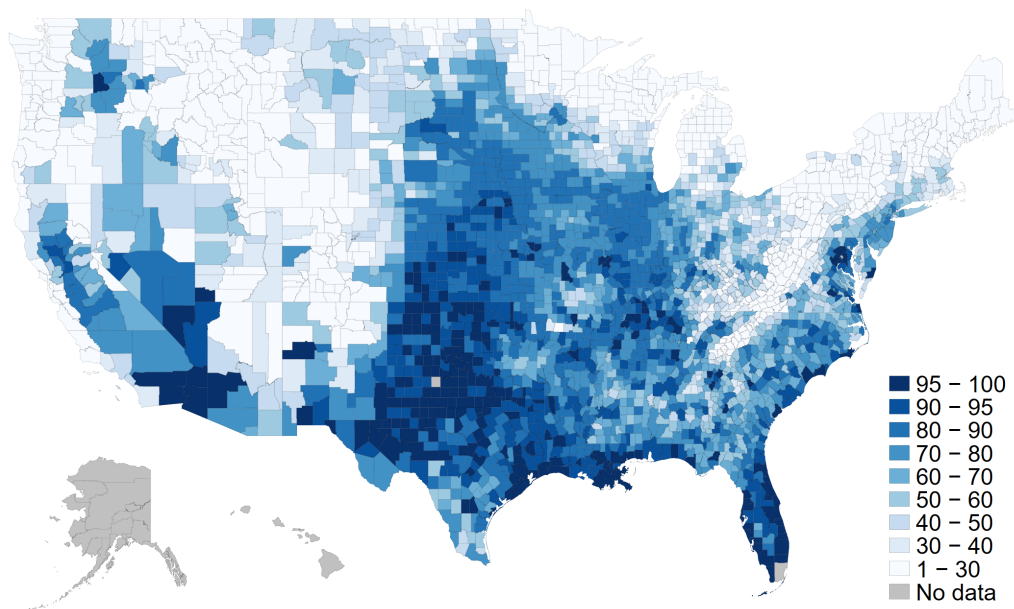


Figure 4: AC penetration in 1990

Notes: Imputed residential AC penetration rates (in percentage of households) by county. Includes residential window and central AC units.

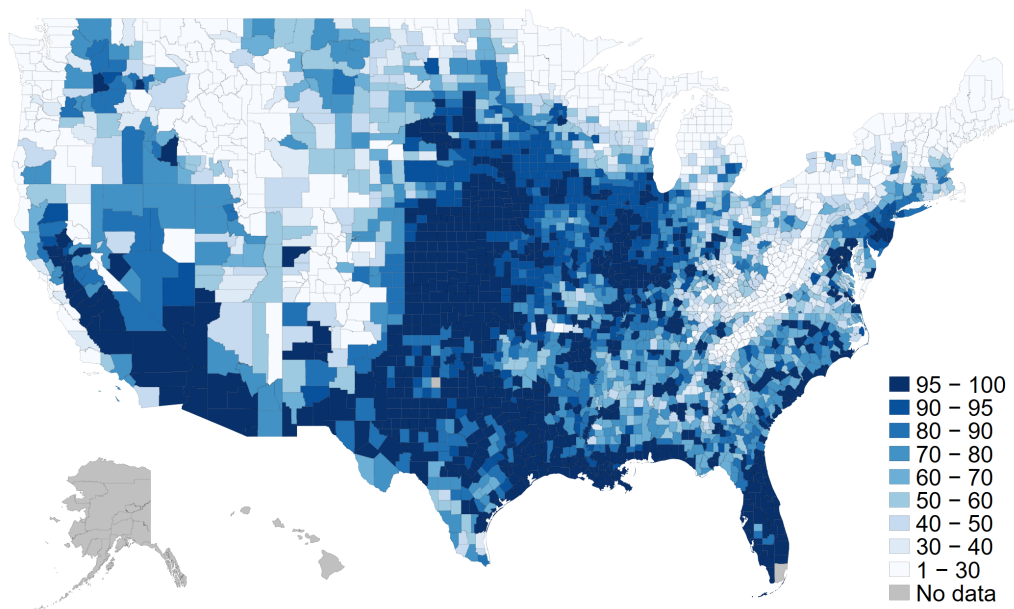
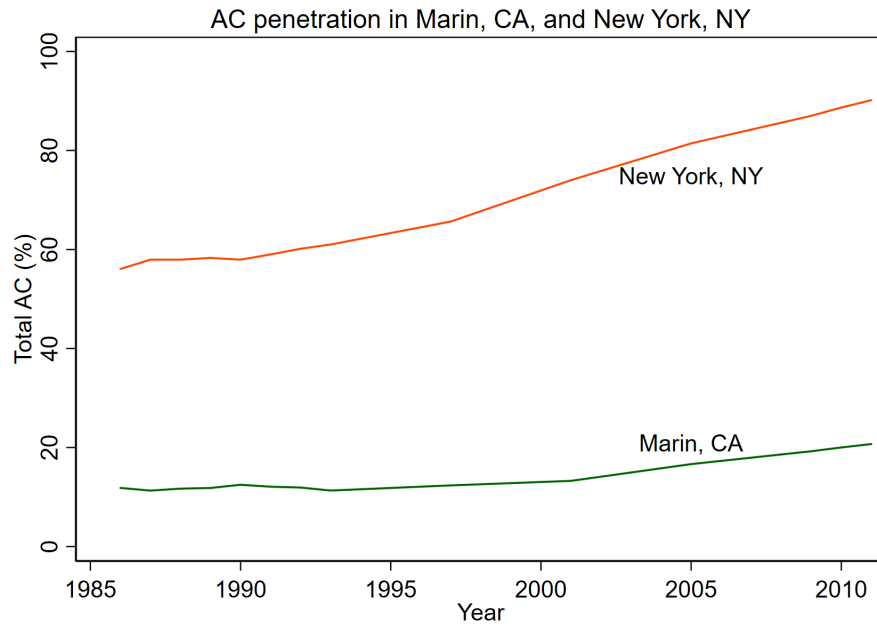
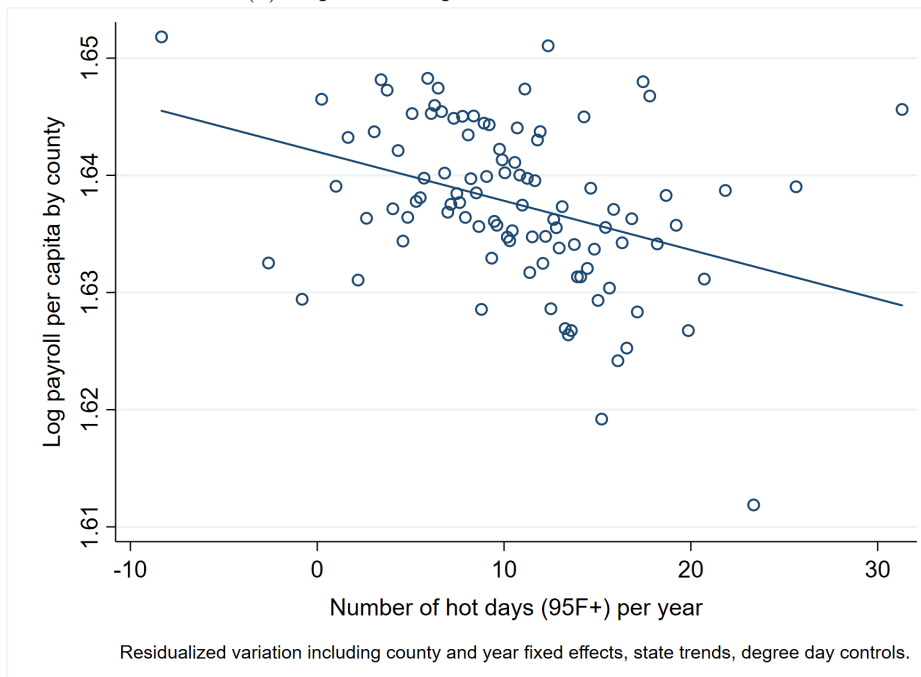


Figure 5: AC penetration in 2010

Notes: Imputed residential AC penetration rates (in percentage of households) by county. Includes residential window and central AC units.

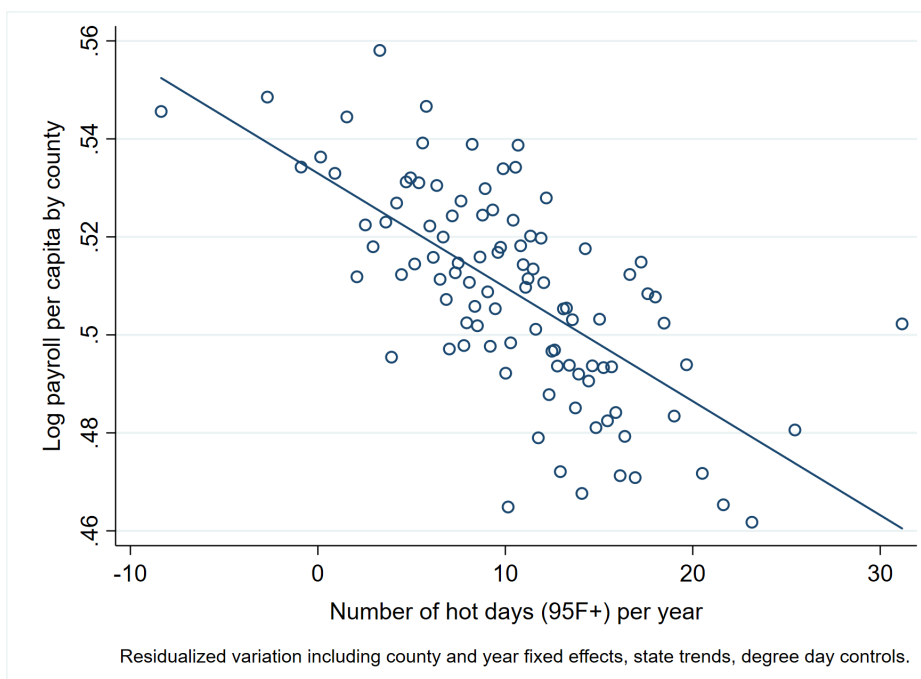


(a) Imputed AC penetration over time

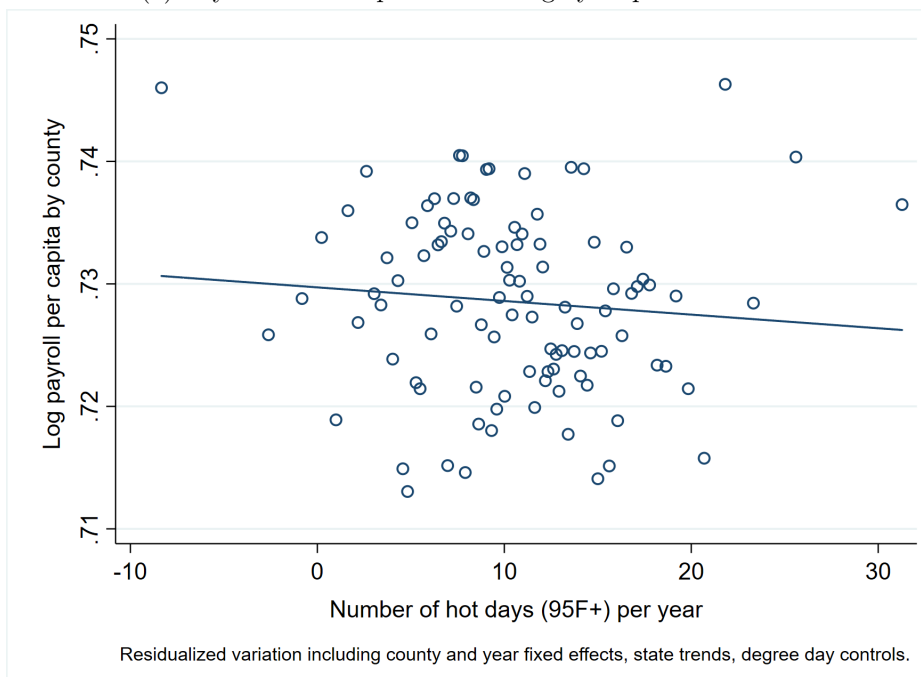


(b) Payroll and Temperature

Notes: Panel a shows residential AC penetration in Grady County, GA, and New York County, NY, 1986-2011. County-level base values are taken from 1980 census and annual rates of change taken at the census region level from RECS (2012), and includes window units and central AC for residential dwellings. Panel b plots residualized variation including county and year fixed effects, state-specific cubic time trends and non-parametric controls for all other degree days. Days with maximum temperature between 70-79°F is the omitted category.



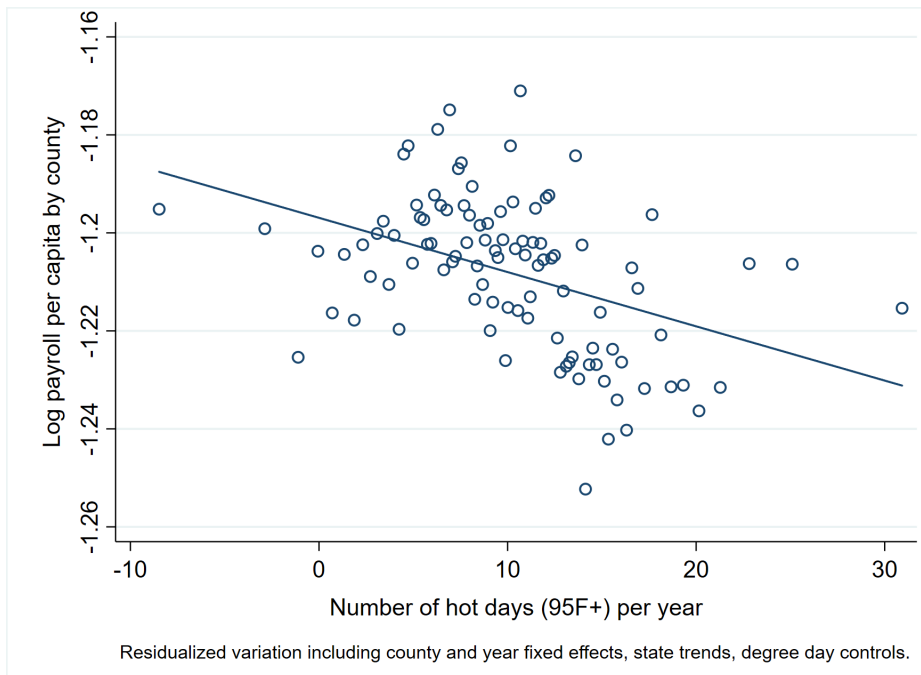
(a) Payroll and Temperature in Highly Exposed Sectors.



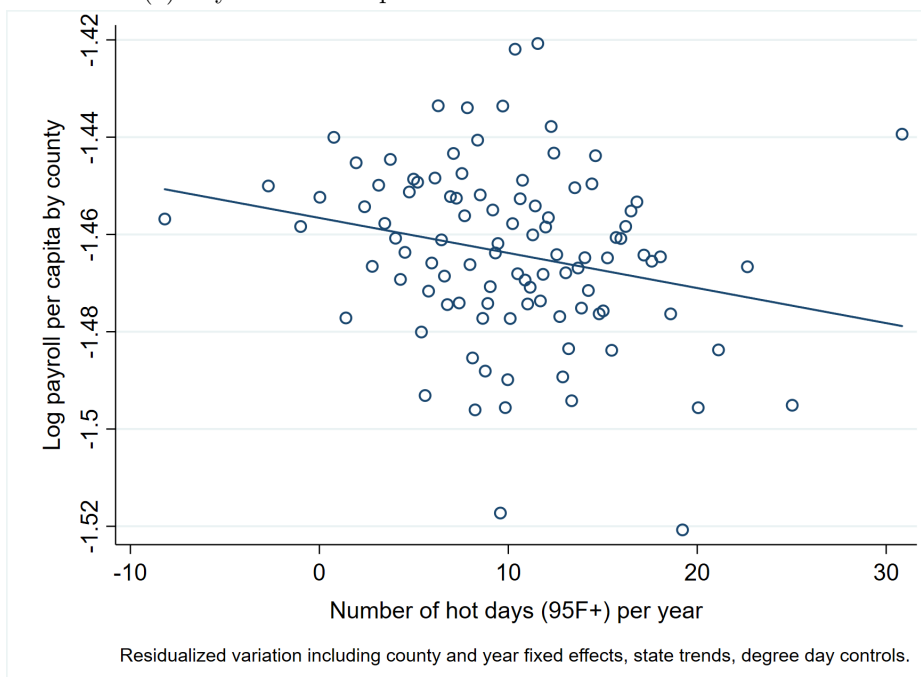
(b) Payroll and Temperature in Non-Exposed Sectors.

Figure 7: Temperature and Payroll by NIOSH Classification

Notes: Residualized variation including county and year fixed effects, and state-specific cubic time trends and non-parametric controls for all other degree days. Days with maximum temperature between 70-79°F represent the omitted category.



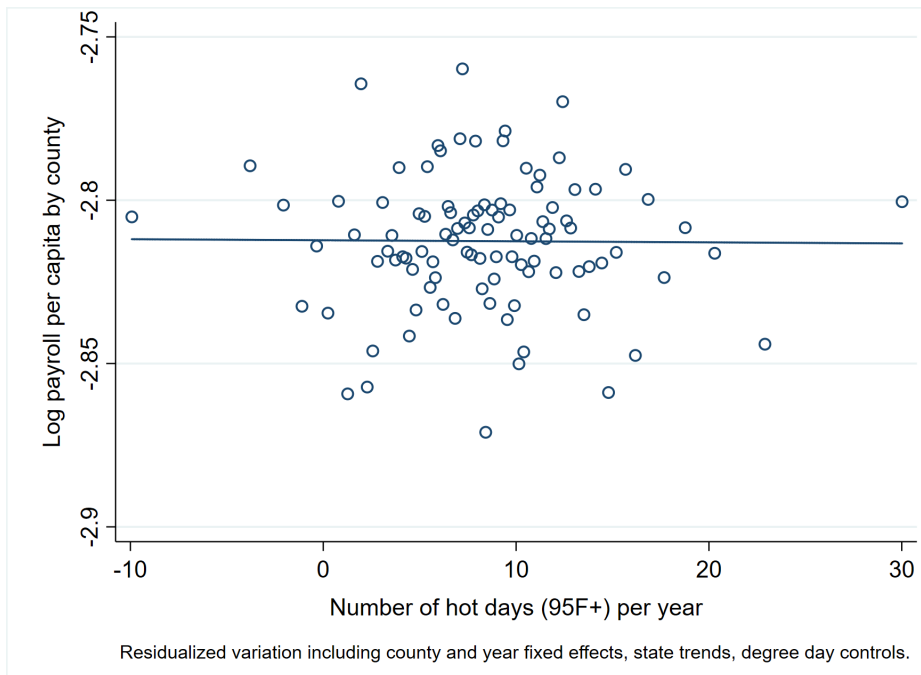
(a) Payroll and Temperature in the Construction Sector



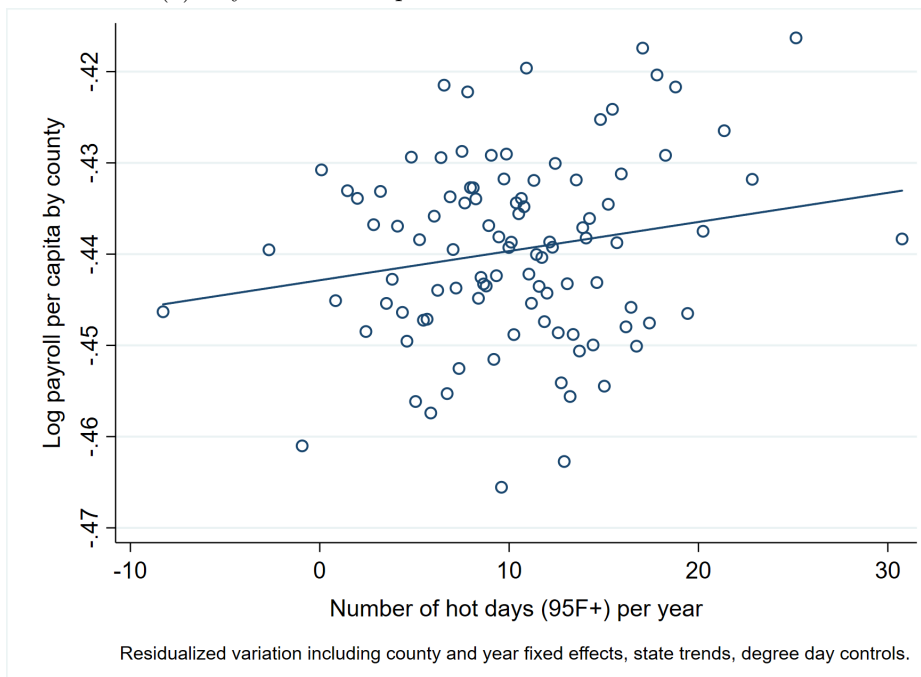
(b) Payroll and Temperature in the Transportation Sector

Figure 8: Temperature and Payroll in Highly Exposed Sectors

Notes: Residualized variation including county and year fixed effects, and state-specific cubic time trends and non-parametric controls for all other degree days. Days with maximum temperature between 70-79°F represent the omitted category.



(a) Payroll and Temperature in the Education Sector



(b) Payroll and Temperature in the Healthcare Sector

Figure 9: Temperature and Payroll in Non-Exposed Sectors

Notes: Residualized variation including county and year fixed effects, and state-specific cubic time trends and non-parametric controls for all other degree days. Days with maximum temperature between 70-79°F represent the omitted category.