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Will We Adapt? Temperature Shocks, Labor Productivity, and Adaptation to Climate Change in the United States (1986-2012)

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Prepared for

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Will We Adapt? Temperature Shocks, Labor Productivity, and Adaptation to Climate Change in the United States (1986-2012)

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January 2016

How effectively will economic agents adapt to climate change? This study assesses the scope for long-run climate adaptation by comparing the economic impacts of daily heat shocks across varying climatic regions within the United States. Using a panel of county-level payroll and weather data (1986-2012), I estimate the causal impact of hot days on local labor product. For the average U.S. county, an additional day above 90°F results in a -0.048% decline in payroll per capita that year, consistent with previous studies (e.g. Hsiang and Deryugina, 2014). Places more prone to extreme heat stress (e.g. Houston) exhibit significantly lower temperature sensitivities than colder ones (e.g. Boston); a year with 10 additional 90°F days reduces output per capita by -2.63% in counties in the coldest quintile; -0.46%, or roughly one fifth that, in the warmest quintile, suggesting significant scope for long-run adaptation to climate change given appropriate investments. However, the fact that even the hottest, well adapted regions of the United States suffer economically meaningful production impacts from extreme heat suggests that climate adaptation may entail non-trivial costs.

JEL Codes: D6, N5, Q59, O13, Q1, Q54
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I. 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?

While it is often assumed that the damages from climate change will be reduced by adaptive responses, particularly in the context of continued economic development (Tol, 2009) and diffusion of technologies, relatively few studies have empirically estimated the potential scope for adaptation to climate change outside of agricultural contexts (e.g. Deschenes and Greenstone, 2013; Burke and Emerick, 2014). Given the gradual and long-term nature of climate change, the potential scope for adaptive investments by firms and individuals is an important parameter in gauging optimal policy responses aimed at curbing greenhouse gas emissions – including a carbon tax or emissions cap.

Using a spatially disaggregated panel of weather and economic data from the United States, and building on recent micro studies which document significant labor productivity impacts of heat stress (Sudarshan et al, 2014; Cachon et al, 2012), this study provides a first pass at estimating climate adaptation in the long run. The findings suggest significant scope for adaptation to climate change – at least in the context of production impacts arising from heat stress of labor inputs[1]. However, the fact that temperature shocks exert statistically significant and economically meaningful impacts on labor productivity even in the hottest and presumably well-adapted regions of the United States suggests that there may be realistic limits to – and non-trivial costs associated with – adaptation to increased heat stress due to climate change, at least using existing technologies.

I characterize implied climate adaptation by first estimating the heat-shock sensitivity of local output, using data from local weather and payroll records at the county level, which provide information on daily weather shocks and their impact on payroll per capita for over 3,000 counties between 1986 and 2012. For the US as a whole, an additional day with daily mean temperatures between 80°F and 90°F results in a -0.028% reduction in the level of per capita payroll that year; a year with an additional day above 90°F leads to a -0.048% decline[2]. Put another way, if the entire United States were to experience summer heat at the level of an average summer in Houston, which features 35 days with mean temperatures above 90°F, the aggregate impact would be roughly -6.27% per capita that year. Moreover, in the subset of industries that are classified by the NIOSH as highly exposed to environmental stressors, these impacts may be twice as large[3].

Leveraging heterogeneity in these short run panel estimates, this study attempts a first-pass at calibrating adaptation in the long run, by providing estimates that may help place bounds on the expected extent of adaptation to longer term shifts in climate. I find substantial geographic

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[1] For a detailed review of the emerging literature on direct impacts of temperature stress on economic activity, see Heal and Park (forthcoming).

[2] A one degree F hotter-than-average year reduces payroll per capita by -0.47%.

[3] These include construction, mining, transportation, wholesale, utilities, and manufacturing industries (National Institute of Occupational Safety and Health).

variation, suggesting that adaptation depends in part on the history of weather shocks in a given locality, notably, the average number of hot days (daily mean temperatures above 80°F). These estimates suggest that the productivity impacts in a world where agents engage in no adaptation may be as much as five times as large as one in which all individuals adopt privately optimal adaptive technologies and norms, though it is unclear how quickly such adjustment might occur.

The central methodological message of this paper is that by exploiting spatial variation in panel estimates across different climate zones, it is possible to approximate the extent of future adaptation by comparing the differences between short run heat-shock sensitivities of local economies that have already optimally adapted to varying levels of local heat stress. The intuition is that the cumulative history of weather shocks in a relatively warm region today may provide a valuable indicator for the extent of long-run adaptive investment that relatively cool regions may eventually undertake in the distant future, assuming similar availability of adaptive technologies (e.g. air conditioning, alteration of norms around time of work); in other words, that cross-sectional gradients in realized output sensitivities reflect net-of-adaptation values across different climates, an intuition that parallels work by Mendelsohn (1994) and others using the Ricardian method in agricultural contexts[4].

Very hot places (e.g. Houston, Orlando) are found to be significantly better adapted to heat stress than colder ones (e.g. Boston, Minneapolis). Regions in the 1st and 5th quintiles of the 80°F-and-above day distribution – which feature, on average, 35 and 3 days per year with mean temperatures above 90°F respectively – suffer short-run impacts of -0.046 percentage points and -0.263 percentage points per additional day above 90°F respectively[5]. The short run impact of an additional hot day falls monotonically as one moves to hotter regions within the US, suggesting that optimizing agents do in fact respond to persistent temperature extremes. It seems Bostonians face fewer incentives to invest in industrial-strength air conditioning than Houstonians do, given fewer hot days per year.

But the persistence of negative impacts across most of the US climate distribution suggests that there may be non-trivial costs to such adaptive investments – both pecuniary and non-pecuniary[6]. The existence of impacts on output across a wide range of (non-agricultural) industries suggests that, from a methodological perspective, using revealed-preference techniques to estimate the extent of future adaptation may be preferable to modeling particular adaptation channels structurally, given the many margins of adjustment that are possible across production contexts.

In sum, these findings build on a growing literature which suggests that secular adaptation to climate change will likely be (1) incomplete even in the long term, and (2) non-trivially costly. 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 Dell et al (2012) and Graff-

[4] The hope is that such an approach may allow integrated assessment modelers to include estimates of weather-driven output and productivity shocks into estimates of the social cost of carbon, with greater confidence regarding the potential for such shocks to persist over the relevant (long) time horizons.

[5] A mean-shift in the US climate distribution of 4.5°F is on the conservative end of estimates for the amount of warming expected by 2100.

[6] Otherwise, and absent behavioral biases that prevent agents from recognizing and responding to temperature-driven output shocks, one would expect all regions of the US to feature similar (low) levels of output sensitivity to extreme heat events.

Zivin and Neidell (2014), and may allow researchers to link the econometrically well-identified studies of weather-driven output shocks (e.g. Hsiang, 2011; Dell et al, 2012) to the more simulation-based estimates of the social costs of carbon (e.g. Nordhaus, 2010; Stern, 2008; Hope, 2009).

I estimate the temperature sensitivity of output in the short run using a differences-in-differences approach. The short-run sensitivity is captured by the impact of the number of extreme heat days in a given year - daytime mean temperatures above 90°F, controlling for humidity - on the level and growth rate of output per capita using panel data and quasi-random variation in daily weather patterns. I focus on the impact of heat stress, though controls for other precipitation and cold days are included. The estimation strategy relies on the assumption that year-to-year fluctuations in the number of extreme heat days in any given county are uncorrelated with unobserved determinants of county payroll, after controlling for time-invariant differences (county fixed effects), state-specific shocks (state-by-year fixed effects), and correlated output shocks at the national level (year fixed effects). The results are robust to alternative characterizations of temperature stress that have been used in the literature to date, including average annual temperatures (Dell et al, 2012; Hsiang, 2011) and cooling degree days (Schlenker et al, 2011; Butler and Huybers, 2012), as well as a variety of alternative specifications.

These results build on an extensive literature on the economic impacts of climate change, reviewed by Tol (2009), as well as the literature on the weather sensitivity of socioeconomic outcomes, reviewed by Dell et al (2014). The estimates of temperature-driven economic impacts are broadly consistent with prior results, including Hsiang (2010), Dell et al (2012), and Burke and Emerick (2013). However, like Hsiang and Deryugina (2014), they also imply that contrary to previous suggestions that developed economies are well-insulated from climate damages[7], even the world's wealthiest economies are currently subject to non-trivial weather-related output losses - impacts which may be exacerbated by future climate change.

The rest of the paper proceeds as follows. Section II presents a simple typology of adaptation mechanisms, and an analytical framework which helps motivate the empirical analysis. Section III discusses the research design. Section IV presents the data, and Section V discusses the results for short-run heat sensitivity an implied long-run adaptation. Section VI interprets the results, and Section VII concludes.

II. Conceptual Framework for Measuring Adaptation

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, 1947; Viner, 1958; Mendelsohn, 1994; Davis and Weinstein, 2002; Cutler, Miller, Norton, 2007; Hornbeck, 2012; Burke and Emerick, 2013). At the most general level, economists have debated this issue theoretically since at least Samuelson (1947), 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.

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[7] Some studies have suggested that developed economies may even benefit from moderate amounts of warming (Tol, 2009; Mendelsohn, 1994).

This issue has taken on increased empirical relevance in the context of climate change, which will take place over the span of multiple decades. Despite a rapidly evolving literature that documents a statistically robust relationship between short-run weather variation (e.g. temperature and rainfall shocks) and economic variables of interest (e.g. mortality, labor productivity, conflict, exports)[8], it remains unclear whether these short-run *weather-sensitivities* are reflective of long-run *climate sensitivity* of social welfare, mainly due to the possibility of adaptation. In particular, the realized welfare costs of climate change will be highly sensitive to the scope, speed, and adjustment costs associated with adaptation in the long-run. This paper focuses on the second of these three important parameters.

Will we adapt to climate change, and how important is adaptation for climate policy? One can imagine three stylized possibilities.

First, adaptive adjustments may be effective at reducing climate impacts, and occur quickly and 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, it may be the case that adaptive investments occur slowly, are prohibitively costly, and/or suffer from market failures. This would suggest that economic damages under climate change would likely be large, implying a more substantial role for public policy in addressing future climate threats. A third possibility is that, regardless of the potential effectiveness of certain adaptive investments, the set of adaptation options actually shrinks in the long run, due to the 'unsustainability' of some current production methods. For instance: due to the drying out of fossil aquifers which currently sustain economic activity in otherwise inhospitable contexts.

The economic literature on adaptation has focused primarily on agricultural contexts (Mendelsohn et al, 1994; Mendelsohn et al, 2000; Schlenker and Roberts, 2011; Butler and Huybers, 2012; Burke and Emerick; 2013)[9]. This paper addresses the prospect of adaptation to the labor productivity and labor supply impacts of heat shocks, primarily on non-agricultural sectors. The intention is to include all possible economic sectors that are subject to temperature-related production impacts arising from thermal stress of the human body – including the labor supply, task productivity, and direct disutility losses this may entail – and to estimate the implied extent of adaptation without designating a particular adaptation mechanism the way many modeling studies do. Given the fact that, in most OECD countries, non-agricultural output accounts for over 95% of total income, addressing adaptation in the context of non-agricultural sectors is of central importance in estimating the true social costs of carbon.

Of course, to the extent that future adaptation decisions may be endogenous to current policy decisions surrounding climate change and economic development, the econometrician must leave open the possibility that such a reduced-form approach may underestimate the extent of

[8] For instance, Greenstone and Deschenes (2013) find that an additional day above 90°F leads to a 0.11% increase in annual mortality in the United States, controlling for location-specific characteristics. 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; a week with six or more days above 90°F reduces output that week by 8% on average. Sudarshan et al (2014) find similar plant-level productivity declines among Indian manufacturers, even when controlling for region, firm, and individual-specific factors.

[9] A limited number of global and regional adaptation cost assessments exhibit a large range and have been completed mostly for developing countries, with the most recent and most comprehensive to date global adaptation costs range from $70 to more than $100 billion annually by 2050 (World Bank, 2010). But the quantity and quality of local studies varies by sector with more treatment of adaptation in coastal zones and agriculture (Agrawala and Fankhauser, 2008).

adaptation that may actually occur. This is especially true in the context of market failures associated with adaptive investments in response to climate change.

The rest of this section briefly summarizes the types of adaptive investments that might occur in response to climate change, with an eye toward generating a typology that informs the particular empirical strategy at hand.

A. Secular versus Directed Adaptation

What are the ways in which individuals, firms and societies may adapt to changing climate? Building on a heuristic developed by Agrawala and Fankhauser (2008), I differentiate between those adaptation mechanisms that one would expect to occur naturally in a market economy as a result of changing climates or incomes, and those that would not occur due to important market failures. For the purposes of this study, I will refer to the former class of adaptation mechanisms as *secular adaptation*, the latter as *directed adaptation*.

Market Failures in Adaptation

There are many ex ante reasons to suspect socially sub-optimal provision of adaptation investments. For instance, many important adaptations will require investments in public goods, which are likely to be underprovided under market equilibrium. Examples may include firm-level "public goods" such as centralized air conditioning, city or municipality level public infrastructure such as emergency heat stations, or national public infrastructure in the form of peak-load electric capacity. Even with active intervention by firms or the public sector, substantial heterogeneity in preferences (e.g. some workers may tolerate heat or cold in the workplace better) coupled with an inability to tailor public good levels to individuals (i.e. to reach Tiebout equilibrium) may also lead to a gap between achieved and socially optimal conditions[10].

There may be behavioral factors which inhibit individuals from "optimizing" adaptation decisions as well. These may include salience, hyperbolic discounting, or other well-documented cognitive biases (Kahneman and Tversky, 1974) which may lead to a substantial delay between the realization of a shift in climate and appropriate adaptive responses (e.g. delaying investment in heat stations until after a significant heat-related mortality event), or even permanent neglect of NPV-positive adaptation investments (e.g. demand-side energy efficiency enhancements). A hyperbolic discounter may be better off in the long run refurbishing his house with a central

[10] There may also be externalities in the form of informational asymmetries and principal-agent problems which cause sub-optimal adaptation outcomes in the labor market. Notably, imperfect observability of worker productivity may necessitate the creation of second-best contracts, the presence of which may dis-incentivize optimal adaptation effort on part of agents (workers) in response to exogenous productivity shocks (Hart, 1988). An example of this may be found in the construction industry, where wages are often paid via fixed per diem contracts but random, unpredictable weather shocks can cause changes in effective labor supply (and productivity). The construction worker knows that he may not be as productive on a hot day, but chooses to go to work anyway. There is some disutility cost to the worker, productivity costs to the principal, but due to the randomness of the shock, the resulting equilibrium wage may be socially sub-optimal. This situation is well approximated by the extensive literature on moral hazard in the context of disability insurance and unpredictable workplace accidents.

HVAC system, but in the short run, renting a window AC unit may be cheaper and more convenient.

All of these factors suggest that there may be situations in which directed public intervention may be required to achieve the socially optimal amount of adaptation investment[11].

B. Adaptation in the Short and Long Run

The types of adaptation mechanisms available will depend on the time-frame of interest. Adaptation to adverse weather conditions may take many forms, some of which can be exercised within the same day, others which may occur over decadal time spans. For instance, in the very short run, individuals may adapt by changing labor supply, either on the intensive margin at the daily level, with individuals choosing to work more or less hours or shifting the timing of work hours during a given day; or on extensive margin at the daily level, choosing not to work at all if conditions are bad enough (Zivin and Neidell, 2014). Individuals may of course also adjust exertion levels (labor effort), or engage in other forms of defensive behavior (e.g. wearing different clothing) without changing labor supply (Park and Heal, 2014).

	Short Run		**Long Run**	
Secular	Intra-day activity substitution Labor effort	Daily labor supply (extensive margin) Inter-day activity substitution AC flow	AC stock Clothing purchases Occupational choice Labor supply extensive (retirement)	Migration Genetic adaptation
Directed	Workplace regulations	Labor agreements (e.g. contract structure) R&D in reducing adaptation flow cost (energy cost)	R&D in reducing adaptation stock costs Infrastructure Migration assistance	Social Norms

Table 1. Possible adaptation mechanisms in response to temperature stress

Notes: A simple typology of adaptation mechanisms, organized along the following two dimensions: secular versus directed, and short-run versus long-run.

In the long run, persistent temperature shocks may lead individuals to change occupations, or exit the labor force completely due to health concerns or disamenity costs. 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, installing an air conditioner

[11] Other possible sources of sub-optimal provision of adaptation are discussed in Agrawala and Fankhauser, 2008, and Hallegatte et al, 1999.

or retrofitting a home with better insulation) may require longer time horizons. Individuals may migrate in response to environmental shocks, or they may devise new protective strategies or adaptive equipment that allows them to maintain high productivity in the presence of persistent environmental stress.

As such, both secular and directed adaptation mechanisms can be categorized as occurring in the short- or long-run. These distinctions are in some sense arbitrary – more of a spectrum than a binary classification – but important nevertheless for interpreting the empirical observations of this study. In general, the literature on short-run versus long-run adjustment has emphasized the fact that firms and individuals are able to adjust more fully in the long run, since they will be able to choose from a wider range of adaptation options.

The empirical strategy employed in this paper takes a revealed preference approach to inferring the extent of adaptation to climate stress, and thus makes the conservative assumption that what is measured econometrically encompasses secular adaptation. This may understate possible future adaptation in response to climate change if targeted public investments are made. It may, alternatively, highlight the need for directed adaptation investments by local and national governments.

Specifically, comparing the realized impacts of temperature stress on output/productivity *inclusive of short run secular adaptations* with the impacts of temperature stress *inclusive of long run adaptation* allows the econometrician to estimate the expected extent of adaptation in the long run. Specifically, by leveraging daily weather data combined with cross-sectional variation in panel estimates, I estimate the gap between climate sensitivity inclusive of 1) short run (intra-annual), secular adaptation mechanisms, and 2) long run (decadal), secular adaptation mechanisms. Differentiating between secular and directed adaptation mechanisms allows us to place a conservative bound on the true welfare impact from the imperfect welfare estimates obtained using observed data.

C. A Model of Adaptation to Production Impacts of Heat Stress

To motivate the empirical strategy, I 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 extreme heat days per year, analogous to the concept of killing degree days in the agricultural literature. It might also correspond average annual temperature or cooling degree days. In any case, T^E is a random variable, the historical distribution of which is a reflection of average climate in that area.

The existing literature suggests that T^E can reduce human task productivity (i.e. labor productivity); and T^{E} may affect the direct utility of workers (e.g. disutility or health impacts from heat stress). 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)[12].

Assume a general production function for firms in the economy, $Y(A, L)$, which take as inputs labor productivity (A), and labor supply (L), where labor supply includes both dimensions of hours and effort. For simplicity, and given the assumption in the previous paragraph, I abstract away from capital inputs in this analysis[13].

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

$$\mathrm{Y}(\mathrm{A}, \mathrm{L}) = \mathrm{Y}\Big(\mathrm{A}(T^{\mathrm{E}}), L(T^{E})\Big)$$

I abstract away from principal-agent problems or labor market frictions, such that the revenue impact of a productivity shock is completely internalized[14]. Workers maximize utility, $U(Y, L, T^{E})$, which is a positive function of production (income), and negative functions of labor supply, labor effort, and temperature stress, which again can cause direct disutility ($\frac{\delta U}{\delta T^{E}} < 0$).

The task productivity literature suggests that physical and cognitive task productivity falls with extreme temperature – both heat and cold. Here, let us focus on the hot end of the temperature-task productivity relationship, such that $\frac{\delta A}{\delta T^{E}} < 0$. 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: $\frac{\delta L}{\delta T^{E}} < 0$[15]. It is possible to show that, absent strong income effects, temperature deviations from the thermoregulatory optimum will affect labor hours and labor effort in the same direction (Park and Heal, 2013), such that heat shocks will reduce effective labor product, net of optimizing responses of workers who may reallocate labor effort and hours accordingly.

As such, I assume that both $\frac{\delta A}{\delta T^{E}} < 0$ and $\frac{\delta L}{\delta T^{E}} < 0$, which implies that extreme heat will reduce total output due to this reduction in total labor product:

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

Given utility-maximizing agents, realized output fluctuations in response to temperature shocks should be net of adjustments on the labor supply/labor effort margin.

[12] 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.
[13] 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.
[14] A stylized representation of a production context that has these features may be a family-owned, family-operated business, or, perhaps, a one-man rickshaw operation.
[15] Graff Zivin and Neidell (2014) document significant changes in hours worked in response to extreme heat and cold, especially in highly exposed sectors.

Adaptive investments

Let us add the ability of firms to undertake adaptive investments, $\alpha(T^E)$, which reduce the negative impact of extreme heat stress by reducing the temperature sensitivity of workers' task productivity:

$$\frac{d^2A}{dT^E d\alpha} > 0,$$

and/or reducing the temperature sensitivity of labor supply (effort and hours):

$$\frac{d^2L}{dT^E d\alpha} > 0.$$

One would expect these adaptations to be a function of the average climate, $\alpha_{\mathrm{it}}(E(T^E))$, and to include physical capital such as centralized cooling systems and/or cultural capital in the form of procedural norms: for instance, adjusting worker shifts across seasons to minimize heat stress, as has been documented in many tropical countries.

Firms will choose to invest in adaptive capital such that the expected marginal benefit – in terms of heat-related damages avoided – associated with additional adaptive investment is equal to the marginal cost. In an unchanging climate, a reasonable proxy for expected benefits will be provided by the average historical incidence of extreme heat events over the period in which the local climate has been observed,

$$E(T^E) \approx \Sigma_{\tau=1}^{\mathrm{t}} T_{i\tau}^E$$

and the output reductions they have caused, where τ represents the first relevant period. Thus, let us assume that these adaptive investments are sufficiently lumpy so as not to be adjustable in response to acute heat stress (the short run), but rather have been chosen prior to the realization of current extreme heat stress, T_{it}^E.

The production function can be written as:

$$\mathrm{Y_{it}(A, L)} = \mathrm{Y_{it}}\left(\mathrm{A}\left(\mathrm{T_{it}}^{\mathrm{E}}, \alpha_{\mathrm{it}}(\Sigma_{\tau=1}^{\mathrm{t}-1} T_{i\tau}^E)\right), L\left(\mathrm{T_{it}}^{\mathrm{E}}, \alpha_{\mathrm{it}}(\Sigma_{\tau=1}^{\mathrm{t}-1} T_{i\tau}^E)\right)\right),$$

where

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

$$\frac{dL}{dT^E} < 0, \frac{\delta^2 L}{\delta T^E \delta\alpha} > 0\ ; \frac{dL}{dT}(T^E, \alpha)$$

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, $\mathrm{T_{it}}^{\mathrm{E}}$, but also the history of temperature shocks in that location – $\Sigma_{\tau=1}^{\mathrm{t}-1} T_{i\tau}^E$, i.e. the local climate – due to the fact that adaptive capital stock will have been chosen to maximize profits subject to the conditions mentioned above.

Application to empirical strategy

The overall effect of adaptive investments will be to reduce the temperature-sensitivity of total output:

$$\frac{d\left|\frac{dY_{it}}{dT_{it}^{E}}\right|}{d\alpha} < 0$$

Thus, in the long run, one would expect firms in hotter climates (i=H) to exhibit higher levels of adaptive investment than cooler ones (i=C):

$$\alpha_{\mathrm{H}} > \alpha_C; \text{ given } E(T_H^E) > E(T_C^E).$$

This paper aims to estimate the production impacts of extreme heat stress, $\frac{dY_{it}}{dT_{it}^{E}}$, in addition to the expected extent of long run adaptation, $\alpha_{\mathrm{H}} - \alpha_C$, by using differences in realized production impacts across various climate regions:

$$\frac{dY_C}{dT_C^E} - \frac{dY_H}{dT_H^E}$$

Given stronger existing evidence for impacts of temperature stress on labor inputs and productivity (A and L), I focus on the temperature sensitivity of total labor product, which is approximated by annual fluctuations in payroll per capita.

III. Research Design

A. Approaches to Empirical Estimation of Adaptation

To estimate the adaptation-inclusive social welfare costs of climate change, one would ideally run the controlled experiment of observing two identical Earths and changing the climate of one and not the other over the course of many decades. Short of this unrealistic ideal, there are several ways one might measure climate damages inclusive of adaptation. Empirical approximations of the ideal experiment have typically either used cross-sectional variation to compare outcomes in hot versus cold areas (e.g. Mendelsohn, Nordhaus, Shaw; 1994; Schlenker, Hanemann, Fisher, 2005), or used within-group variation over time to compare a given area's outcomes under hotter versus cooler conditions (e.g. Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009).

Cross-section approach

Using cross-sectional data, Mendelsohn et al (1994) estimate a version of the following equation:

$$y_i = \alpha + \beta_1 T_i + X_i + \epsilon_i \tag{1}$$

where T, X, ϵ denote some average temperature variable, a vector of other weather controls (e.g. average annual precipitation, snow days), and a location-specific error term respectively. Mendelsohn et al (1994) use land values as the dependent variable, y_i , as land values should in theory represent the discounted value of the future stream of profits that could be generated with a given parcel of land, including possible adaptation. Thus, when comparing agricultural land in, say, Kansas and Texas, if $y(T_{kansas}) = V_o$, and $y(T_{Texas}) = V_1$, then $V_1 - V_0$ should represent the expected adaptation-inclusive estimate of climate damages were climate change to cause the average annual temperature of Kansas to move toward that of Texas[16].

Panel approach

Pioneered by Deschenes and Greenstone (2007), the panel approach estimates the following:

$$\ddot{y}_{it} = \alpha + \beta_1^{PANEL}\ddot{T}_{it} + \beta_2\ddot{X}_{it} + \gamma_i + \epsilon_{it} \qquad (2)$$

where the $\ddot{}$ superscript denotes de-meaned differences, and γ_i denotes region fixed effects.

In this case, β_1^{PANEL} represents the causal impact of temperature deviations from the region-specific average temperature on output deviations from trend. They are, in some sense, estimates of the short-run impact of temperature fluctuations on economic activity.

Many recent studies take this approach, including Dell, Jones, Olken (2011, 2012), Deryugina & Hsiang (2011), and Sudarshan et al (2014). Many then combine these weather-economy response coefficient estimates with climate model projections to estimate the expected costs of future climate change.

What might be some of the limitations this approach? Suppose the temperature-output response functions with and without long-run adaptation are as depicted below. If what one is interested in from a policy standpoint is the true long-run social costs of climate change[17], $(V_0 - V_1)$, 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 which occurs over the long run.

[16] As many have since noted, this approach may suffer from omitted variable bias to the extent that omitted, location-specific factors also determine y_i (e.g. natural resource endowments, productivity differences, technology, industry composition). Provided that one can control for key observable inputs, and to the extent that such cross-sectional methods are calibrated with experimental studies that document yield sensitivities to various agricultural inputs, one can be reasonably confident that they allow us to uncover an informative estimate of the scope for long-run adaptation. This approach seems somewhat less credible in the context of non-agricultural output, where analogs to crop-specific yield functions are harder to justify, and unobservables such as human capital or institutional factors play an arguably more important role.

[17] Note that $V_0 \ldots V_2$ represent net present values of annualized output/productivity.

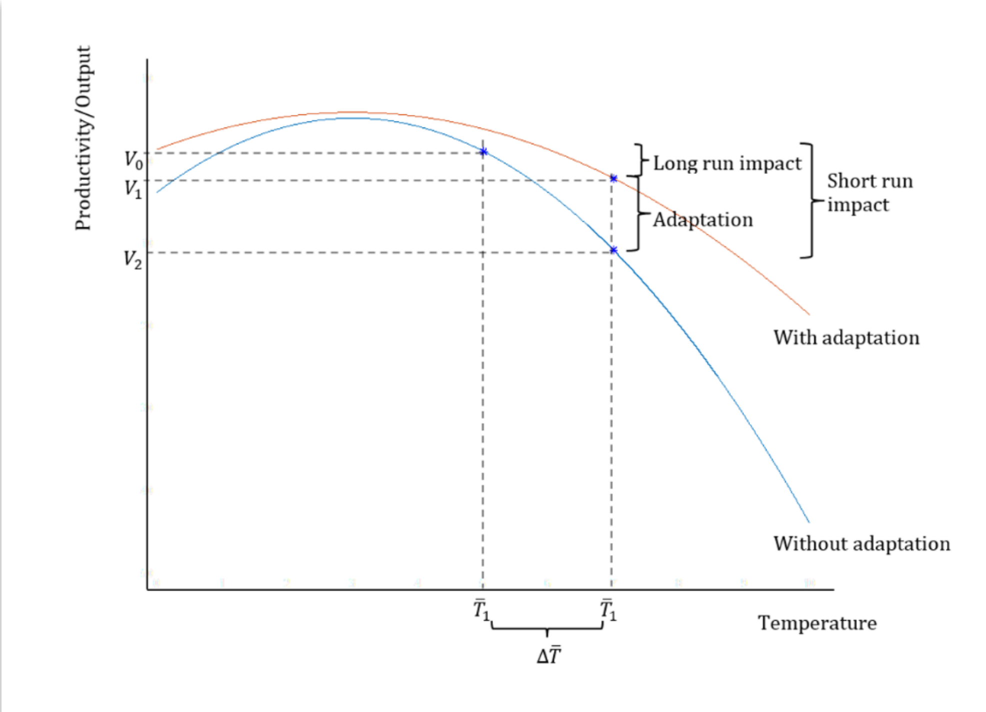

Figure 1 Potential bias in estimating climate damages without taking future adaptation into account

B. A Combined Approach: Cross-Sectional Variation in Panel Estimates

Where does this leave the econometrician interested in estimating adaptation-inclusive climate damages using observed – as opposed to simulated – data?

Due to omitted variables concerns in cross-sectional regressions, the recent literature has preferred the panel approach in estimating causal impacts of temperature stress. While using short run weather variation helps to solve identification problems, the prospect of medium- to long-run adaptation may make such panel estimates less than ideal. To the extent that such short run estimates do not account for adjustments that individuals may make in the long run (but not in response to a few short-run shocks), they might overstate damages from longer-run changes in climate (a la Samuelson's LeChatelier principle).

In light of these respective pros and cons, this paper combines the cross-section and panel approaches to estimate adaptation, exploiting the exogeneity of short-run weather shocks while allowing for gradients in these causal impacts by long-run average climate[18]. Because short-run weather variation is plausibly random, one can estimate the causal impact of temperature on output using panel data. Because regional differences in levels of adaptive capital (e.g. air conditioning) likely reflect differences in long-run climates, the cross-sectional variation in these

[18] This approach is similar in spirit to that taken by Graff-Zivin and Neidell (2013) in estimating adaptation in the context of time-use, as well as Dell, Jones, and Olken (2012). Neither study found statistically significant differences, though the point estimates were suggestive of non-trivial but limited adaptation across climate zones.

short-run panel estimates may be used to infer differences in optimal levels of adaptation to various levels of climate change.

To measure adaptation, I assess cross-sectional heterogeneity in short-run panel estimates, by comparing the β_1-coefficients from the following regressions:

$$\ddot{y}_j = \alpha + \beta_{1J}^{\Delta\text{Panel}} \ddot{T}_{jt} + \beta_2^{\Delta\text{Panel}} \ddot{X}_{jt} + \ddot{\gamma}_j + \ddot{\eta}_t + \ddot{\epsilon}_{jt}$$

$$\ddot{y}_k = \alpha + \beta_{1K}^{\Delta\text{Panel}} \ddot{T}_{kt} + \beta_2^{\Delta\text{Panel}} \ddot{X}_{kt} + \ddot{\gamma}_k + \ddot{\eta}_t + \ddot{\epsilon}_{kt}$$

where j and k denote counties with different histories of extreme temperature shocks, $\ddot{\gamma}_j$, $\ddot{\gamma}_k$ denote region fixed effects, and $\ddot{\eta}_t$ denotes year fixed effects. For instance, one might compare counties in the Kth quintile of the extreme heat day (80°F and above) distribution, to counties in the Jth quintile[19].

One would thus expect the same heat event to lead to smaller output shocks in places that are better adapted to heat, compared to a locale with lower average temperatures. This may be due to obvious differences such as higher installation and utilization rates of air conditioning equipment, or subtler adaptations such as working hours or differences in workplace dress codes.

To the extent that the per-heat-day impact is reduced in hotter locales, one might interpret this discrepancy as reflective of long term adaptation[20]. Because year-to-year variation in extreme heat days is quasi-random, the econometrician may interpret each panel estimate as a causal impact specific to regions in the US which have, over the 1986-2012 period, experienced higher or lower numbers of extreme heat days per year on average. In theory, it is possible to use these estimates to trace out an optimal adaptation function, which provides adaptation-inclusive short run sensitivities for varying "climates", as measured by the expected incidence of extreme heat days per year, though general equilibrium responses – including changes in industrial composition – would ideally be taken into account.

IV. Data and Summary Statistics

A. Weather and Economic Data

I use payroll data from the County Business Patterns database from 1986-2012, which records annual and 1st quarter payroll for roughly 3,000 US counties by five-digit NAICS classification. Payroll includes all forms of compensation, such as salaries, wages, commissions, dismissal pay, bonuses, vacation allowances, sick-leave pay, and employee contributions to qualified pension

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[19] Specifically, I estimate $\beta_1^{PANEL:j}$ using extreme heat days (90°F and above) as the independent variable, controlling for precipitation and snow ($\ddot{X}_{jt}, \ddot{X}_{kt}$).

[20] Reasons why this method may be incomplete or provide biased estimates of adaptation are discussed in the results section.

plans paid during the year to all employees[21]. County specific payroll data is measured at the annual level, save for 1st quarter payroll, which is recorded separately.

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, payroll data from the CBP allows one to isolate production impacts on non-agricultural sectors, as well as to distinguish, as I do below, between sectors that are more or less exposed to temperature stress. Second, changes in per capita payroll provide close proxies to changes in total and marginal labor product, separately from changes in capital expenditures, though it is impossible to know with certainty the extent of wage rigidities present in the contexts presently analyzed. Importantly, payroll does not include direct expenditure on heating or cooling (which may be the case for total income, for instance). This means that one is in principle able to estimate the implied marginal costs of adaptation separately from the marginal benefits.

For instance, if a manufacturing firm pays workers' wages as a function of hours worked and items produced, fluctuations in payroll arising from temperature shocks would reflect changes in labor supply and labor productivity (as well as, in principle, demand for the product itself) which arise in response to heat stress. If, in addition, firms respond by running air conditioning equipment at a higher utilization rate ("adaptive expenditure/investment"), this added cost would be reflected in lower profits or net income, thus conflating "raw" output shocks with short-run adaptive responses. Payroll, which more closely approximates marginal product of labor than capital, seems less likely to do so.

This data is matched with daily weather data from the PRISM model, which provides temperature, dew point, and precipitation readings for a 2km x 2km grid of the contiguous United States[22]. Daily max, min, and average temperatures, in addition to precipitation and humidity are area-weighted to the county level, and heat indices are constructed according to a standard temperature-humidity model.

Population data is taken annually at the county level from the US Census.

B. Variable Definitions

To isolate the impact of temperature on non-agricultural sectors, I subtract agricultural payroll from total annual payroll for each county-year. Dividing by population and taking logs, I obtain county-year observations for log non-agricultural payroll per capita for 3,007 US counties over the period 1986-2012. All regression results feature log non-agricultural payroll per capita as the dependent variable, and the incidence of extreme temperature events as the independent variable. The results are robust to including agriculture, and to running a growth rates specification, in the spirit of Dell, Jones, and Olken (2012) as discussed in greater detail in the Appendix.

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[21] 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. This definition of payroll is the same as that used by the Internal Revenue Service (IRS) on Form 941 as taxable Medicare Wages and Tips (even if not subject to income or FICA tax).

[22] Thanks to Wolfram Schlenker for providing weather data and code.

Past literature has documented a persistent, non-linear relationship between temperature and economic outcomes, particularly in the context of extreme heat stress (Schlenker and Roberts, 2009; Hsiang, 2010; Deschenes and Greenstone, 2011; Burke and Emerick, 2014). Where data has been available, this relationship has been captured using the concept of temperature days: for instance, growing degree days, GDD, 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.

Here, I use the concept of extreme heat days, which are defined as days with average humidity-inclusive heat indices above 90°F, following Deschenes and Greenstone (2011) and Barreca et al (2013). Deschenes and Greenstone (2011), Hsiang (2010), Sudarshan (2014), find days above 80°F, 85°F or 90°F respectively to be significant heat thresholds that lead to discernable impacts on human performance in field settings[23]. This concept is also analogous also to Killing Degree Days in the agricultural literature, which has a kink point of roughly 77°F, 25°C (Schlenker and Roberts, 2007; Burke and Emerick, 2013)[24].

The most non-parametric approach would be to construct variables that capture the number of days in each county-year over the full distribution of temperatures, where temperature days are defined as days in a county-year where the daily mean temperature is in one of any number of temperature bins spanning the relevant temperature range from below 0°F to above 100°F (e.g. Hsiang and Deryugina, 2014). However, using US temperature and mortality data, Deschenes and Greenstone (2011) and Barreca et al (2013) show that a more parsimonious model that focuses on the upper and lower tails of the daily temperature distribution provide similar point estimates for mortality responses[25].

As such, I focus on the 90°F threshold as a conservative definition of extreme heat, though the results are robust to alternative specifications, including multiple critical temperature-bins and a fully non-parametric temperature bin specification[26]. The main results are also robust to alternative measures of temperature, including those that have been used in the literature in the absence of daily weather data, including annual average temperature and cooling degree days.

[23] The kink point is lower in lab studies (e.g. Sepannen, 2008). This could be due to the fact that most lab experiments impose something akin to a no-adaptation constraint. 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.

[24] I also use alternative measures of temperature shocks, including cooling degree days and average annual temperatures (daytime high temperatures inclusive of humidity), and present these results in the appendix. For the most part, the results are consistent across different measures of temperature, though they are sharpest using the extreme heat day definition.

[25] This also allows for an implicit statistical decomposition of spread-preserving mean-shifts in climate versus year-on-year changes in temperature variance, which may be important to the extent that future climate change may involve *changes* in local climatic distributions in addition to *warming* represented by shifts in the mean.

[26] For instance, the number of days below 15°F, the number of days between 15°F and 25°F, the number of days between 80°F and 90°F, and the number of days above 90°F, where the number of days in the 26°F - 79°F bins are excluded. Here, the choice of the 25°F cutoff for cold days is motivated by symmetry. Given the fact that the optimal temperature zone implied by the US data is around 52°F (a fact confirmed by Hsiang and Deryugina, 2014), 25°F and 80°F represent roughly symmetric deviations from this optimal external temperature. The results presented below are robust to various alternative degree day specifications, as well as regressions that take the entire temperature distribution by 5 degree bins into account.

C. Summary Statistics

Over the period 1986 to 2012, the average US county experienced approximately 12 days with daily mean heat indices above 90°F. The average number of days between 80°F and 90°F was roughly 78[27]. In effect, the average US county experiences approximately 90 days per year where heat stress may, in the absence of any adaptive technologies, be relevant for human agents.

There is substantial variation in the incidence of hot days across different climate regions. For instance, Texas averages over 48 such days per year; Massachusetts, less than 3. Conversely, the number of extreme cold days is much greater in the Northeast and Central Plains regions than in the South. Subdividing the sample by quintile of the extreme heat incidence distribution, one can see the wide discrepancies in average heat stress across major metropolitan areas (Table 2)[28].

Temperature and Payroll in the Cross-Section

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 (90°F+) per year on average features 0.478% lower non-agricultural payroll per capita, controlling for precipitation and snow (the coefficient on temperature is significant at a p-value of 0.01; Table 3).

Using annual average temperatures to check consistency with the existing literature, I find that counties with one degree F hotter annual temperatures are associated with -0.924% over the pooled sample (Figure 2)[29]. This is consistent with the cross-sectional gradient documented by Dell and Acemoglu (2010), who find a within-country slope of roughly -1% across municipalities in North and South America. Moreover, fitting a quadratic specification yields a single-peaked relationship between temperature and implied output, suggesting an optimal temperature zone around 52°F average annual temperature[30] (Figure 6, Appendix). This is consistent with Seppanen and Fisk (2007) who find that both extreme heat and extreme cold are detrimental to task productivity in lab experiments, and Hsiang and Deryugina (2014).

In principle, one could argue that these cross-sectional gradients represent temperature-output response functions that are inclusive of long-run adaptations, especially in the latter years of the sample. However, it seems likely that omitted variables are driving part of this relationship, especially in the context of labor productivity. The US Southeast is poorer than the Northeast for historical reasons that are not directly related to temperature stress including, for instance, legacies of the Civil War[31].

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[27] The average number of extreme cold days below 15°F and between 15°F and 25°F were 35 and 24 per year respectively.

[28] It is worth noting that much of California, despite featuring warmer annual average temperatures, are very rarely subject to days above 90°F, due to the moderating influence of the Pacific. Many fall in the 1st (coolest/mildest) quintile of the extreme heat day distribution, despite having a relatively warm (above median) average annual temperature.

[29] The same coefficients are -2.34%, -1.04%, -0.24% in years 1990, 2000, and 2010 respectively.

[30] Note that this is somewhat lower than the physiological optimum implied by the medical and task productivity literature (65°F). Some of this may be due to the fact that average annual temperatures include nighttime low temperatures.

[31] As an illustrative case in point: the fact that hotter regions of the US have grown more slowly, but places with high incidence of extreme cold days have grown more rapidly (Figure 3) suggests that, in order to credibly assess

V. Results

The empirical strategy involves two key steps. First, I estimate the causal impact of extreme heat stress on output for the average U.S. County, and use variation across NAICS industry classifications to verify whether the effect is consistent with thermal stress of labor inputs. In the second step, I estimate the spatial heterogeneity in this panel estimate across regions with differing histories of extreme heat stress to calibrate the scope for long run adaptation.

A. Estimating the Short-Run Effect of Extreme Heat on Economic Activity

Does extreme heat reduce labor product in the United States? To estimate the causal impact of extreme heat on local labor product, the baseline panel specification estimates the following equation (referred to henceforth as the "baseline specification"):

$$\ddot{y}_{it} = \beta_0 + \beta_1 \ddot{T}_{it} + \beta_2 \ddot{P}_{it} + \beta_3 \ddot{S}_{it} + \ddot{\gamma}_i + \ddot{\eta}_t + \ddot{\theta}_{st} + \ddot{\epsilon}_{it}$$

Here, y_{it} is log annual payroll per capita for non-agricultural sectors, T_{it} denotes a vector of temperature day variables, specifically the number of extreme heat days with daily mean temperatures above 90°F, as well as a variable for the number of extreme cold days (e.g. daily mean temperatures below 25°F), to isolate the impact of extreme heat. P_{it} denotes annual precipitation (in 10 inch increments), S_{it} denotes the number of snow days, and γ_i, η_t, and θ_{st} represent county-, year-, and state-by-year- fixed effects respectively. The coefficient on extreme heat days represents the contemporaneous impact of a year with one additional 90°F-plus day on payroll per capita that year. This framework estimates the causal impact of extreme temperature days on non-agricultural output by county, in effect uncovering the average treatment effect of a year with one additional extreme heat day in lieu of a day in a "less extreme" temperature bin (25°F to 80°F).

The results are presented in column 1 of Table 4, with standard errors clustered at the state level. A year with one additional extreme heat day is associated with a -0.026 percentage point reduction in per capita payroll, significant at 99% confidence[32]. Put another way, the baseline specification suggests that, for the U.S. as a whole, a year with ten additional extreme heat days

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the causal impacts of temperature stress on labor productivity, one must leverage within-group temperature variation in the panel.

[32] Extreme cold days do not seem to have a significant impact on output. Increased precipitation and snow days depress output by -0.275% and -0.015% respectively, but the estimates are noisy and statistically insignificant. I also test whether hotter-than-average years cause output fluctuations, as has been documented in much of the previous macro literature on temperature impacts. Using average annual temperature as the explanatory variable, I find that a 1 degree F hotter-than-average year does not have a statistically significant impact on output for the US as a whole, though the point estimate is negative: -0.022%. This is consistent with a model of thermal stress with an implied optimal temperature zone, and a model in which much of the welfare costs arise from extreme events. A hotter-than-average year in relatively hot places (e.g. Houston) would likely correspond to a year with a hotter summer in which average heat stress is elevated, leading to a negative impact; in relatively cold places (e.g. Minneapolis) this may correspond to a year with a milder winter in which average cold stress is reduced more than heat stress increased, which would lead to a positive impact. On net, the predicted impact is ambiguous. Using average daily maximum temperatures, however, is suggestive of significant heat-related impacts. For the US as a whole, a year in which average daily maximum temperatures are elevated by 1 degree F is associated with a -0.29% reduction in non-agricultural payroll per capita, an effect that is significant at the 0.01 level. Using average daily minimum temperatures, I find no effect: the point estimate is virtually zero (-0.019 with standard error of 0.200).

is associated with -0.26% lower payroll per capita, controlling for precipitation and snow, as well as time-invariant characteristics at the county level (e.g. proximity to major trading centers), correlated shocks at the national level (e.g. recessions), and state-specific trends (e.g. a shale-gas boom in North Dakota) – that is, county, year, and state by year fixed effects respectively. This estimate is consistent with previous findings in the literature, though smaller in magnitude. For instance, Hsiang and Deryugina (2014) find that, relative to a day with an average temperature of 15C (59°F), a day at 29C (84°F) lowers annual income by roughly 0.065% in US counties.

To the extent that weather shocks are spatially correlated within states, state-year fixed effects may suppress some of the relevant signal, providing conservative estimates. Furthermore, if weather shocks are measured imprecisely (for instance, due to there being fewer weather stations than counties) then one would expect these estimates to be attenuated toward zero.

Impacts by Temperature Intensity; Alternative Temperature Day Binning

Next, I test whether the impact varies by heat intensity, as suggested by the medical, epidemiological, and task-productivity literatures, and also whether the average treatment effect is robust to different temperature day classifications. I do so by allowing for five temperature bins, which correspond to extremely cold (daily mean temperature below 15°F), cold (between 16 and 25°F), mild (26-79°F), hot (80-89°F), and extremely hot (90°F and above) days respectively. Results from the baseline specification with this new temperature bin structure are presented in Table 4, Column 2.

Hot days seem to exhibit the pattern predicted by the physiological model. Extreme heat days (90°F and above) reduce payroll per capita by -0.048% per day; heat days (80°F to 89°F) reduce output by -0.028% per day[33]. Extreme cold days have negative but statistically insignificant impacts on output. The increase in the point estimate for 90°F days suggests possible attenuation bias in estimates using the 3-bin classification, due to the relatively rarity of 90°F events.

B. Mechanisms: Effective Labor Supply?

What are the possible channels through which these impacts arise? As Dell, Jones and Olken (2012) note, many macroeconomic models of climatic effects emphasize a limited set of channels, most notably agriculture. Much of the microeconomic and experimental literature, by contrast, considers a wider range of factors, including those which operate through thermal stress of the human body such as physical and cognitive labor productivity, labor supply, health, and rates of violent conflict – all of which could have economy-wide implications (Park and Heal, 2013).

A benefit of the macroeconomic approach is that the econometrician can remain somewhat agnostic regarding specific causal mechanisms. This is especially useful in the context of climate policy, considering the fact that, in a perfectly competitive world, the pecuniary impact of

[33] Allowing for extreme heat days in this way causes the coefficient on precipitation to become significantly negative, which suggests that using annual averages or too few temperature bins may obscure important correlation in annual weather patterns - for instance, the varying impacts of cold and wet winters followed by hot and dry summers.

temperature stress net of adaptive behaviors would represent a sufficient statistic for welfare analysis.

By focusing on non-agricultural payroll, this analysis attempts to isolate the impact as it operates through the suite of causal mechanisms related to thermal stress of the human body. Changes in payroll might be thought of as net fluctuations in the wage bill after firms and individuals each optimize internally, be that in the form of adjustments to labor supply, labor effort, involuntary changes in labor productivity, or short- and long-run investments in adaptive behavior. Whether or not this occurs in the context of labor market rigidities may alter the distributional consequences, but to a rough approximation one might suppose that these results are reflective of the net impact of temperature stress on the total labor product of a local economy, net of short-run adaptations.

To further isolate the labor productivity mechanism, I categorize industries based on *National Institute for Occupational Safety and Health (NIOSH)* definitions of heat-exposed industries (NIOSH 1986). "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.

Running the baseline specification for highly exposed industries, I find evidence for more acute impacts in sectors where workers are exposed to the elements; an additional extreme heat day causes a -0.0735% decline in payroll per capita, as opposed to -0.0484% for all industries (Table 4: Columns 3 and 4). The point estimate for the subset of non-exposed industries (e.g. real estate, retail, education, health) is -0.0192%, and statistically insignificant.

These results are consistent with a story of labor productivity decline due to reductions in cognitive capacity and physical functioning from thermal stress of the human body, as well as shocks arising from reduced innovation, reduced labor effort, and reduced labor supply[34].

Overall Effect Magnitudes

Taken together, these estimates suggest that many regions in the US suffer non-trivial productivity losses due to routine temperature stress, with exposed sectors such as construction and mining bearing an outsized burden, results which are consistent with the existing literature (Hsiang and Deryugina, 2014; Dell, Jones, and Olken, 2012; Hsiang, 2011).

Assuming, conservatively, that impacts scale linearly with the number of extreme heat days, a year with 10 additional 90°F-or-above days would result in -0.192% to -0.735% lower output per capita for the average US County, depending on the industry. While an unlikely scenario, if the entire country to experience a year with extreme heat stress corresponding to an average year in Houston, which experiences 35 days per year with daily mean temperatures above 90°F, and 164 days per year between 80 and 90˚F, the US economy would experience a -6.28% decline in total output per capita; -11.17% per capita in highly exposed sectors.

[34] Of course, it is impossible to rule out other channels that may be correlated with temperature shocks, such as knock-on effects from declines in agricultural yield, or reduced consumption demand due to cloudiness or storms.

C. Estimating Long-Run Adaptation to Extreme Heat

Given the prospect of long-run adaptation to changes in climate, might it be possible to infer the expected rate of adaptation by comparing short-run impacts across different climate zones within the United States[35]?

The panel estimates reported above are analogous to short-run average treatment effects of randomly assigned extreme temperature days for the median US county, which corresponds to an average annual temperature of 54°F, and experiences approximately 12 days above 90°F per year.

I use the term "short-run weather sensitivity" to denote the treatment effect of a year with one additional extreme heat day (90°F+) on the underlying level of payroll per capita for a county of any given climate. In some sense, this may be interpreted as the reduced form impact of temperature stress on annual output allowing for all flow changes in short-run adaptive investments to year-specific heat shocks, and taking into account the stock of all long-run adaptive investments made by agents in that region to date.

According to the EIA, nearly all households in Texas 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 (Energy Information Agency, 2009)[36]. Such differences in AC represent but one of a potentially very large number of minor adaptations that local workers, consumers, and firms have evolved over the years in response to different climates.

Thus, the same 90°F day may have a very different short run impact in Houston than it might in Boston. I exploit this difference to estimate what the impact of climate change may be, loosely speaking, on Boston's economy were its climate to become like Houston's, allowing for long-run adaptations using existing technologies.

To the extent that the panel estimates are identified using annual output data, they represent net-of-short-run-adaptation estimates. That is, the coefficients estimated here represent the heat-sensitivity of local production, inclusive of the protection offered by all technologies and behaviors that can be adopted within any given year (in addition to long-run adaptive investments in capital stock). What might these short run adjustments correspond to in practice? It seems plausible that individuals may adjust labor supply decisions on the intensive margin, AC usage along the intensive margin, and perhaps labor supply decisions on the extensive margin at the daily level, such that realized output fluctuations at the annual level in any given region are net of these adjustments.

The heterogeneity in short-run weather sensitivities across climate zones may thus provide information about the effectiveness of longer term adjustments, including air conditioning

[35] The fact that the US has a relatively intra-nationally mobile labor force should help us in this context: in theory, one would expect arbitrage opportunities in terms of wage gaps or production efficiencies arising from climatic differences to be taken up more readily.

[36] For average Texas households, 18% of total energy usage is devoted to cooling, compared to 1% for Massachusetts households.

quantity and quality, workplace attire, habits to cope effectively with heat stress, timing of work hours, or individual- and firm-location and operating hours decisions.

Implied Extent of Adaptation

Results from running the climate-specific regressions are reported in Table 5. A county in the bottom quintile of the extreme heat day distribution (e.g. San Francisco, Minneapolis) exhibits a short-run weather sensitivity of approximately -0.263 percentage points per extreme heat day (90°F+). A relatively hot county at the top quintile of the US average temperature distribution (e.g. Houston) has a short-run weather sensitivity of -0.046 percentage points per extreme heat day: roughly one fifth the size. The impact of an additional extreme heat day is roughly 83% smaller in counties in the top quintile of historical extreme heat incidence, compared to counties in the bottom quintile.

Running the analysis by thirds yields similar results. Both specifications suggest monotonically declining temperature sensitivities as one moves to regions with greater degrees of perennial heat stress. These results suggest significant scope for long run adaptation (Table 6).

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. Counties in the top quintile of extreme heat exposure suffer routine heat-related output impacts of approximately -1.65% per year[37]. This is despite near universal air conditioning in many parts of the US South and Southwest (Energy Information Agency, 2009). Rates of AC penetration in much of the US South were already above 80% as of 1980, and 87% of all US households were equipped with AC as of 2009.

Robustness Checks

To test the robustness of the findings discussed above, I allow for lagged impacts of temperature and precipitation, including lags of up to five years to the baseline panel specification, as well as alternative characterizations of temperature stress, and a model with growth rate (as opposed to levels) effects of temperature shocks.

The key result – of significant negative impacts that vary systematically according to historical heat exposure – remains unchanged. Allowing for lagged impacts actually increases the magnitude of the impacts by up to 30%, which suggests serial correlation in temperature shocks, likely driven by multi-year ENSO cycles, and some corresponding year-to-year adjustment. I also find evidence of non-trivial lagged impacts, particularly in the year following a temperature shock, which may suggest the presence of substantial labor market rigidities. Lagged impacts are discussed in greater detail in the Appendix.

Second, I examine whether *relative* extreme temperatures affect output, in order to address the possibility that individuals respond to unexpected or unseasonal weather – in addition to or instead of responses to absolute temperature thresholds. Categorizing "relative extreme heat days" as days in which mean temperatures are one or more standard deviations above the county-

[37] The average incidence of extreme heat events in the top quintile is 34.8 per year, and each additional day is associated with -0.046% lower payroll per capita in these counties.

month-specific average over the sample period (for instance, in the average county, this might correspond to a 60°F day in January, or a 100°F day in July), I run the baseline specification with measures of relative extreme heat and relative extreme cold days.

The results from running the baseline panel using relative extremes are mixed. Relative extreme heat days have significantly negative impacts in cooler regions, but positive impacts in very hot regions. Relative extreme cold days have significantly negative impacts in both very cold and very hot places, with very extreme cold (2 standard deviations below the county-month average) causing -0.23% to -0.26% lower payroll per capita in warmer counties (counties in the top two quintiles of the extreme heat distribution). Parsing out the varying impacts of absolute heat versus unseasonably warm temperatures seems to be an important area for future research.

Finally, I examine whether the observed impacts are primarily levels effects, which are reversed once temperatures return to normal, or growth rate effects, which persist as permanent diminutions to the growth trajectories of the affected regions. I find that, for US counties, extreme temperature seems to exert a levels effect on output, albeit one with relatively long persistence; while growth rates return to normal within 3 years of a heat shock, the level of output remains below pre-shock trend for up to 8 years in some cases.

D. Potential Sources of Bias

Adaptation involves many factors, including future technological change, which the econometrician may not be able to capture using historical data. As such, there are several reasons why the parameters uncovered here may be biased estimates of the true scope for long-run adaptation.

Downward Bias (Underestimating the scope for adaptation)

Future technological change may imply greater scope for adaptation than implied by this study. Life-threatening heat, though not uncommon, still occurs at relatively infrequent intervals in most developed economies. As warming intensifies in R&D intensive economies, this may raise the incentive for further technological innovation. If cheaper, more effective cooling technologies are developed in response to more frequent heat waves, even historically cool areas may be able to utilize effective cooling systems at low cost, reducing their temperature sensitivity by more than observed historical gradients would predict.

Similarly, targeted government intervention to solve market failures or public good problems associated with adaptive investments (e.g. upgraded energy infrastructure) in the future may also lead to more effective adaptation to heat stress than is currently the case, even in very hot regions of the United States.

Upward Bias (Overestimating the scope for adaptation)

It is possible that the set of available adjustments to climatic shocks in the short run is larger than the long run possibility set. There could be short-run responses to weather shocks, such as pumping groundwater for irrigation in a drought year, which cannot be sustained in the long run if the underlying resource is depletable (Fisher et al, 2012). Thus it is in principle difficult to even sign the "bias" implicit in estimates of impacts derived from short-run responses to weather (Burke and Emerick, 2014)[38].

Furthermore, one must be cautious in extrapolating even unbiased estimates of long-run adaptation to temperature stress into the future, as even the longest time frames discussed here will not capture out of sample properties of the climate-economy response function. To the extent that there are important non-linearities in this function, temperature-precipitation interactions, or general equilibrium effects (Dell et al 2014), this approach will not provide a full account of the possible costs of climate change.

VI. Discussion

What do these results imply for long run climate adaptation? First, there seems to be significant scope for adaptation to heat stress, a finding that is consistent with Barreca et al (2013) who find substantial declines in heat-related mortality in the United States due to electrification and air-conditioning[39]. 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 uncover adaptation cost functions. Given the paucity of reliable adaptation cost estimates, despite their policy importance, this seems to be a critical area for future research.

Conversely, the fact that even the hottest, presumably well-adapted places of the United States, which one of the world's most air-conditioned countries, suffers routine temperature-related productivity and output shocks may not bode well for many developing nations. The magnitude and persistence of the impacts – upwards of several percentage point declines in annual payroll per capita from routine heat stress – suggest non-trivial costs and possible limits to adaptation, at least using existing technologies. Construction workers must, for the foreseeable future, work outdoors and be exposed to the elements, as will miners and agricultural workers.

Furthermore, 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). Based on this relationship and relatively low income levels for many households in warmer parts of South Asia, Latin America, and Sub Saharan Africa, on might infer that these coefficients represent conservative damage estimates for most of the developing world. Of course, to the extent that previous findings suggest that poor countries experience markedly different climate impacts compared to rich countries (Dell et al, 2013), one must be careful in extrapolating analyses of rich-countries to assess impacts in poorer regions or at the global level. However, the fact that most global integrated assessment models have historically assumed mildly positive impacts of increased temperatures on rich countries suggests that using data from rich countries to establish a lower bound on labor productivity related climate impacts at the global level would be an important contribution.

[38] In some sense, this is a contradiction of Samuelson's LeChatelier principle.
[39] These findings are also consistent with Butler and Huybers (2013) who use a similar approach in the context of US maize production.

A. The Labor Productivity Impacts of Climate Change

These estimates are consistent with an emerging literature which suggest physiological impacts of temperature stress with economically relevant consequences – be that in the form of changes in morbidity, attention, labor supply, labor effort, or task productivity (Heal and Park, forthcoming). The fact that payroll in highly exposed industries is more adversely affected by extreme heat stress suggests that the impact of temperature on output operates, in part, through physical exposure, though the findings from this study cannot distinguish conclusively between impacts on task productivity, labor supply, or labor effort.

Given well-documented wage rigidities, it seems likely that a non-trivial portion of these impacts are related to, though not entirely explained by, reductions in labor supply. Graff Zivin and Neidell (2013) document substantial contractions in labor supply on hot days in those US industries with high exposure to extreme temperature and weather shocks. They find that, for highly exposed occupations (e.g. construction), temperature above 100°F (37°C) lead to 23% lower labor supply than temperatures between 77-80°F (25-27°C).

The fact that the same set of highly exposed industries exhibit steeper payroll declines in response to hot days – approximately -0.0735% per day above 90°F, as opposed to -0.0484% for the average industry and -0.0192% for non-exposed industries – suggests similar mechanisms may be at play. This study thus lends evidence in support of adding labor productivity impacts into integrated assessment models of climate change.

VII. Conclusion

This paper has used county-level payroll and weather data to calibrate a new assessment of the likely long run economic impacts of climate change, inclusive of adaptation. The picture that emerges suggests that the labor productivity impacts of global warming may be non-trivial, but that adaptation may effectively reduce a large proportion of such damages.

The impact of an additional hot day with average temperatures (heat indices) above 90°F is -0.046% in a hot region such as Houston and -0.243% in a colder region such as Minneapolis. This suggests that, in the long-run, economic agents may indeed reduce the impacts of increased temperature stress through adaptive investments. However, the extent of adaptation is incomplete throughout much of the distribution, suggesting that even in the long run, adaptation to heat stress may be incomplete, at least using existing technologies. Furthermore, the sizable magnitude of heat-related productivity losses in many regions of the US suggests that the investments required to mitigate these impacts are non-trivially costly.

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. This method has the benefit of not requiring the analyst to simulate all adaptation mechanisms.

A natural question that arises is whether the extreme heat 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 documented here, combined with previous (larger) estimates of labor productivity and agricultural output declines due to heat stress in developing countries (Sudarshan et al, 2014;

Schlenker and Lobell, 2010) suggests that the long-run impacts of climate change may be more severe for the developing world than previously estimated.

The two main lessons of this analysis are as follows. Firstly, the sharp reduction in short-run temperature-sensitivity in hotter and more extreme climates suggests that adaptation may indeed play an important role in reducing the realized economic impacts from climate change, at least in the context of labor input impacts operating through thermal stress of the human body. Secondly, these estimates suggest that, despite the large scope for adaptation, the costs associated with such adaptive responses are likely substantial, and that there may be realistic limits to adaptation to heat stress.

The fact that the relationship between temperature days and output is significant in the United States, one of the world's wealthiest and technologically advanced economies, underscores the climate-dependency of much of economic activity, and suggests furthermore that there may be realistic limits to secular adaptation driven by rising incomes. Even if developing countries such as India or China were to raise their standard of living to US levels[40], they may potentially still experience temperature-driven productivity losses of multiple percentage points output per year.

[40] This is also in the absence of directed technical change that dramatically raises the effectiveness and reduces the costs of climate-control technologies.

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Appendix

Summary Statistics					
	Quintile of US Climate distribution: Historical Incidence of 80F+ days (1986-2012)				
	1st	**2nd**	**3rd**	**4th**	**5th**
Representative City	San Francisco, CA	Boston, MA	New York, NY	Atlanta, GA	Houston, TX
VARIABLES					
Median # of days below 15 °F	55.79	39.35	20.47	6.78	.70
Median # of days between 15-25 °F	52.38	48.92	40.73	26.03	8.03
Median # of days between 80-90 °F	26.92	58.99	89.39	120.56	164.24
Median # of days above 90 °F	.47	2.89	8.04	19.71	34.81
Observations	15522	16042	18954	14638	15388

Table 2 Summary Indicators of Temperature Stress across Climate Regions of the US (daily mean temperatures)

Notes: Climate quintiles are defined in terms of the historical incidence of the number of days with mean temperatures above 80 per year, averaged over the period 1986-2012.

Cross Section – Pooled OLS (1986-2012)				
	(1)	(2)	(3)	(4)
VARIABLES	Log Payroll per capita	Log Payroll per capita	Log Payroll per capita	Log Payroll per capita
Average annual temp (F)	-0.009246***			
	(0.001)			
Precipitation (mm)	0.081852***	0.043751***	0.057014***	0.052843***
	(0.003)	(0.003)	(0.003)	(0.003)
Days with snow per year	0.000948***	0.000772***	-0.000065	-0.000111
	(0.000)	(0.000)	(0.000)	(0.000)
Average daily maximum temperature (F)		-0.045693***		
		(0.002)		
Days per year above 80°F			-0.002535***	
			(0.000)	
Days per year above 90°F				-0.003072***
				(0.000)
Days per year between 80-90°F				-0.002386***
				(0.000)
Observations	72,789	72,556	72,789	72,789
R-squared	0.026	0.034	0.038	0.038

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Temperature and Output in the Cross-section for all US counties

Notes: This table presents results from a pooled OLS regression of all US counties over sample period (1986-2012). Output is measured in terms of log non-agricultural payroll per capita; temperature in terms of daily averages.

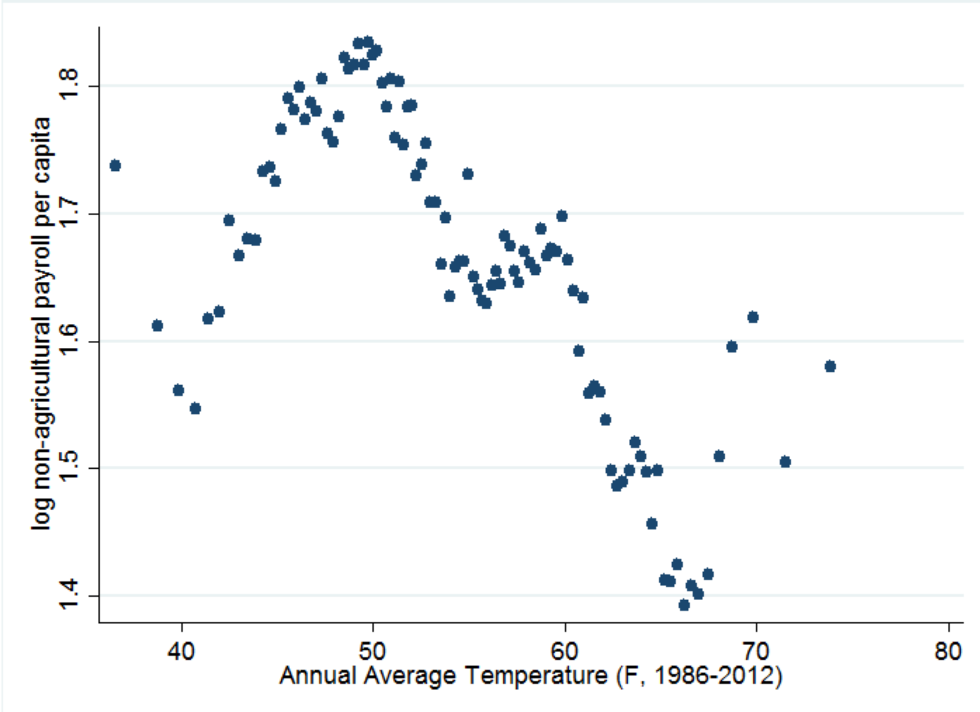


Figure 2 Temperature and output (non-agricultural payroll) per capita in the cross-section

Notes: Binned scatterplot of all US counties over sample period (1986-2012). Output is measured in terms of log non-agricultural payroll per capita; temperature in terms of daily averages. Controls for annual precipitation and snow are included.

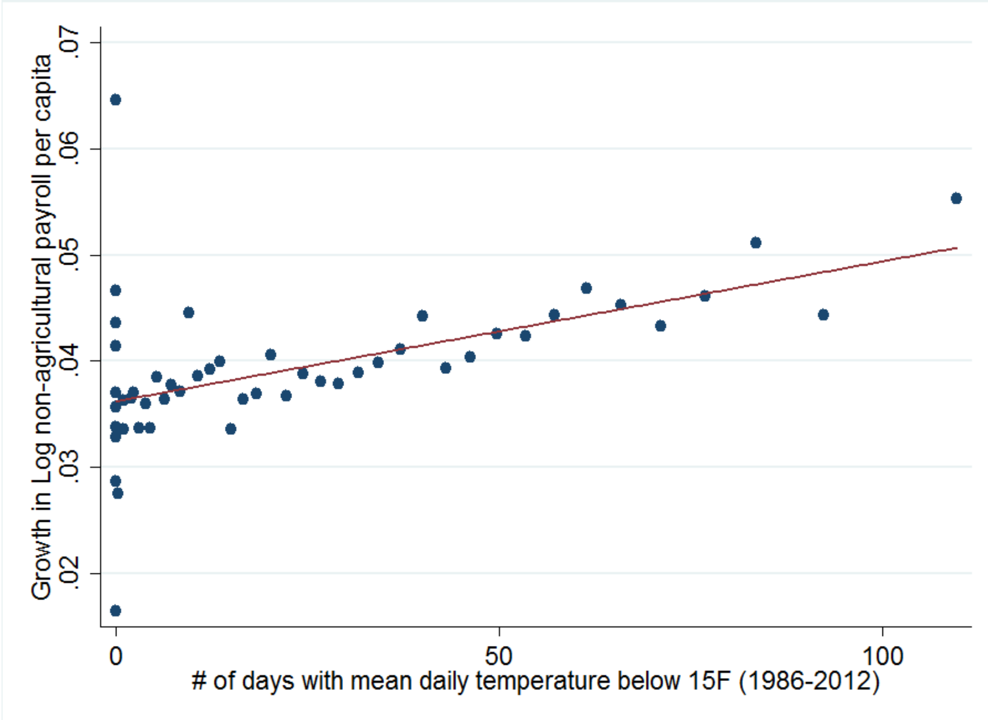


Figure 3 Incidence of extreme cold stress and output growth rates in the cross-section

Notes: Binned scatterplot of annual growth rates and the number of extremely cold days from a pooled OLS regression of all US counties over sample period (1986-2012). Output is measured in terms of log non-agricultural payroll per capita; temperature in terms of daily averages. Controls for annual precipitation and snow are included.

Table 4: Panel Regressions for all U.S. counties (1986-2012)

	(1)	(2)	(3)	(4)
VARIABLES	All Sectors	All Sectors	Highly Exposed Sectors	Highly Exposed Sectors
	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita
# of days below 15°F	0.000191	-0.000090	0.000475**	-0.000230
	(0.000127)	(0.000259)	(0.000285)	(0.000215)
# of days between 15°F and 25°F		-0.000310		-0.000784***
		(0.000237)		(0.000251)
# of days between 80°F and 90°F		-0.000281***		-0.000519***
		(0.000097)		(0.000110)
# of days above 90°F	-0.000267***	-0.000484***	-0.000333**	-0.000735***
	(0.000084)	(0.000133)	(0.000168)	(0.000136)
# of days with snow	-0.000147	0.000055	-0.000146	0.000389
	(0.000142)	(0.000)	(0.000)	(0.000)
Annual precipitation (10 inches)	-0.002715	-0.005152**	-0.003012	-0.007603***
	(0.001955)	(0.002)	(0.003)	(0.003)
Observations	72,789	72,789	58,386	58,386
R-squared	0.950	0.950	0.926	0.926

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: The Impact of Heat Shocks on Payroll per capita, All US counties, 1986-2012

Notes: This table presents results from panel regressions using baseline specification using 3 temperature bins (15F and below, 15-90F; 90F and above; columns 1 and 3**)** and 5 temperature bins (15F and below, 15-25F; 25-80F; 80-90F; 90F and above; columns 2 and 4**)** for all US counties. All regressions include county, year, and state by year fixed effects, as well as controls for precipitation and snow days per year. Robust standard errors clustered at the state level. Coefficients expressed as changes in log non-agricultural payroll per capita. Highly exposed sectors adhere to *National Institute for Occupational Safety and Health (NIOSH)* definitions of heat-exposed industries.

Table 5: Panel Regressions by Quintile of Extreme Heat Day distribution (1986-2012)

	5th	**4th**	**3rd**	**2nd**	**1st**
Representative City	Minneapolis, MN	Boston, MA	New York, NY	Atlanta, GA	Houston, TX
Annual impact of an additional 90°F+ day	-0.263***	-0.191***	-0.051**	-0.041	-0.046**
	(0.000921)	(0.000704)	(0.000209)	(0.000266)	(0.000165)
Observations	14,609	14,225	16,387	13,284	14,206
R-squared	0.955	0.959	0.954	0.932	0.940

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Estimating implied Long-Run Adaptation, US counties 1986-2012 (by quintile)

Notes: This table presents results from panel regressions using the baseline, 3-temperature bin specification (15F and below, 15-90; 90 and above**)** by quintile of the US extreme heat day distribution, where quintiles are defined by historical incidence of days with mean temperatures of 80°F and above. All regressions include county, year, and state by year fixed effects, as well as controls for precipitation and snow days per year. Robust standard errors clustered at the state level. Coefficients are expressed as percentage points of annual per capita payroll.

Table 6: Heterogeneity in Panel Estimates by Thirds of the Extreme Heat Distribution (1986-2012)

	All Sectors			Highly Exposed Sectors		
	Bottom third	Middle third	Top third	Bottom third	Middle third	Top third
VARIABLES	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita
# of days below 15°F	0.000226	0.000235	0.000847	0.000541*	0.000650	0.001725
	(0.000222)	(0.000203)	(0.000702)	(0.000292)	(0.000433)	(0.001170)
# of days above 90°F	-0.001949***	-0.000589***	-0.000467***	-0.001738**	-0.001004***	-0.000471**
	(0.000497)	(0.000139)	(0.000142)	(0.000738)	(0.000277)	(0.000177)
# of days with snow	-0.000191	-0.000111	-0.000248	-0.000298	0.000207	-0.000474
	(0.000248)	(0.000257)	(0.000324)	(0.000298)	(0.000312)	(0.000499)
Annual precipitation (10 inches)	-0.003178	0.001365	-0.005188	-0.004838	0.001663	-0.005401
	(0.004210)	(0.003511)	(0.003428)	(0.005097)	(0.003399)	(0.005398)
Observations	24,997	22,203	25,515	21,436	17,015	19,865
R-squared	0.956	0.952	0.937	0.932	0.934	0.910

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Estimating implied Long-Run Adaptation, US counties 1986-2012 (by thirds)

Notes: This table presents results from panel regressions using the baseline, 3-temperature bin specification (15F and below, 15-90; 90 and above**)** by quintile of the US extreme heat day distribution, where quintiles are defined by historical incidence of days with mean temperatures of 80°F and above. All regressions include county, year, and state by year fixed effects, as well as controls for precipitation and snow days per year. Robust standard errors clustered at the state level. Coefficients expressed as changes in log annual per capita payroll.

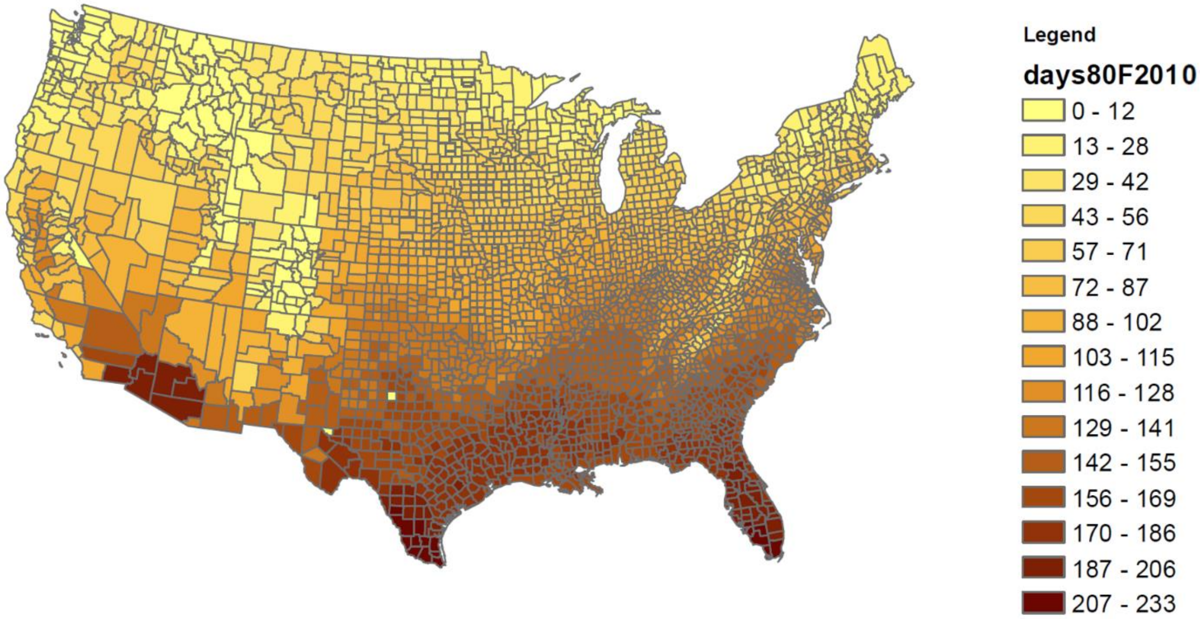


Figure 4: Incidence of hot days per year (daily mean heat index above 80F in 2010)

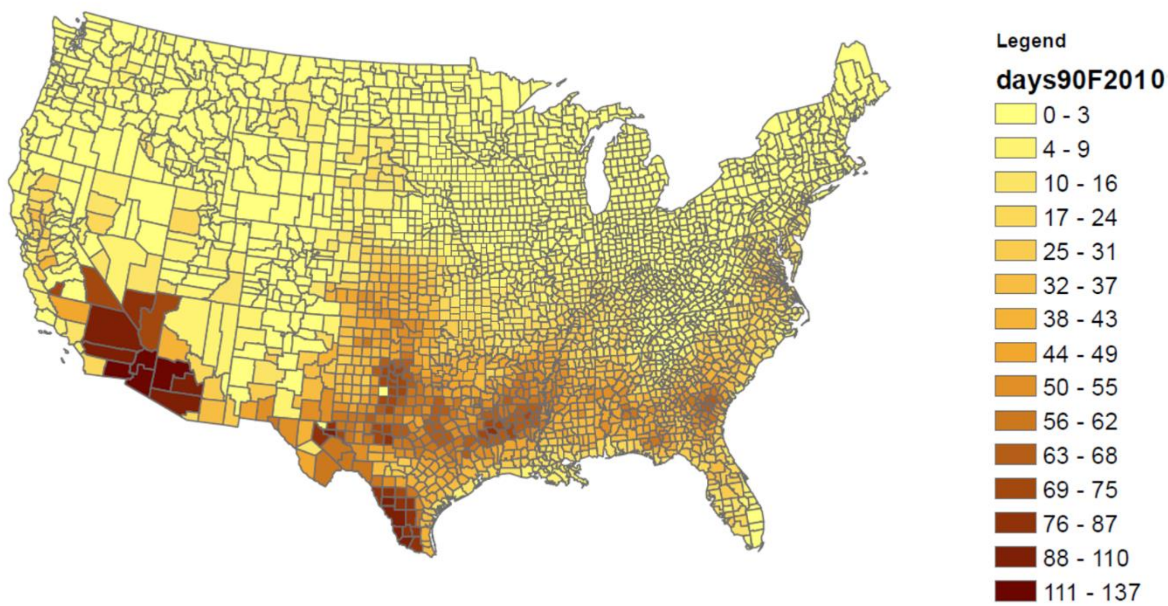


Figure 5: Incidence of hot days per year (daily mean heat index above 90F in 2010)

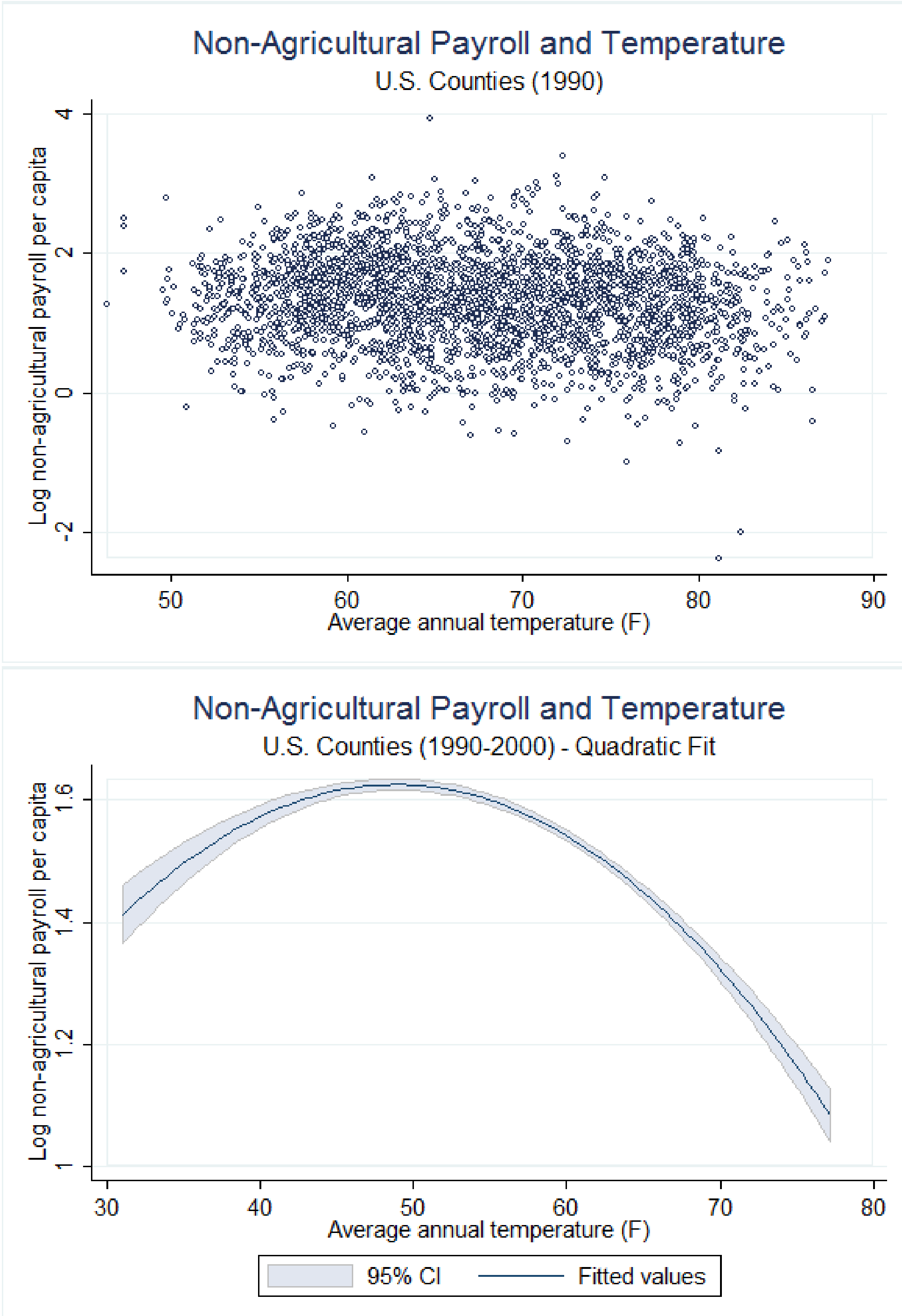


Figure 6: Temperature and Output in the Cross-Section. US Counties, 1990-2000

TABLE 7
Summary of Number of Days Above Threshold, Average Annual Temperature (all US counties by year)

	Above 90	Above 80	Average Annual Temperature
1986	12.28	93.41	56.38
1987	12.76	100.32	56.41
1988	19.64	99.89	55.61
1989	8.31	86.73	55.11
1990	16.46	90.52	57.36
1991	10.00	99.41	57.13
1992	4.51	70.64	55.67
1993	13.23	82.47	55.49
1994	7.58	89.07	56.16
1995	13.59	90.51	56.25
1996	8.69	84.73	55.41
1997	9.24	80.64	55.78
1998	19.75	100.67	58.02
1999	14.95	90.66	57.29
2000	18.03	89.74	56.34
2001	11.08	92.29	57.11
2002	13.01	102.11	57.29
2003	10.05	86.00	56.48
2004	5.14	81.95	56.86
2005	13.08	98.79	57.32
2006	17.36	94.94	58.11
2007	11.31	104.29	57.57
2008	9.87	85.70	56.59
2009	10.20	75.22	56.50
2010	16.72	103.07	57.18
2011	25.81	98.88	57.61

TABLE 8
Summary of Year on Year Change in Number of Days Above Threshold and Average Annual Temperature (all US counties by year)

	Above 90	Above 80	Average Annual Temperature
1987	0.48	6.91	0.03
1988	6.88	-0.43	-0.80
1989	-11.33	-13.15	-0.49
1990	8.15	3.78	2.24
1991	-6.46	8.89	-0.23
1992	-5.49	-28.76	-1.46
1993	8.71	11.83	-0.18
1994	-5.64	6.59	0.67
1995	6.01	1.45	0.08
1996	-4.90	-5.78	-0.84
1997	0.55	-4.09	0.37
1998	10.51	20.02	2.24
1999	-4.80	-10.01	-0.73
2000	3.08	-0.91	-0.95
2001	-6.95	2.55	0.77
2002	1.93	9.82	0.17
2003	-2.96	-16.11	-0.80
2004	-4.90	-4.05	0.38
2005	7.94	16.84	0.46
2006	4.27	-3.85	0.78
2007	-6.04	9.35	-0.53
2008	-1.45	-18.59	-0.99
2009	0.34	-10.48	-0.09
2010	6.52	27.84	0.69
2011	9.09	-4.19	0.42

Table 9: Heterogeneity in Panel Estimates by Quintile of Extreme Heat Distribution (1986-2012)

	5th quintile	4th quintile	3rd quintile	2nd quintile	1st quintile
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita
# of days below 15°F	0.000080	0.000447	0.000010	0.000415	0.003204**
	(0.000240)	(0.000280)	(0.000303)	(0.000833)	(0.001121)
# of days above 90°F	-0.002624***	-0.001903**	-0.000518**	-0.000410	-0.000469**
	(0.000921)	(0.000704)	(0.000209)	(0.000266)	(0.000165)
# of days with snow	-0.000240	-0.000196	0.000100	-0.000495	0.000357
	(0.000313)	(0.000195)	(0.000301)	(0.000500)	(0.000703)
Annual precipitation (10 inches)	-0.001638	-0.003255	-0.000107	-0.005432	-0.000674
	(0.00611)	(0.00323)	(0.00345)	(0.00511)	(0.00301)
Observations	14,609	14,225	16,387	13,284	14,206
R-squared	0.955	0.959	0.954	0.932	0.940

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Estimating implied Long-Run Adaptation, US counties 1986-2012 (by quintile)

Notes: This table presents results from panel regressions using the baseline 3-temperature bin specification (15F and below, 15-90; 90 and above**)** by quintile of the US extreme heat day distribution, where quintiles are defined by historical incidence of days with mean temperatures of 80°F and above. All regressions include county, year, and state by year fixed effects, as well as controls for precipitation and snow days per year. Robust standard errors clustered at the state level. Coefficients expressed as changes in log non-agricultural payroll per capita.

Table 10: Heterogeneity in Panel Estimates by Quintile of Extreme Heat Distribution (1986-2012)

	5th quintile	4th quintile	3rd quintile	2nd quintile	1st quintile
	(6)	(7)	(8)	(9)	(10)
VARIABLES	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita
# of days below 15°F	-0.000368	0.000021	-0.000266	0.000184	0.003655***
	(0.000388)	(0.000445)	(0.000483)	(0.000955)	(0.001072)
# of days between 15°F and 25°F	-0.000525	-0.000467	-0.000226	-0.000203	0.000712
	(0.000335)	(0.000282)	(0.000310)	(0.000555)	(0.000835)
# of days between 80°F and 90°F	-0.000018	-0.000335*	-0.000600***	-0.000417	-0.000034
	(0.000300)	(0.000175)	(0.000094)	(0.000338)	(0.000224)
# of days above 90°F	-0.002457**	-0.001891**	-0.000762***	-0.000680**	-0.000487**
	(0.001063)	(0.000719)	(0.000234)	(0.000316)	(0.000204)
# of days with snow	0.000103	0.000127	0.000257	-0.000383	-0.000374
	(0.000402)	(0.000326)	(0.000412)	(0.000557)	(0.001172)
Annual precipitation (10 inches)	-0.002609	-0.007819*	-0.004986	-0.008411	-0.000509
	(0.004991)	(0.003921)	(0.003223)	(0.005438)	(0.004045)
Observations	14,609	14,225	16,387	13,284	14,206
R-squared	0.955	0.959	0.954	0.932	0.940

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Estimating implied Long-Run Adaptation, US counties 1986-2012 (by quintile)

Notes: This table presents results from panel regressions using the baseline specification with 5 temperature bins (15F and below, 15-25F; 25-80F; 80-90F; 90F and above) by quintile of the US extreme heat day distribution, where quintiles are defined by historical incidence of days with mean temperatures of 80°F and above. All regressions include county, year, and state by year fixed effects, as well as controls for precipitation and snow days per year. Robust standard errors clustered at the state level. Coefficients are expressed as changes in log non-agricultural payroll per capita.

Robustness Checks

Absolute vs Relative Extremes

It is unclear whether the adverse impacts of temperature shocks are primarily a function of the absolute temperature experienced (e.g. 92F), or relative temperature deviations from the period-specific average for that region (e.g. +20F temperature anomaly). Studies that use rainfall shocks as identifying variation often use relative severity to define an extreme rainfall event: for instance, 1 or 2 standard deviations above the period-specific average for any given region. To test whether, in the context of extreme temperature stress and labor product, the impacts arise primarily from absolute or relative levels, I run the same baseline specification from above using relative heat and extreme heat and relative cold and extreme cold days, defined as days with daily mean temperatures 1 and 2 standard deviations above and 1 and 2 below the month-specific averages for each county over the sample period (1986-2012).

The results from this regression are presented in Table 12 (below). Relative extreme heat days have an ambiguous impact on output. Relatively hot days with temperatures 1 SD above the monthly mean seem to reduce output per capita by -0.023%. But more extreme heat anomalies have a positive impact of +0.060%. It is possible that years with more extreme positive temperature anomalies are years with milder winters. By this definition, January days in Boston where temperatures reach 60 degrees F would be counted as extreme positive anomalies. One might then be tempted to adjust the definition to truncate the temperature day variables only to include “hotter than usual” summer days and “colder than usual” winter days. But it is worth noting that this puts us back in a world in which absolute temperatures matter, and it is unclear where to draw the line for “winter/summer” or for “heat” vs “cold”.

The question of whether human activity is more sensitive to unexpected temperature shocks as opposed to shocks that are severe relative to an absolute biological benchmark seems to be an important one that remains unresolved.

Table 12: Relative Extreme Temperature Days

	5th quintile	4th quintile	3rd quintile	2nd quintile	1st quintile
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita	Log non-agricultural payroll per capita
# of relative cold days (-1SD)	-0.000713***	0.000319	0.000700	0.000812	-0.000209
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
# of relative cold days (-2SD)	0.000954	0.000407	-0.001353	-0.002647**	-0.002318**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of relative heat days (+1SD)	-0.000919**	-0.001595***	-0.000610**	-0.000024	0.000392***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
# of relative heat days (+2SD)	-0.001160	0.000216	-0.000037	-0.000699	0.000734
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	14,609	14,225	16,387	13,284	14,206
R-squared	0.948	0.950	0.950	0.925	0.936

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: The Impact of Relative Extreme Temperature Shocks on Payroll per capita

Notes: This table presents results from panel regressions by quintile of the US extreme heat day distribution, where quintiles are defined by historical incidence of days with mean temperatures of 80°F and above, using relative extreme temperature days as explanatory variables. Relative extreme heat days are defined as days with mean temperatures 1 and 2 standard deviations above and below county-month-specific mean temperatures from 1986-2012. All regressions include county, year, and state by year fixed effects, as well as controls for precipitation and snow days per year. Robust standard errors clustered at the state level. Coefficients are expressed as changes in log non-agricultural payroll per capita.

Levels versus Growth Rates

DJO (2012) extend Bond et al (2010) to write a simple production function as follows:

$$Y_{it} = e^{\beta^{levels}T_{it}} A_{it} L_{it}$$

$$\frac{\Delta A_{it}}{A_{it}} = g_i + \beta^{growth} T_{it}$$

where β^{levels} captures the levels effect of temperature shocks on output, and β^{growth} captures the growth rate effect of temperature shocks on output growth.

Taking logs of the production function, dividing by population, and differencing with respect to time, the growth rate in output per capita can be expressed as:

$$g_{it} = g_i + (\beta^{levels} + \beta^{growth})T_{it} - \beta^{levels} T_{it-1}$$

This model describes the particular case wherein the levels impact of a temperature shock is reversed within a year (t-1). A more flexible specification would allow for lagged impacts of up to L years:

$$g_{it} = \gamma_i + \gamma_{rt} + \Sigma_{j=0}^{L} \rho_j T_{it-j} + \epsilon_{it}$$

Where γ_i denotes county fixed effects, γ_{rt} denotes region-year fixed effects, and T_{it-j} represents a vector of temperature and precipitation variables with up to L lags included. The summation of the lagged ρ_j coefficients represents β^{growth} the growth effect of temperature shocks on output.

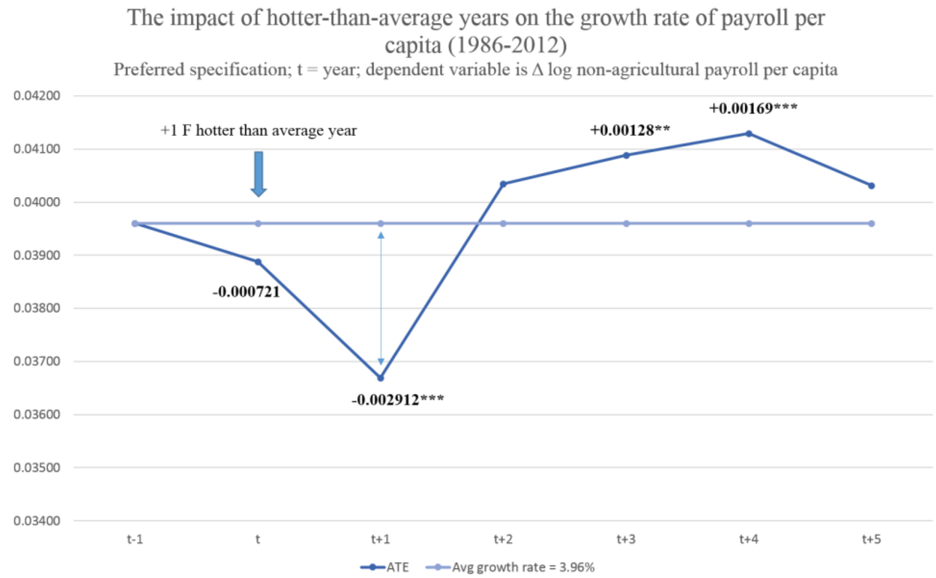
As DJO note, a levels effect would be reversed when the temperature shock is reversed. To the extent that temperature effects are levels effects, even if the levels effect is a lagged effect arising from temperature shocks from more than a year prior (for instance, temperature affected the amount of automobile subcomponents produced in year t-2, which affects the final amount of automobiles produced and sold in year t), the cumulated sum of the temperature effect and all of its lags should be zero.

Following Dell, Jones, Olken (2012) I estimate a rates of change variant of baseline panel specification from above:

$$\Delta\ddot{y}_{it} = \alpha + \sum_{l=0}^{5} (\beta_{1l}^{\Delta Panel} \ddot{T}_{i,t-l}) + \sum_{l=0}^{5} (\beta_{2l}^{\Delta Panel} \ddot{X}_{i,t-l}) + \gamma_i + \theta_{st} + \epsilon_{it} \quad (3)$$

Taking the full panel, and allowing for up to 5 lags in temperature and precipitation, I find that a 1 degree Fahrenheit hotter-than-average year reduces payroll growth by roughly -0.29 percentage points relative to the county-specific trend (-0.52% per degree C): an effect that is reversed within 3 years of the original shock.

The short-run magnitude of the impact seems consistent with Dell, Jones, Olken, (2012) who find that a one degree Celsius hotter-than-average year reduces growth rates by 1.1 percentage points. However, unlike DJO, I find no evidence for long-run persistence of this growth rate effect. The effect reverses itself once the temperature shock dissipates, resulting in “catch-up” growth. The sum of the lagged coefficients is not significantly different from zero, suggesting a levels effect rather than a growth rate effect.



A lagged levels specification suggests an impact of approximately -0.48 percentage points per degree F hotter-than-average. This translates into roughly -0.86 percentage point decline per degree Celsius, which is consistent with Hsiang (2011), who finds a levels effect of approximately -2.4 percentage points in Caribbean economies. Expressed in the form of a levels effect, one can see that, while the impact of the heat shock is eventually reversed, it takes a local economy several years for the level of per capita payroll to catch up to the pre-shock trend.