Mandated versus Voluntary Firm Investment in Climate Adaptation*

Evidence from Workplace Safety

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Abstract

Technologies to mitigate the e ects of climate change on worker health and productivity exist, but will employers adopt them? This depends on how labor markets work. Using data from over 11 million worker's compensation claims and high-frequency weather data (2000-2018), we explore the relationship between temperature and workplace safety, as well as the role of adaptation investments in mitigating this relationship. Hotter temperature increases workplace injury risk substantially, with days above 90°F leading to 6 to 9 percent more injury claims relative to a day in the 50s. Consistent with a model in which adaptation is technically feasible but costly, we find evidence for elevated accident risk in both indoor (manufacturing, warehousing) and outdoor (construction, agriculture) industries, and for types of injuries that are ostensibly unrelated to direct heat exposure (e.g. falling from heights, mishandling heavy equipment), which suggests that official statistics may understate heat-related injury burdens by a factor of four or more. Exploiting variation in what is to our knowledge the first workplace heat safety mandate, we provide evidence that firms and workers may not operate at the Pareto adaptation frontier in private equilibrium. (JEL codes: J20, J32, I18, Q50)

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1 Introduction

Workplace exposure to environmental hazards is remarkably common, especially at the lower end of the wage distribution. Worldwide, an estimated 1.3 billion individuals work in agriculture and construction, two sectors where the vast majority of work occurs outdoors (World Bank, 2017). In the US, 78 percent of the roughly 105 million workers without a bachelor's degree report routine exposure to harsh environmental conditions such as extreme temperature or poor air quality at work, including in predominantly indoor industries like warehousing, food-preparation, and manufacturing (Maestas et al., 2017).

Understanding the welfare implications of such environmental hazards is challenging, in part because working conditions are jointly determined by firms' and workers' decisions. While a growing body of scholarship examines the reduced-form effects of environmental shocks on labor market outcomes, relatively little is known about whether and how workers and firms adapt to such shocks, and whether policy has a role to play in facilitating adaptation investments.[1]

Understanding the labor market consequences of temperature shocks is particularly important in the context of a changing climate. Much of the U.S. South for instance has already seen a doubling of the number of days above 90°F relative to 1980, and is expected to experience at least 50 more such days per year by 2040-2050, even with aggressive mitigation efforts.[2] Recent evidence suggests that hotter temperature can adversely affect health (Deschênes and Greenstone, 2011; Barreca et al., 2016), cognition (Graff Zivin et al., 2017; Park, forthcoming), and decision-making (Heyes and Saberian, 2019), which could in turn have important implications for worker productivity and safety. The overall welfare implications however, including for climate damages and the social cost of carbon, will depend in large part on the scope for adaptation to such adverse effects (Kahn, 2016).

In this paper, we examine the potential for adaptation to climatic shocks in labor markets, focusing in particular on the effect of heat on workplace safety. We do so by measuring how temperature affects injuries on the job net of endogenous employment responses, examining

[1]See Hanna and Oliva (2015) and Graff-Zivin and Neidell (2012) for the effects of air pollution on labor supply and labor productivity respectively. See Graff Zivin and Neidell (2014) for the effect of temperature on labor supply, and Dell et al. (2012); Adhvaryu et al. (2014); Somanathan et al. (2018); Zhang et al. (2018) for effects of temperature on labor productivity.

[2]While some parts of the U.S. will benefit from a reduction in extreme cold days, many are expected to experience a net increase in extreme temperature days, often defined as days with high temperature above 90°F or below 32°F, (Reidmiller et al., 2018). Even with the most aggressive mitigation policies outlined in the Paris Accords (RCP 4.5), some parts of the world are expected to experience over 150 additional days per year where temperatures reach above 90°F.

the role of adaptation investments in reducing the impact of temperature on injuries, and assessing how various market imperfections may influence firms' adaptation decisions.

Our analysis focuses on workers and firms in the state of California. We leverage a rich administrative dataset which includes the universe of worker's compensation claims over the period 2000-2018. This data represents a far more comprehensive picture of workplace injuries than most publicly available data sets, and covers a wide range of industries and average climates.[3] It also spans the introduction of what is to our knowledge the first major government adaptation policy aimed at regulating workplace heat safety, as described below. Linking injury information for 11 million claims to daily weather data at the zip code level, we exploit quasi-random variation in local temperature to estimate the marginal impact of temperature on injuries. Causal identification relies on the premise that idiosyncratic variation in daily temperature within a given zip code-month is uncorrelated with unobserved determinants of injury risk, and that the resulting effect on injuries is unaffected by potential endogenous changes in labor inputs, assumptions which we interrogate in further detail below.

We find that hotter temperature significantly increases the likelihood of injury on the job. Across all workers in California a day with high temperatures between 90 and 95°F leads to a 6 to 9 percent increase in same-day injury risk, relative to a day in the 60's. A day with highs in the 100 to 105°F range leads to a 10 to 15 percent increase.[4]

To help interpret our empirical findings, we outline a simple model of safety investment in the presence of temperature shocks. We model injury risk as a function of both direct physiological risk (e.g. heat stroke) and adaptation investments that improve overall safety but at a cost (e.g. air conditioning, construction of shade structures). Under reasonable assumptions, hotter temperature increases workplace injuries across a wide range of settings, net of endogenous adaptation investments by firms.[5] For instance, consider a firm operating a shipping warehouse. In response to extreme temperature conditions, the firm could do nothing and face the possibility of higher worker turnover and higher compensating differentials; reduce

[3]For instance, this is true compared to OSHA records, which have substantially higher reporting thresholds. Automatic reporting there is triggered only when a worker is killed, or more than three workers are hospitalized. The resulting estimates of the effects of heat on this outcome are also less likely than information on wages or employment to be upward biased due to confounding effects of heat on productivity and worker utility.

[4]We fail to find evidence of significant impacts of extreme cold, or significant positive employment responses of a magnitude that would account for these large effects. The point estimates are substantially noisier for extreme cold, however, possibly due to the rarity of such days (e.g. days with highs below 32F) given the relatively mild winter climate of most of California.

[5]Existing empirical assessments of temperature-safety relationships will almost always capture a combination of these two effects, even in cases where the reduced form is causally well-identified, as in the burgeoning weather-economy literature (Graff Zivin and Neidell, 2014; Dell et al., 2014).

labor inputs; or invest in physical assets and procedures that cool the facility and/or increase safety precautions. All of these options entail some cost, meaning that faced with temperature extremes, firms have an incentive to reduce the level of safety provision relative to more optimal conditions.

The model implies that we should expect hotter temperature to affect realized injuries even in settings that do not involve direct exposure to the elements (e.g. indoor manufacturing), and for injury types ostensibly unrelated to heat exposure (e.g. falling from heights, mishandling equipment). We find evidence of both. The effect of heat on injuries holds not only for such industries as agriculture, utilities and construction, where work occurs primarily outdoors, but also for some industries where work typically occurs indoors. In manufacturing, for instance, a day with highs above 95°F increases injury risk by approximately 7 percent relative to a day in the low 60's. In wholesale, the effect is nearly 10 percent.

While we find that injuries tagged as being caused by extreme temperature spike on hotter days, we also find that the vast majority of the additional injury burden associated with extreme temperature comprises those not typically associated with extreme temperature, such as being struck by a moving vehicle or dropping harmful substances onto a body part. Because the latter constitutes the overwhelming majority of claims, the smaller marginal effect translates into a much larger total effect, which we estimate to have led to approximately 81,000 additional injuries in California over the period 2000-2018, or roughly 4,500 per year. This is at least five times the number of annual heat-related workplace injuries recorded in official statistics.[6]

A potential concern with our empirical strategy is that labor supply or demand may be endogenous to daily temperature shocks. If hotter temperatures lead to increased labor demand the observed change in injuries will not be entirely due to heat's effects on safety, and estimates that do not measure changes in the denominator (injuries/worker-hours) may be biased upward. On the other hand, if hotter temperature leads to a reduction in labor supply our estimates may understate the impact of temperature on injury risk. To address this concern, we estimate potential labor input responses to temperature shocks separately. We find no evidence that hotter temperature systematically increases employment or hours,

[6]This is compared to the 850 claims per year tagged as being caused by extreme temperature in the California worker's compensation microdata. Cal-OSHA's official records suggest fewer than 60 heat illnesses per year in the state, suggesting an even larger discrepancy.

suggesting our results to be unbiased and possibly conservative estimates of the effect of temperature on injury risk.[7]

As one way of examining the role of labor market frictions, we assess whether firms in more concentrated labor markets choose not to engage in costly adaptation investments. We find that the same temperature event leads to a greater increase in workplace injuries in more concentrated labor markets, consistent with this possibility.[8] Indeed, it appears that many of the injuries documented in our data were preventable using existing technologies, suggesting substantial scope for adaptation. In a second set of analyses we exploit variation in workplace heat safety investments arising from a mandated workplace heat standard to explore the effect of policy on the relationship between temperature and injuries. In 2005, California became the first state to implement legally binding heat-related workplace safety regulation. This policy involved an intensive information campaign, worker training programs, and mandates for the provision of water, rest breaks, and shade for a subset of firms during "high heat", defined as days with highs above 95°F. It was unusually vigorously enforced, with Cal OSHA having issued over 18,000 citations for the heat standard alone as of 2018.

We find economically and statistically significant reductions in the impact of days with temperature above 95°F in the period between 2006 and 2018 relative to the period 2000 to 2005. We find no evidence that the temperature-sensitivity of injuries changed significantly at other parts of the daily temperature distribution, or that this effect is driven by differences in overall injury reporting rates in the pre- and post-periods. The difference remains significant across a range of robustness tests, including analyses that omit the period after the Great Recession and placebos that use alternative policy cutoffs. This is consistent with the policy having led to increased adaptation investment with respect to extreme heat in particular, though it may also be driven by correlated secular trends in workplace safety, or contemporaneous policies at the state or Federal level.

Contrary to previous studies that emphasize physical limits to adaptation, we find that

[7] If our results mask intra-day or intra-week reductions in labor inputs, the implication would be that our point estimates *understate* the magnitude of the effect in terms of injury rates per worker-hour. Alternatively, in settings where extreme temperature leads to intra-day/week increases in labor inputs, for instance to meet production quotas, our estimates would be upward biased.

[8] As described below, the difference in temperature-injury relationships captured using this approach does not appear to be driven by correlated differences in geography, as occupations with higher concentration within a given zip code appear to exhibit higher temperature-sensitivity of injuries. However, because our variation in monopsony is cross-sectional, it is possible that these differences are driven by correlated unobservable characteristics of workers who are more likely to work in more heavily concentrated labor markets. While only suggestive, these results point to a possible role for public policy in facilitating adaptation on efficiency grounds.

the reduction in heat-related injuries was not limited to "cooler" climates. Even in parts of California that experience over 50 days above 95°F per year, roughly equivalent to the 95th percentile of the US climate distribution, we find a significant reduction in heat-related injuries after the policy was implemented. This cautions against characterizing adaptation in terms of physical limits (Kjellstrom et al., 2016), as adaptation technologies and practices may enhance people's ability to work safely and effectively in the heat. At the same time, our findings suggest that, even when adaptation is technically feasible, its adoption and implementation is by no means automatic.

To understand the welfare implications of our results we turn to a third set of analyses. We examine the California safety standard's impact on wages and employment in order to assess how mandated adaptation costs compare to the combined willingness to pay of workers and firms. We find evidence consistent with the policy having been potentially efficiency-improving. Using data from the QCEW and a triple difference strategy that utilizes variation in policy treatment across industries within California compared to similar differences outside of California, we find that the policy had a small negative effect (-2 to -3 percent) on wages per worker and a zero or modest positive effect (+0 to +4 percent) on employment. These effects are remarkably consistent with Lee and Taylor (2019), who find using plant-level data from US manufacturing that randomized OSHA safety inspections lead to large reductions in fatality rates, a 2 to 3 percent reduction in hourly wages, and an 8 to 10 percent increase in employees per establishment. Taken together, these findings suggest that safety investments triggered by such policies were valued by workers at more than the cost to firms.

The rest of the paper is organized as follows. Section 2 presents motivating stylized facts and a simple conceptual framework. Section 3 presents the data and summary statistics. Section 4 assesses the causal impact of temperature on injury risk. Section 5 explores potential mechanisms and implications for adaptation investment. Section 6 assesses the effect of the policy. Section 7 discusses and concludes.

2 Background and Conceptual Framework

2.1 Temperature Stress and Workplace Adaptation

Many aspects of production may be sensitive to temperature. Temperature changes can pose direct health hazards to workers which require costly safety investments to mitigate.[9] They may also impose indirect costs by reducing labor productivity or supply, as well as direct costs in the form of increased energy outlays (Deschênes and Greenstone, 2011; Auffhammer and Mansur, 2014).[10] Recent evidence also suggests that elevated temperature can reduce cognitive performance (Graff Zivin et al., 2017; Park, forthcoming) and influence decision-making and emotional affect (Heyes and Saberian, 2019; Baylis, 2020). These findings inform our decision to model exposure to extreme temperature as affecting injury risk through a number of channels.

Two recent papers - Page and Sheppard (2018) and Dillender (2019) - explore the impact of extreme temperature on workplace injury risk using quasi-experimental research designs, but present conflicting evidence. Page and Sheppard (2018) finds evidence of a monotonic relationship between temperature and injury risk across the U.S. using publicly available OSHA data, whereas Dillender (2019) suggests a U-shaped relationship in Texas. Dillender (2019) uses workers compensation claims and represents the analysis closest in spirit to this paper, but differs in several important ways. First, we assess the potential for adaptation using variation in what is to our knowledge the first mandated climate adaptation policy operating through the labor market. Second, unlike Dillender (2019), we embed the analysis in a model of workplace safety investments that allows us shed light on potential mechanisms and the structure of adaptation costs empirically. Third, Dillender (2019) uses workers compensation claims data from Texas, which is one of few states that *do not* require mandatory workers

[9] For instance, in seminal work, Deschênes and Greenstone (2011) find that an additional day with mean temperatures above 90°F leads to a 0.11 percent increase in annual mortality in the United States. The epidemiological and occupational health literature has long noted the potential links between extreme temperature and safety, but many of these studies are either cross-sectional in nature or follow time-series analyses for an individual plant or city, making it difficult to draw causal inference (Ramsey et al., 1983; Ramsey, 1995; Adam-Poupart et al., 2014; Kjellstrom et al., 2016).

[10] Graff Zivin and Neidell (2014) document contractions in labor supply on hot days, at least for those U.S. industries classified by the National Institutes of Occupational Safety and Health (NIOSH) as being highly exposed. They find that, for exposed industries such as construction, days with temperature above 100°F (37°C) lead to 23 percent lower labor supply than temperatures between 77°-80°F (25°-27°C). Other studies find micro- and macro-evidence for productivity impacts, though the mechanisms remain debated. Adhvaryu et al. (2014), Somanathan et al. (2018) and Zhang et al. (2018) document significant negative impacts of extreme heat on manufacturing productivity in Indian and Chinese firms respectively, controlling for plant-specific productivity and seasonality in production. Deryugina (2017) find impacts of hot days on county-level income in the United States, building on work by Hsiang (2010), Dell et al. (2012), and Burke and Emerick (2016) looking across countries.

compensation insurance, whereas this study uses workers compensation claims from California, where workers compensation insurance is mandatory, and claims-level information on industry and occupation permit a richer analysis of potential mechanisms.

While studies in agriculture have suggested significant scope for adaptation in response to shocks to crop yield (Mendelsohn et al., 1994; Burke et al., 2015), evidence of adaptation to labor input shocks is more limited. Some recent studies have emphasized physical constraints to working in the heat based on bio-engineering simulations, which limit the scope for adaptation by design (Kjellstrom et al., 2016). These studies leave aside the fact that, even when adaptation is technically feasible, its uptake and beneficiaries will depend on the magnitude and composition of the realized cost of the adaptation technology.[11]

2.2 Conceptual Framework

We develop a simple conceptual framework that fixes ideas and guides our empirical analysis. We begin with the recognition that the risk of injuries on the job is determined in large part by actions taken by workers and firms. Profit-maximizing firms trade off the costs and benefits of a range of production inputs and technologies, which may include investments in working conditions. Utility-maximizing workers weigh the benefits of such occupational characteristics as workplace safety or scheduling flexibility against the prospects of working with lower pay (Rosen, 1974; Jones-Lee, 1974). As such, while there are reasons to believe environmental conditions affect workplace safety, realized injury risk is likely not a deterministic function of ambient environmental conditions.

2.3 Temperature, Injury Risk, and Safety Investment

In its simplest form, workplace injury risk can be expressed as a function of ambient temperature T and safety investments S:

$$Risk = R(T, S) \tag{1}$$

S may include physical investments in protective equipment or machinery as well as procedural elements such as worker training or safety-enhancing alterations to production processes.

[11] We use "technology" in the broadest sense to include both technical innovations (e.g. A.C.) and changes to production practices (e.g. working at different times).

These investments may entail pecuniary and non-pecuniary costs to the firm.[12] Firms face a tradeoff between increasing safety investment at some cost, which we denote $C(S; w(R), Z)$, and maintaining lower levels of safety but needing to pay higher wages as hazard pay $w(R)$, where $w_R \geq 0$.[13] We make the usual concavity assumptions regarding the production of realized safety, and denote all other factors that influence firm safety costs (e.g. whether or not work occurs indoors vs outdoors) with the vector Z. We present a formal model in the Appendix, and present a stylized version here for ease of exposition.

For simplicity, suppose T represents deviations from some thermoregulatory optimum. Since both direct physical risk and endogenous firm responses depend on T the relationship between injury risk and temperature can be expressed as the total derivative of equation 1:

$$\frac{dR}{dT} = \underbrace{\frac{\partial R}{\partial T}}_{(1)} + \underbrace{\frac{\partial R}{\partial S}\frac{dS}{dT}}_{(2)} \quad (2)$$

As shown above, the reduced form effect of temperature on injury risk depends on two distinct components: (1) the direct "biological effect" of temperature on injury risk, and (2) the role of adaptive investments in determining safety more broadly. Data limitations imply that empirical investigations likely paint only a partial picture of this total derivative.

Why might firms change safety investment in response to changes in temperature? To the extent that compensating differentials hold, if only in expectation, firms would have an incentive to minimize worker turnover and future wage increases: $\frac{dS}{dT} > 0$, so long as $\frac{\partial R}{\partial T} > 0$ and $w_R > 0$.[14] On the other hand, firms may reduce safety investments in response to changes in temperature if it increases other costs or reduces product demand. It is therefore

[12] In addition to direct costs of equipment or machinery, firms may incur opportunity costs such as the time required to train employees and provide breaks, or lost production from operating a conveyor belt more slowly. Typically, workplace safety investments are modeled as being provided by the firm as job amenities. Some have suggested that workplace safety investments are provided by individual workers as well (Guardado and Ziebarth, 2019).

[13] For expositional clarity, we forego formal treatment of the "kissing equilibrium" generated by sorting on heterogeneous workers and firms as in Rosen (1974), and simply note that, in a given labor market, workers and firms will agree to a market-clearing wage-offer curve, the slope of which will be represented by the term w_R. We note that, while it is standard in the literature to assume that workers have full information on firm-specific injury risks R, in practice, it may be possible for informational imperfections to drive a wedge between actual and perceived risks.

[14] Compensating differentials provide *ex ante* compensation for injury risk. Workers can also be compensated by *ex post* payments in the form of workers compensation insurance. As is standard in the literature, we assume that workers compensation insurance payments typically offer incomplete compensation for all of the costs of injuries (Ehrenberg and Smith, 2016). Estimates suggest that worker's compensation typically covers less than 25 percent of the total costs of accidents (Leigh, 2011). In addition, firms taking part in employer-provided health insurance programs may pay for added risk in the form of higher insurance premiums, as well as sick leave and potential disability payments. Dobkin et al. (2018) find that social insurance only covers 60 percent of total costs associated with hospitalizations when these costs are measured to include lost future earnings, even for those with health insurance.

theoretically possible to observe $\frac{dR}{dT} > 0$ even in settings where the direct "biological effect" is small or even zero, due to the effect of temperature on costs and the associated reduction in overall levels of safety investment, as in the case of indoor warehousing workers noted above.

One practical implication of equation 2 is that it may be difficult to measure $\frac{\partial R}{\partial T}$ experimentally, since running an experiment that holds adaptation investments fixed and tallies resulting injuries would be unethical, and in situ settings where adaptation investments are completely fixed may be rare. An important limitation of engineering estimates of the effect of hotter climates on labor (e.g. Sherwood and Huber (2010); Kjellstrom and Crowe (2011)) is that they must rely on simulated estimates of $\frac{\partial R}{\partial T}$ which are then extrapolated to future climates without information on potential changes in adaptation investments. However, equation 2 also implies that there is a reasonably broad set of conditions under which we would observe a positive relationship between extreme temperature and injuries net of endogenous responses ($\frac{dR}{dT} > 0$), which motivates our empirical strategy below.

2.4 Empirical Application

In order to estimate the effect of high-frequency variation in temperature on injury risk, the econometrician must account for the fact that observed injury counts represent a combination of changes in risk and potential changes in worker-hours:[15]

$$Injuries = Risk \times WorkerHours = R(T) \times L(T) \tag{3}$$

Any observed temperature-injury relationship can therefore be decomposed into a combination of $\frac{dR}{dT}$ and $\frac{dL}{dT}$:[16]

$$\frac{dINJ}{dT} = \frac{dR}{dT}L(T) + \frac{dL}{dT}R(T) \tag{4}$$

Prior evidence suggests that environmental externalities including air pollution (Hanna and Oliva, 2015) and hot temperature (Graff Zivin and Neidell, 2014) may reduce same-day labor

[15] So far, we have couched the analysis in terms of injury risk, which represents a stochastic probability. Such risks are often expressed as an injury rate: for instance, injuries per 100,000 FTE workers per year. However, spatially and temporally granular measures of injury rates are often not available. We are aware of no publicly available data sets that measure injury risk at the daily level, for instance. Often, the best available measures are industry or occupation-level averages of injury rates measured annually. The paper that comes closest to measuring injury rates intra-annually is Lavetti (2020), who studies deep-sea fisherman by voyage.

[16] To be exact, one could further decompose the term to allow for separate responses on the intensive and extensive margins: $\frac{dL}{dT} = \frac{dEmp}{dT}\frac{dHrs}{dT}$.

supply, which would mean that $\frac{dL}{dT} < 0$, and estimates of $\frac{dINJ}{dT}$ that do not take these changes into account would understate the true change in injury risk. Alternatively, one can imagine settings where product demand increases on hot days (e.g. emergency healthcare services, ice cream vendors), leading to increased labor demand $\frac{dL}{dT} > 0$.

We note that the vast majority of existing studies on the effect of extreme temperature on injury (with the notable exception of Dillender (2019)) are either cross-sectional analyses that suffer from the usual omitted variable bias or case studies wherein endogenous responses are not accounted for, limiting the policy relevance of reduced form estimates even in the few cases where effects are causally well-identified.

In addition, the above framework suggests that, across a wide range of settings, extreme temperatures lead to increases in realized, net-of-safety-investment injury risk. In the appendix, we present a model of firm production and worker utility maximization to derive the conditions under which this prediction holds. The model predicts a positive temperature-risk relationship if: (i) product markets are perfectly competitive (labor markets need not be perfectly competitive), (ii) costs are convex, preferences are concave, and production inputs are not gross complements, and (iii) extreme temperature either affects injury risk directly ($\frac{\partial R}{\partial T} > 0$), and/or increases firm costs, and/or reduces labor productivity.

One implication is that, even in settings where there is little to no direct exposure, extreme temperature can raise injury risk due to cost-minimizing firm responses. These may include indoor settings where labor is not directly exposed to the elements, if climate control is sufficiently costly or heat adversely affects other production costs. This is important because it suggests that heterogeneity in the main effect should not necessarily track the indoor/outdoor status of a job or industry. Rather, we should expect to see significant effects in some indoor industries to the extent that higher outdoor temperatures make cooling or other adaptation investments more costly, and/or the level of total compensation for the marginal worker is insufficiently high for such amenities to be provided in equilibrium. The vast majority of existing research and policy focuses on outdoor workers and a subset of exposure-induced heat illnesses as opposed to injuries broadly (e.g. Jacklitsch et al. (2016)), despite the large number of manual occupations that engage primarily in indoor work.

Finally, whether or not policies aimed at encouraging adaptation investments improve social welfare will depend on whether workers and firms are operating at the Pareto adaptation frontier ex ante. Given compensating differentials, we would expect some of the costs of an adaptation policy, if binding, to be passed on to workers in the form of lower wages. The greater the costs of such investments, and the more the investments are orthogonal to productivity, the larger the negative impact on employment, wages, and firm profitability. In the presence of behavioral, informational or other labor market frictions, however, mandated benefit policies may improve efficiency.

3 Data and Summary Statistics

3.1 Worker's Compensation Claims

We combine confidential records of workplace injuries in California from the Department of Workers' Compensation (DWC) over the period 2000 to 2018 with zip code level information on daily temperature from the same period. A significant advantage of the workers' compensation data relative to other measures of injuries is its relative comprehensiveness, though anecdotal reports suggest that many minor injuries still go unreported. California legally obliges employers to maintain worker's compensation insurance, regardless of the number of employees or size of establishment. Failure to provide coverage is a criminal offense punishable by a fine of not less than $10,000 or imprisonment for up to one year or both, and the state can issue penalties of up to $100,000 against illegally uninsured employers.

The workers compensation records include the zip code of the worksite at which the injury took place, and the date of injury as reported on the First Report Of Injury (FROI). In addition to information on the date and location of these incidents, our data details the cause of injury (e.g. fall), type of injury (e.g. strain), and body parts affected by the injury (e.g. knee), as well as information on industry classification by claim.We collapse the 11,146,912 individual injury records for which site of injury information is available to the zip code- and day-level, resulting in a balanced panel with 11,596,536 zip code-day observations from 2000 to 2018.

3.2 Local Weather Data

We combine these injury records with gridded reanalysis data on daily maximum temperatures by the PRISM Climate Group, which provides daily meteorological information at a 4km by

4km resolution for the continental United States. We obtain the PRISM data for the period 2001 to 2018, and match workplace injuries with daily temperature records based on the zip code of the injury sites and the reported date of injury. To account for possible non-linearity in effects, we assign the maximum temperature recorded on any given zip code-day to a vector of 15 temperature bins, using 5°F increments ranging from below 40° to above 105°F.[17] To control for potential effects of rainfall on workplace safety, we link each zipcode-day observation with its corresponding daily precipitation record. We assign precipitation records to a vector of four rainfall bins, namely: days with no precipitation, days with less than half an inch of precipitation, days with half an inch to one inch, and days with more than one inch of precipitation.

3.3 Employment, Wages, Hours

We take information on employment and wages by county, 2-digit industry, and quarter from the QCEW for the period 2000 to 2018. To avoid spurious results arising from selection into and out of the sample, we retain only the subset of county-industries for which there are no missing observations between 2000 and 2018. This results in a balanced panel of 1,865,016 county-industry-quarter observations. We merge this information with the PRISM data by county-quarter, aggregating the temperature variables into a vector containing the counts of the number of days in each temperature bin, and precipitation into a variable indicating the total amount of precipitation in that county-quarter in inches.

We collect monthly data on hours worked from the U.S. Current Population Survey (CPS) from 2000 to 2018 (Flood et al., 2020). The CPS asks a rotating sample of workers representing the U.S. labor force a series of questions each month, including the "actual hours worked last week," where "last week" refers to the week including the 12^{th} day of the month. We collect the full sample of responses to this question and keep all workers who report being employed and in the labor force during the month sampled.[18] Using the merged PRISM data we calculate the number of days in the reference week in each temperature and precipitation bin.

[17] We determine the upper and lower cutoff of the range based on the distribution of commonly observed temperatures in California, plotted in Figure B2.

[18] We code as missing respondents who report hours worked greater than 168, and link all respondents to their households and merge the matched data to our PRISM weather data using the county reported in the CPS household data. On average, workers report working 38.6 hours in the reference week but responses range from 1 to 168 hours worked. The CPS does not report county of residence in the individual respondent files. However, respondents can be linked to surveyed households using respondent to household links provided by the CPS.

3.4 Industry Information and Labor Market Concentration

We generate industry (NAICS) and occupation (SOC) codes for a subset of the injury claims in our data set. We do this by taking industry codes provided in the raw claims data, removing clearly erroneous codes, and parsing the remaining codes using a tool provided by the National Institute of Occupational Safety and Health (NIOSH).[19] This tool allows us to assign probabilistic matches of occupation codes to 2-digit NAICS code-occupation description pairings in the raw data. For instance, an observation with NAICS code "11" and occupation description "Day Laborer" would be assigned to SOC code 45-2092, "Farmworkers and Laborers". Of the 12.86m claims in our original data set, approximately 7.71m have both an occupation description and a valid NAICS code, and we are able to assign SOC code matches for approximately 0.73m occupation descriptions that occur at least 10 times in our raw data. The median match probability is 89 percent. This allows us to assign SOC codes to approximately 1.195m observations, to which we assign local Herfindahl-Hirschman Indices (HHI) information by occupation and commuting zone (CZ) from Azar et al. (2020).

3.5 Summary Statistics

Table 1 presents summary statistics for injuries (Panel A) and temperatures (Panel B). On average, there are roughly 1.01 injuries per zip code-day in California during the sample period. Injuries officially classified as being caused by extreme temperatures are relatively rare, with an average of approximately 850 cases per year, which amounts to 14,574 between 2001 and 2018. This number is already at least 15 times larger than official statistics reported by Cal-OSHA, suggesting significant under-counting in publicly available records. As shown in table B1, the most frequently recorded incidents include back injuries (14%), injuries of fingers, hands, and shoulders (11, 9 and 5%), strains (30%), contusions and lacerations (11%). In total, injuries of core body organs account for 20 percent of observed injuries.

Figure 1 shows the spatial distribution of injuries across California, expressed in terms of raw injuries and injuries per establishment, illustrating the pervasiveness of workplace injuries across industries and geography. Figure 2 plots changes in injuries over time. Workplace injuries appear to be pro-cyclical (Panel A, figure 2), and also seasonal, with more injuries occurring during the summer months.

[19] Available here: https://wwwn.cdc.gov/nioccs3/

Panel B of Table 1 summarizes the zip code-level exposure to extremely high temperatures. On average, daily maximum temperatures exceed 80°F and 90°F on 56.4 and 24.6 days per year respectively. Given California's size and varied topography, both average climates and daily temperature fluctuations vary considerably across the state, in many cases even within counties. For instance, the high temperature on a given day may vary by over 25°F across zip codes within Los Angeles County alone. Some parts of California such as San Francisco experience few if any days above 90°F per year, whereas others such as Bakersfield experience many dozens each year.

4 Empirical Analysis (1): Temperature and Injuries

4.1 Empirical Strategy

In our first empirical examination we exploit variation in local temperatures on any given day within zip code and month (Figure 2 and 3), and rely on the fact that this variation is plausibly exogenous to unobserved determinants of workplace injuries, net of location-specific seasonality. Specifically, we examine whether realized injuries are higher on a hotter-than-average day within a given zip code-month-year cell. In the context of our analytical framework we are estimating the $\frac{dINJ}{dT}$ object on the left-hand side of equation 4, or the total impact of higher temperatures on workplace injuries inclusive of any changes in labor supply.

We implement this empirical strategy with regressions of the form:

$$F(Inj_{icdmy}) = \Sigma_{k=1}^{K} \quad {}^{k}Temp_{icdmy} + \Sigma_{p=1}^{P}\delta^{p}Precip_{icdmy} + \eta_{im} + \quad {}_{my} + \epsilon_{icdmy} \tag{5}$$

where $F(Inj_{icdmy})$ denotes a transformation of the count of injuries in zip code i located in county c on day d, month m and year y. Below, we present results using OLS (raw counts, injuries per worker), inverse-hyperbolic sine (IHS) transformations, and a Poisson specification, to assess the sensitivity of the findings to zero observations and outliers. For parsimony, we harmonize the main figures and tables using the IHS specification, noting that these estimates appear to be the most conservative. $Temp_{icdmy}$ denotes a vector of K daily maximum temperature bins, ranging from below 40° to above 105° Fahrenheit in 5° Fahrenheit increments. $Precip_{icdmy}$ denotes a vector of P precipitation bins, assigned based on daily precipitation in inches. η_{im} denotes a zip code-calendar-month fixed effect, which accounts for all time-invariant determinants of workplace safety by zip code (e.g. rural vs. urban locations, high vs. low income areas), as well as zip code-specific seasonality in injury risk (e.g. regional differences in construction or agricultural harvest seasons). $_{my}$ captures month × year fixed effects, which account for any state-wide economic shocks and macroeconomic trends.

To further account for potential spurious correlation between local warming trends and economic conditions, we also present estimates that replace $_{my}$ with $_{cmy}$, a county × month × year fixed effect. This latter control is feasible given the relatively large counties in California – there are approximately 30 zip codes per county – and potentially important for identification, as trends in economic conditions and regional warming/cooling patterns might be spuriously correlated.[20] ϵ_{icdmy} denotes a zip code-date specific error term. Standard errors are clustered at the level of county and calendar month to account for possible serial correlation in risk within zip codes as well as spatial correlation in temperature shocks. The main results are robust to various alternative levels of clustering (e.g. zip code, zip code and date), which we present in Table B7.

Our analysis identifies residual injury risk as a function of idiosyncratic (daily) temperature shocks *net of current adaptation investments*. The key parameters of interest are the $\Sigma_{k=1}^{K} \; {}^{k}Temp_{icdmy}$ coefficients. In particular, we are interested in the effect of days with especially cold or hot temperatures, where the 's are interpreted as increases in injury incidence relative to a day in the optimal (omitted) category, which we set to 60-65°F following existing studies (e.g. Graff Zivin and Neidell (2014)). The main identification assumption necessary to interpret these coefficients as causal is that residual variation in temperature – net of the fixed e ects and controls noted above – is uncorrelated with residual variation in the error term. In other words: that within a given month and year, and net of zip code-specific seasonality in injury risk, zip code-days with hotter temperature are not correlated with unobserved determinants of injury risk, an assumption we find to be highly plausible. The main threat to identification comes from potential endogenous changes in labor inputs, a possibility we discuss in greater detail below.

[20] See Figure B1 for warming and cooling trends observed in the data.

4.2 Main Effect

The main results from running equation 5 are presented in table 2. As shown in column (3), a day with highs between 85 and 90°F appears to increase injuries by 0.026 arcsinh points (se=0.0078), which represents an approximate increase of 4.8 percent relative to the baseline mean in the omitted category of days with highs in the 60 to 65°F range. A day in the 100 to 105°F range leads to an increase of approximately 6.6 percent, an effect that is statistically significant at the 5 percent level. Adding month-year fixed effects (column 4), or a more restrictive set of controls that include county-by-month-year fixed effects (column 5) does not alter the profile or significance of these effects materially.[21]

Figure 4 plots these coefficients and their 95 percent confidence intervals, again omitting the 60 to 65°F bin. Days with highs in the 80's and above clearly lead to increased injuries, with progressively hotter days leading to more injuries relative to milder days in the 60's. Interestingly, the point estimate appears to drop off slightly at temperatures above 105°F, though the estimates are substantially noisier given the relative rarity of such extreme events.

In contrast to Page and Sheppard (2018) and Dillender (2019), we find no evidence for significant impacts of extreme cold, though the point estimates on colder bins is positive. These estimates are noisier, possibly due to the relatively limited number of extremely cold days in much of California. There appears to be some evidence indicating that the optimal temperature for workplace safety – at approximately 50 to 55°F – may be below the range suggested by studies of thermal comfort or mortality (Deschênes and Greenstone, 2011; Albouy et al., 2016). This suggests that the magnitudes relative to an ideal working temperature are approximately 25 to 50 percent larger than those reported above given our selection of omitted category.

4.3 Robustness of Reduced Form

Given the non-normal distribution of injury counts at the zip-code day level, we present results running variants of equation 5 using a Poisson specification. As shown in columns (1) - (5) of Table 3, heat's effect on injuries remains highly significant and exhibits the same pattern of increasing intensity on hotter days. The point estimates are more precise and all are

[21] Coefficients on the colder temperature bins are suppressed for parsimony. The full set of temperature coefficients are presented in Appendix table B5.

significant at the 1 percent level, apart from the noisier 105°F bin. The implied magnitudes are somewhat larger using the Poisson specification: a day with highs in the 85 to 90°F range increases injuries by approximately 6 percent (compared to 4.8% above), whereas days in the 100 to 105°F range lead to a 9 percent increase relative to days in the 60 to 65°F range. Again, the optimal temperature range from a workplace safety standpoint appears to be lower than previous studies of heat and human performance, implying that relative to an optimal day in the 50s, a day in the 100 to 105°F range increases injuries by upwards of 15 percent (Figure 5).

We provide a series of additional robustness checks in the Appendix. These include specifications that present simple OLS on injury counts (Table B4), and ones that divide injuries by the number of workers in each county-quarter (Figure B3).[22] The results are remarkably consistent across these alternative specifications.

To allow for the possibility of "Monday effects", or the possibility that daily temperature within a month may be correlated with start or end of month effects in work patterns, we run versions of equation 5 that include day of week and day of month fixed effects (Table B6). The results are essentially unchanged. Table B7 probes the sensitivity of the main effect to alternative clustering of standard errors, and suggests the results to be insensitive to sensible alternative clustering, including those that allow for spatial correlation of temperature within counties and serial correlation across days.

Because many workplace injuries are reported to the worker's compensation division a few days after an injury occurs – either because the worker shows up to the hospital in the days following an incident, or because an acute injury is being treated in the ER first and claims filled out later – it is possible for the reported date of injury to exhibit some error in recall. Consistent with this possibility, we find using a dynamic distributed lags variant of equation 5 that heat increases injury risk in a two-day window spanning the reported date of injury on the claim (Figure B4). We find no evidence that hotter temperature more than 2 days before or after the reported date of injury significantly affects injury risk. We also find that, using 3-day or 5-day rolling averages of temperatures and injuries results in larger and more precise estimates across the board. This suggests that the same-day effects presented

[22]While the results are robust to this alternative characterization of the dependent variable, we note that if endogenous labor input responses are occurring at the daily level, such relatively crude controls for worker-hours may introduce additional measurement error.

above, even when expressed relative to the 'optimal' 50 to 55°F bin, may understate the true, error-in-recall-adjusted effect of heat by upwards of 50 percent (Table B5).

4.4 Endogenous Labor Responses

As we describe in our analytical framework, labor inputs may be responsive to extreme temperature, either due to changes in optimal labor supply (e.g. due to differences in the marginal utility of leisure versus labor under extreme temperatures) or changes in labor demand (e.g. due to declining marginal labor product or changes in product demand). In principle, this could occur on either the extensive (employment) or intensive margin (hours). This may affect the 'base' from which any given increase in injury counts may be drawn.[23] Our estimates thus far measure the total effect of heat on injuries ($\frac{dINJ}{dT}$). To understand how temperature increases the *risk* of injury per worker-hour ($\frac{dR}{dT}$) it is necessary to account for these labor responses ($\frac{dL}{dT}$). If labor inputs increase in response to hotter temperature, our point estimates of heat-injury relationships may overstate the true effect on injury risk. If labor inputs tend to decrease in response to hotter temperature, our estimates likely understate the true effect on injury risk. Finally, as equation 4 suggests, if there are no labor supply responses to heat then our estimates reflect the change in risk per unit of work ($\frac{dINJ}{dT} = \frac{dR}{dT}$).

Our prior given existing work (Graff Zivin and Neidell, 2014) is that the effects presented above are more likely to understate than overstate the true relationship. We further probe this using data on employment and hours from the QCEW and CPS respectively.

4.4.1 Employment

We estimate the effect of temperature on employment using data from the QCEW and running regressions of the following form:

$$ln(Emp_{ijqy}) = \Sigma_{k=1}^{K} \quad {}^{k}Temp_{iqy} + \delta Precip_{iqy} + \eta_q + \quad {}_{ij} + \theta_{jy} + \epsilon_{ijqy} \tag{6}$$

where $ln(Emp_{ijqy})$ denotes log monthly employment by county i, industry j, quarter q, and year y, and η_q, $\quad_{ij}$, and θ_{jy} denote quarter, county $\times$ industry, and industry $\times$ year fixed

[23] We note that many existing studies of workplace safety use injury rates by imputing hours worked based on a formula suggested by the Bureau of Labor Statistics (BLS). In brief, the imputation assumes a fixed number of hours worked per FTE worker employed in a given establishment, firm, or industry. In a world where either labor supply or demand are endogenous to temperature, this approach may mischaracterize true changes in safety risk, due to the fact that both the numerator and denominator may be changing in counteracting directions.

effects respectively.

We find no evidence of significant employment responses to hot temperature. As shown in Table 4, days with max temperature above 90°F have a reasonably precisely estimated zero effect on log quarterly employment, with 95 percent confidence intervals that rule out employment effects larger than +0.068 percent or smaller than -0.02 percent per 100°F day. If we assume that *every* work day in the quarter we above 100°F, this would imply an effect size of approximately -1.3 to +4.4 percent quarterly employment. The effect of days in the 90s is even smaller, with a 95 percent confidence interval of -0.022 percent to +0.026 percent. This finding holds across a range of specifications, including ones that account for possible spurious correlation between regional or state-level warming trends and trends in economic conditions (columns 4 and 5). It remains possible that more temporary, same-day increases in employment are offset by reductions on other days within the quarter, or vice versa, which would be undetectable using this data.

We do however find evidence of significant negative employment impacts of cold days – days with max temperatures below 30°F – and some evidence of reduction due to higher precipitation. The effect of a day with highs below 30°F is to reduce quarterly employment by approximately 0.1 percentage points, significant at the 1 percent level. The implied magnitude is that, if every workday had highs below 30°F, quarterly employment would be reduced by 6.6 percent (-0.1 x 66 workdays) relative to a quarter where every workday had highs in the 60's.

We find no evidence that 90°F days change quarterly employment significantly.[24] Looking across industries by 2-digit NAICS code, we find that the zero average effect masks some heterogeneity by industry for more extreme days. In construction, manufacturing, retail, and finance and insurance, we observe small positive employment effects of days above 100°F; whereas in agriculture, education, utilities, accommodation and food services, we see small negative effects. For instance, a 100°F day increases quarterly employment by approximately 0.15 percent (significant at 1 percent) in construction, and by 0.06 percent in manufacturing (significant at 10 percent). In accommodation and food services, we see a reduction in employment of 0.11 percent per 100°F day. Precipitation has particularly large negative employment effects in agriculture, mining, construction, transportation, and accommodation and

[24] Accommodation and food services is a notable exception.

food services. It seems possible that some portion of the temperature-injury relationship in construction, manufacturing, and retail may be driven by changes in labor inputs, though it is difficult to assess without temporally (daily) and geographically disaggregated data on hours worked whether the magnitude is sufficient to account for all or even the majority of the relationship.

4.4.2 Hours Worked

Similarly, to assess the impact of exposure to high temperatures on hours worked we estimate variants of the following equation:

$$IHS(Hrs)_{iswy} = \Sigma_{k=1}^{K} \; {}^{k}Temp_{iswy} + Precip_{iswy} + \eta_{im} + \; {}_{sy} + \epsilon_{iswy} \tag{7}$$

where $IHS(Hrs)_{iswy}$ denotes the IHS transformation of hours worked in MSA i, state s during week (month) w and year y. $Temp_{iswy}$ denotes a vector of K 5°F temperature bins, ranging from below 40° to above 105° F, where each MSA-day during the reference week is assigned to a bin according to daily maximum temperature. $Precip_{iswy}$ is the total precipitation during the reference week in the MSA. η_{im} denotes an MSA × week (month) fixed effect. ${}_{sy}$ denotes a state × year fixed effect, and ϵ_{iswy} denotes an error term. Standard errors are clustered at the county level. We also include various state-by-month and state-by-year trends in robustness checks. We weight all regressions using the full period link weights provided by IPUMS.

Table 5 provides results from running variants of equation 7. As shown, we fail to find evidence that hotter temperature significantly increases or decreases weekly hours worked. When we focus on the subset of workers in highly exposed industries, or those that spend more than 20 percent of their time exposed to the elements based on occupation information from O*NET, we find a similar zero effect, though point estimates for the hottest temperature bins are insignificantly negative across the board.

4.5 Interpretation

Our results here indicate that high temperatures increase injuries in the workplace. We've presented evidence that suggests higher temperatures do not significantly increase either the number of workers employed or hours worked by individual workers. While it is possible that, given the relative coarseness of the employment/hours data, undetected positive employment effects are upward-biasing the effect of daily temperature on injuries, the relative magnitude of the changes in employment and hours as well as the pattern of heat's effect on injuries across industries suggest that it is unlikely for endogenous labor input responses to be solely responsible for the temperature-injury relationships documented here. In the Appendix, we discuss various alternative explanations, including potentially endogenous incident reporting, which we also take to be unlikely to be driving our results.

5 Empirical Analysis (2): Mechanisms & Adaptation Costs

Our first set of results suggests that extreme temperature has a significant impact on workplace injuries and workplace injury risk, net of potential endogenous safety or labor input responses. However, it is unclear to what extent such heat-injury relationships are simply due to "unavoidable" direct exposures, or a result of cost-minimizing decisions on part of firms who can choose the level of effective safety investment.

5.1 Outdoor vs Indoor Work Settings

One important upshot of viewing adaptation as an investment in worker safety undertaken by cost-minimizing firms is that we would predict heat to influence safety decisions for both indoor as well as outdoor workplaces. Whereas workers in predominantly outdoor industries such as agriculture or construction may experience increased risk due to direct exposure, indoor workers in manufacturing, automobile repair, or warehousing may also be affected if providing cooling in such workplaces is sufficiently costly. Using incident-level information on workers' industry at the 2-digit NAICS level, we assess whether the effect of heat on injuries is limited to outdoor industries.

Figure 6 shows the results of running equation 5 by industry for select industries where work is likely to occur predominantly outdoors (top panel: agriculture, construction, utilities), as well as for industries where work is likely to occur primarily indoors (bottom panel: manufacturing, wholesale trade, warehousing). As is clearly visible in these cases, hotter temperature can increase injuries in both indoor and outdoor work settings. In the case of manufacturing, a day in the 95 to 100°F range increases injuries by approximately 10 percent relative to days in the 60 to 65°F range. In wholesale trade, this effect is almost 15 percent. Other predominantly indoor industries where we observe significant positive heat-injury relationships include sub-segments of retail trade (NAICS = 44, e.g. automobile parts dealers), accommodation and food services (72, e.g. hotels, restaurants, drinking establishments).[25] We do not find strong temperature-injury relationships in information (51), finance and insurance (52), management of companies (55) or healthcare and social services (62).

5.2 Heterogeneity by Injury Type

To the extent that the heat-injury relationship is in part a function of endogenous safety investments, it should not be limited to those injuries that arise from direct exposure to the elements. This is important because in examining the impact of heat on workplace injuries the public health literature has focused nearly exclusively on the subset of incidents that are classified as "heat illnesses", including heat syncope, heat rash, or heat stroke. In many manual-labor intensive industries accidents arising from mistakes or inattention cause far more injuries than heat illness and firms invest considerable time and energy in preventing these accidents. Given existing work linking extreme temperature to reduced cognitive performance and attention (Seppanen et al., 2006; Graff Zivin et al., 2017; Park, forthcoming; Cook and Heyes, 2020), one possibility is that some of these injuries of inattention may not be unrelated to temperature. Further, it implies that the cost firms incur to minimize error-induced workplace injuries may be higher on hotter or colder days.

Using claims-level information on the official cause of injury, in addition to information on the body part(s) affected, we provide evidence that heat not only leads to direct health risks ($\frac{dR}{dT}$), but also increases overall injury risk, due perhaps to increased costs of ensuring a given level of safety ($\frac{dS}{dT}$). For instance, injuries in our data are classified as being caused by a "Fall, Slip, or Trip","Moving part of Machine", "Lifting" or "Crash of Vehicle", as well as "Extreme Temperature". There is also a separate variable that records the body part(s) affected, including such entries as "Ear", "Eye", "Back" or "Cardiovascular system".

Table 6 presents results of estimating the main effect on two mutually exclusive subsets of the data: injuries classified as being caused by "Extreme Temperature" and all others. The top

[25] Within manufacturing, the industries with the largest impacts appear to include food processing, textiles, and apparel manufacturing. We note that manufacturing and kitchen workers, despite being located indoors, are considered highly exposed to heat by NIOSH.

panel of figure 7 presents the resulting coefficients graphically. Perhaps not surprisingly, there is a very strong relationship between hot temperature and injuries tagged as being caused by "Extreme Temperature". A day with max temperature in the 90 to 95°F range increases the frequency of such claims by approximately 276 percent (p=0.01) relative to the mean: a day above 105°F, by approximately 760 percent (p=0.01). Days with temperatures below 80°F exhibit no statistically significant increase in the number of claims tagged as caused by extreme temperature. We find no evidence for cold temperatures causing an increase in such claims, though as mentioned above, most work in California occurs in milder climates, limiting the number of days with highs below freezing.

When we replace the outcome variable with all other injuries, we find a positive relationship between hot temperatures and claim frequency. The magnitude of this relationship is perhaps not surprisingly smaller in percentage terms, but nevertheless statistically significant and economically meaningful. A day in the 90 to 95°F range leads to a 4.5 percent increase (significant at p=0.05), and a day in the 100 to 105°F range leads to a 6.1 percent increase (significant at p=0.05). Even days in the 80 to 85°F range result in a 3.2 percent increase in injury claims (p=0.10). In terms of the total number of injuries, these "non-heat-related" claims comprise the vast majority of residual injury burden associated with extreme heat. Over the period 2000-2018, there were on average 654,000 such claims per year in California, compared to 850 injuries caused by "Extreme Temperature" per year. These findings are consistent with (Dillender, 2019), who also finds effects of temperature on claims not classified as temperature-related.

When we look at the effect of temperature on injuries and illnesses that involve core body organs versus those involving extremities, we see similar positive effects of heat on both types (bottom panel of Figure 7, columns 3 and 4 of Table 6). We take this to be consistent with heat affecting not only heat illness, as has been the focus of most public health studies and regulatory analyses, but workplace safety risk more generally. These findings are consistent with temperature exposure reducing cognitive performance and decision-making ability, which could directly affect worker safety in environments that feature heavy machinery, moving vehicles and objects, or working on elevated surfaces. It seems plausible that a non-trivial proportion of the injuries attributed to falling from a ladder or being struck by a crane that occur on a hot day may not have otherwise occurred were it not for the disruptive influence of extreme temperature on cognition and attention. Given the significant positive relationship between temperature and injuries not categorized by California policymakers as being related to temperature, we find it unlikely that the main effect documented here is driven entirely by endogenous reporting and/or regulations unique to the California setting.

5.3 Heterogeneity by Local Labor Market Concentration

Our model also provides predictions regarding the profile of environmentally-induced workplace injuries according to local labor market imperfections, including search costs and resulting monopsony power. Emerging evidence suggests that monosponistic labor markets may be more prevalent than previously assumed (Naidu et al., 2016; Manning, 2020). All else equal, we would expect workers in more monopsonistic labor markets to tolerate greater workplace disamenities before terminating employment relationships. To the extent that safety is a component of total compensation, this would imply that firms would (a) provide less safety for a given wage ex ante, and (b) face a lower compensating differential with respect to reductions in workplace safety and thus be expected to respond less to elevated risk due to extreme temperature.[26]

We assess heterogeneity in the main effect by level of labor market concentration, using occupation-by-commuting zone measures of HHIs. As shown in figure 8, the temperature-injury relationship appears to be far more pronounced in labor markets with above median HHIs, where percentiles are defined across all occupation-CZs in the US from 2013-2016. While our measures of labor market concentration do not vary experimentally, and are extrapolated backward in time based on estimates from 2013-2016, they nevertheless capture variation in HHIs across occupations within a given commuting zone, making it less likely that our estimates are driven by geographic differences in unobserved dimensions of workplace safety. Naturally, it is possible for workers in more concentrated labor markets to exhibit characteristics that make them more prone to heat-induced injury (e.g. worse baseline health or higher risk tolerance) irrespective of firm investments. Nevertheless, we take these results as suggestive of the possibility that labor market frictions affect the realized level of adaptation to environmental shocks.

[26] We note that, in the presence of wage rigidities (e.g. minimum wages), firms may alter the composition of total compensation to favor safety and other non-wage amenities. We leave an exploration of this possibility to future work.

5.4 Official Statistics of Heat-Related Safety Burden

One important implication of these estimates is that workplace safety risks due to hotter temperature may be a far more pervasive phenomenon than official statistics suggest. To estimate the total magnitude of heat-induced workplace injuries, we use the $\Sigma_{k=1}^{K} \ ^{k}Temp_{idmy}$ coefficients from the main (IHS) specification above, noting that this likely provides a conservative estimate. We multiply the percentage increase in injury risk for each temperature bin above 80° Fahrenheit with the average number of days in each temperature bin observed in California over the study period. Aggregating across temperature bins, and taking the 50 to 55°F bin as the "optimal" reference bin, we obtain an estimate of 4,500 injuries caused by hotter temperatures per year in California, or approximately 81,000 over the study period. We note that, using the Poisson specification, this figure would be nearly 30 percent larger. These estimates suggest that official statistics may understate the injury/illness burden associated with hotter temperature substantially. For instance, relative to official heat-illnesses as reported by Cal-OSHA (approximately 60 per year), the actual number of heat-related workplace injuries and illnesses may be over 75 times larger.

It appears that official statistics in the U.S. and elsewhere may understate the contemporary public health burden associated with temperature exposure on the job. According to the latest Centers for Disease Control (CDC) criteria document, a rule-making guidebook, the number of heat-related injuries is reported as being around 4,000 per year in the entire United States (Jacklitsch et al., 2016). [27]

6 Empirical Analysis (3): Adaptation Policy (Workplace Safety Mandate)

We have shown that hotter temperature increases workplace safety risk net of potential endogenous labor input responses and firm/worker safety investments. The latter channel, while possibly important in understanding adaptation to climate change, is often difficult to observe. In this section, we exploit potential changes in the heat-sensitivity of firm safety investments

[27] The CDC notes that such figures may be underestimated due to the challenges of attributing individual cases to extreme temperature, but few estimates of the magnitude of under-counting exist. For instance, according to Jacklitsch et al. (2016): "Estimating the public health impact of extreme heat is difficult because hospitals and health care providers are not required to report heat-related illnesses, such as heat stroke and heat exhaustion, to public health agencies. In addition, heat-related deaths are often misclassified or unrecognized."

arising from what is to our knowledge the first mandated workplace heat safety standard. The predicted effects of such a policy are ambiguous ex ante.

6.1 Policy Background: California Heat Illness Prevention Standard

We exploit the fact that, in the US (and possibly globally), there have never been legally binding mandates specific to heat-related illnesses and injuries at the Federal level, and that, in late 2005, California passed what was then the only binding workplace heat-illness prevention standard in the country.[28] The California Heat Illness Prevention (HIP) standard (Cal/OSHA subchapter 7, group 2, article 10, section 3395) was filed on August 8th 2005 as an emergency measure implemented within 17 days and was initially effective for 180 days, and subsequently passed by the State Assembly on July 7, 2006.[29]

The standard applies to all "outdoor places of employment", broadly defined. It requires employers to provide a range of structural, informational, and procedural investments aimed at reducing heat-related safety risks. For instance, it mandates access to shade and water, in addition to provisioning employees and managers with training on how to prevent heat illness. The policy also mandates paid rest breaks of 5 minutes each hour on days with temperatures expected to reach above 95°F for a subset of exposed industries including agriculture, mining, landscaping, and construction, as well as a buddy system that prohibits workers from engaging in solo work on high heat days. There is an emphasis on provision of information to both managers and workers, including through formal training, media advertisements, and community outreach. For instance, the Division of Industrial Relations (DIR) sponsored the airing of informational radio ads (over 9,000 airings) and highway billboards, as well as a series of webinars and training programs. We reproduce text from Cal-OSHA's website on one component below:[30]

"*Employers must train all employees, both supervisory and non-supervisory, on the risk*

[28] The other prominent heat-related workplace policy that we are aware of is the Chinese worker heat subsidy program, which pays workers additional wages on days with high temperatures and which went into effect in 2012 (Zhao et al., 2016).

[29] In California, an emergency measure can be filed in "a situation that calls for immediate action to avoid serious harm to the public peace, health, safety, or general welfare." As soon as it is filed, it is effective for 180 days and can be readopted for two 90-day periods. HIP was implemented as a permanent regulation on July 7th, 2006, after two readoption periods. In the analyses that follow, we treat 2006 as the first year in which the policy is active, though we assess alternative break-points as well. We note that, as the legislation was put into effect as an emergency measure, pre-emptive investments by firms may have been less likely than in other regulatory settings. However, as we discuss, firms with indoor workplaces may have taken the policy as a signal of potential future indoor regulation.

[30] Full text available at: https://www.dir.ca.gov/dosh/heatillnessqa.html. For information on specific informational interventions, see: https://www.dir.ca.gov/dOSH/HeatIllnessCampaign/Heat-Illness-Campaign.Evaluation-Report.Summer-2012.pdf

factors for heat illness, signs and symptoms of heat illness, methods to prevent heat illness, and policies and procedures established to comply with this regulation. Training must be provided before the beginning of work involving a risk of heat illness. ... As a best practice, some employers use a daily "tailgate meeting" approach, starting out each work shift with a brief safety reminder about issues considered particularly relevant to the work to be performed that day."

The policy was followed by a vigorous enforcement regime. Figure B7 shows the frequency of the subset of Cal-OSHA inspections that resulted in a violation of the HIP standard between 2006 and 2017. Figure 9 plots their locations over time. Employers found to have been in violation of the standard could be fined up to $250,000 or shut down until safeguards were put in place.[31] Inspection data from OSHA suggests that there have been over 18,000 recorded violations of the standard since 2006.

6.2 Effect of Policy on Injuries

6.2.1 Event Study

To assess the effectiveness of the policy, we first investigate changes in temperature-related injury risk in an event study framework. To the extent that the policy specifically targets heat-related adaptation investments, we might expect the temperature-sensitivity of injuries documented in section 4 to be reduced after the policy relative to before. To test this we augment equation 5 with an indicator variable for post-2005:

$$F(Inj_{icdmy}) = \Sigma_{k=1}^{K} \theta^{k} Temp_{icdmy} \times Post_{dmy} + \Sigma_{k=1}^{K} \ {}^{k} Temp_{icdmy} + \\ \Sigma_{p=1}^{P} \delta^{p} Precip_{icdmy} + Post_{dmy} \times \eta_{im} + \ _{cmy} + \epsilon_{icdmy} \quad (8)$$

As in equation 5, $F(Inj_{idmy})$ denotes an IHS transform of the count of injuries (or other variations, including Poisson) in zip code i located in county c on day d, month m and year y, and $_{cmy}$ denotes county × month × year fixed effects. In contrast to equation 5, we allow η_{im} to vary by "treatment" period – that is, before and after the policy – to ensure to the extent possible that comparisons of the effect size are not confounded by secular trends in

[31] Some examples are presented here: https://www.ehstoday.com/construction/article/21906709/california-worksites-shut-down-for-heat-regulation-violations.

injury counts after 2005 (e.g. due to the 2008 recession). ϵ_{icdmy} again denotes a zip code-date specific error term. Standard errors are clustered two-way at the level of county by calendar month. If the policy was binding we would expect the difference between θ^k coefficients after the policy and θ^k coefficients before the policy to be negative.

Figure 10 plots the temperature coefficients (θ_1 - θ_K) and their associated 95 percent confidence intervals pre- and post-2005. The effect of hotter temperature on injury risk appears to be significantly lower in the period following policy adoption relative to prior to adoption. Table 7 presents each of the coefficients, their respective p-values, and the results from tests of significance in the differences between them (pre- vs post-). As shown, the temperature-sensitivity of injury claims is statistically significantly different for the 100 to 105°F bin (p=0.01) as well as the 105°F and above bin (p=0.10).We find no evidence that temperature sensitivity of injuries are significantly different at other parts of the temperature distribution, though the post-period coefficients for temperatures above 70°F are uniformly lower than their respective pre-period counterparts.

6.2.2 Robustness

We take this evidence to be consistent with some combination of information provision and/or mandated safety investment having led to a reduction in the heat-injury relationship. However, alternative interpretations are possible. For instance, if the ensuing recession of 2008 led to a tighter labor market and a lower willingness on part of workers to report injuries conditional on their occurrence, and the reduction in the proportion of injuries reported is lower for those injuries that tend to occur on hotter days, then it is possible for the effects noted above to be driven by a spurious relationship between time and the profile of injuries across temperature days. While we cannot rule out this possibility, several additional robustness checks suggest it to be unlikely as the only mechanism.

When we compare the temperature-profile of injuries using alternative time cutoffs, including a comparison of two periods after 2006, we find little evidence of significant changes. In addition, when we estimate separate interactions for each of the temperature bins for each year of the sample, we find a reduction in the heat-sensitivity of injury post-policy. These changes are statistically significant at the 5 percent level in nearly all of the post-policy periods. Figure 11 plots the results from one subset of these interactions, plotting the interactions between the 95 to 100°F bin and each year prior to and after 2005 separately, with their respective 95 percent confidence intervals. Figures B10 and B11 present similar plots for additional temperature bins. While it is difficult to state definitively that this pattern of reduced heat-sensitivity is due to the policy *per se*, taken together, the evidence presented in figures 11, B10 and B11 suggest that there is a significant non-transitory reduction in the heat-sensitivity of injuries post-policy.

It is possible that other factors affecting the temperature-sensitivity of injuries happen to coincide with the adoption of the standard, including possible secular trends in technology. If the reduction in heat-sensitivity of injuries is driven by changes in technology over time, we might expect similar differences to manifest across arbitrary time cutoffs unrelated to the policy. In Figure B8, we present analogous plots using time cutoffs that bisect the pre-2005 and post-2005 periods. In neither case do we find any evidence for changes in the temperature-injury relationship over time. In Figure B9, we present analogous plots that omit the period after 2010, as well as omit the year 2006 in order to account for possible effects of false precision due to a longer post-period, or idiosyncrasies of the reference year, and find that this has little effect on the main result.

6.3 Limits to Adaptation

Previous work has emphasized potential "limits" to the extent to which adaptation can mitigate the impacts of high heat on worker safety, particularly in outdoor work environments (Kjellstrom and Crowe, 2011; Kjellstrom et al., 2016; Dillender, 2019). For instance, Dillender (2019) finds that the heat-sensitivity of mining injuries is not significantly different in historically warmer versus cooler parts of the United States, which, combined with evidence of limited scope for reduced labor inputs, is taken to suggest limits to adaptation. Here, we probe this idea further, leveraging the wide range of average climates that occur within the state of California.

Running variants of equation 5 separately for different terciles of the California climate distribution (which, for the purposes of this exercise, we define in terms of the number of days above 95°F during the study period), we find little evidence that the temperature-sensitivity of injury varies significantly across climates, consistent with Dillender (2019). However, when we further interact the temperature coefficients to explore the change in temperature-sensitivity over time by climate tercile (pre- vs post-2006), we observe that heat-injury relationships appear to fall significantly across the climate distribution. As shown in Figure B12, even in the hottest tercile – which averages 52 days above 95°F per year – the coefficient on days above 100°F is significantly different (p=0.03) in the period 2006-2018 relative to the period 2001-2005. Such climates are roughly equivalent, in terms of frequency of extreme heat events, to the 95th percentile of the US climate distribution. This cautions against characterizing adaptation to climate change in the workplace in terms of physical "limits", at least in the context of workplace safety. Our results suggest that even firms in very hot areas are in fact able to adapt to extreme heat. This suggests that the achievable limits of adaptation may be endogenous to the investments undertaken by workers and firms, and possibly the presence or absence of policies that mandate such investments.

6.4 Interpretation

We interpret these results as suggesting that workplace adaptation investments can be effective even in areas that have experienced historically high average temperatures. The simplest explanation for our results is that the mandated benefits – water breaks, shade structures, etc – directly reduced the impact of temperatures on workers in ways that reduced injury risks. It is possible that the policy reduced risk via other channels as well. It may be that the policy, by providing information regarding the true safety risks of high temperature, helped induce additional safety investments, even in some "unregulated" industries. This would certainly be consistent with qualitative accounts of CalOSHA field operatives as well as previous survey-based analyses which suggest that managers are often not fully aware of the suite of health risks faced by workers, and rely in part on OSHA guidelines to anchor expectations regarding underlying environmental risks (Levine et al., 2012; Jia et al., 2016). The frequency and geographic breadth of enforcement activity could have strengthened either channel. Johnson (forthcoming) for instance finds that firms within a 50 mile radius of plants found to be in violation of OSHA safety standards subsequently improved workplace safety, irrespective of the specific type of violation. Finally, it may be that what we observe is simply the result of secular changes in adaptation technology that happened to coincide with the policy.

6.5 Welfare Implications of Policy: Effect of Policy on Wages and Employment

While these findings are suggestive, on their own they cannot tell us whether a policy improved efficiency, which depends on net benefits and costs. If markets are in competitive equilibrium, there is no efficiency case for mandated benefits of the kind described above. Where employers and employees can negotiate freely and frictionlessly over the total compensation package, they can be expected to reach a mutually beneficial outcome. Non-wage benefits, including safety, would be provided up to the point where an extra $1 spent by employers on benefits is valued by employees at exactly $1. On the other hand, theory suggests that there may be instances when mandated benefits could improve efficiency (Summers, 1989). First, this may be the case if there are behavioral or informational frictions, either on part of employer or employee – for instance, if one or both parties do not fully understand heat related safety risks or the true cost-effectiveness of various adaptation options. Second: if there are externalities associated with the adaptation investment. For instance, to the extent that worker's compensation insurance is only partially experience-rated, injuries at a more lax establishment would impose negative externalities on others (Ruser, 1985).

Even without obvious behavioral failures or externalities, search frictions may prevent the kind of bargaining described in the perfectly competitive case above. In such a world it is possible that heat safety investments are more valuable to workers than they are costly to firms, but do not occur in private equilibrium. One might then expect a binding safety mandate to lead to reduced wages but possibly increased employment. Alternatively, in a world where government mandates prove to be more costly to provide than their value to workers, we might expect both negative wage and employment e ects. Finally, if there are sufficient fiscal or other externalities as above, it remains possible that a policy is efficiency-enhancing even if it results in negative wage and employment affects.[32]

[32] An additional implication is that, when using observed behavior in labor markets to estimate the scope for adaptation to climate change it is important to consider the underlying market structure. This is true both for estimating adaptation-inclusive damage functions as well as for inferring welfare costs of avoidance behavior. One immediate implication is that, depending on the joint distribution of climate parameters and the degree of labor market frictions, existing empirical estimates of adaptation may be biased in ways that make it difficult to bound adaptation costs (Carleton et al., 2018).

6.5.1 Wages and Employment

Here, we assess the costs of the policy to workers and firms using data on wages and employment. We focus on the effect of the policy on wages and employment by 2-digit industry and county-quarter, using data from the QCEW (2001-2017), and a triple difference estimation strategy. Unlike the case of injuries, we are able to assess using non-California data whether the effects we observe are driven by California-specific policies or other national or regional trends coincident with the 2005 standard.

Specifically, we run regressions of the following form:

$$ln(Y_{ijqy}) = POST_{iqy} \times TREAT_j \times CA_i + \quad + \zeta_{ij} + \phi_{qy} + \epsilon_{ijqy} \quad (9)$$

where $ln(Y_{sjqy})$ represents the outcome variable (log employment, log wages per worker) for county i, industry j, state s, quarter q, and year y. CA_i is a dummy denoting counties in California, $POST$ is a dummy for post q2 of 2005. $TREAT$ is a dummy for whether or not industry j was "treated" by the policy, which may depend on one's hypothesis regarding the relevant policy features (e.g. information treatment vs direct mandates). We therefore present results for three alternative definitions of treated industries. The first includes all industries that are either directly regulated as "high heat" industries in the text of the standard, or appear to have been significantly affected by some dimension of the policy based on the empirical analysis in section 6.2 (we call these "All affected" industries); the second considers only the subset of affected industries that are explicitly targeted in the standard ("Regulated and affected"); and the third is to consider industries that appear to have been affected in terms of injuries but were not directly targeted as part of the mandate ("Unregulated but affected"). is a vector of all two-way interactions and individual dummies (e.g. $POST_{iqy} \times CA_i$). ζ_{ij} denotes a vector of county-by-industry fixed effects, which account for time-invariant county-level differences in economic conditions affecting each industry. ϕ_{qy} represents a vector of quarter-by-year fixed effects, which account for all correlated economic shocks across the country.

The identification assumption is that the difference in outcomes between treated and untreated industries is evolving similarly across states (CA vs others) save for the policy. If this assumption is true, then identifies the causal effect of the policy on employment and wages, relative to its effect on untreated state-industry-quarter cells. This assumption would be violated if there are compositional changes in the California economy that are systematically different from the rest of the country, or other contemporaneous shocks that have differential affects across industries and states. While we cannot directly verify these parallel trends assumptions, plotting trends in wages and employment for affected and unaffected industries is instructive (Figures B13 and B14). Trends in wages and employment in affected industries appear to be roughly parallel prior to the implementation of the policy. However, it is clear from these figures that the Great Recession had a large impact on wages and employment, and that its impacts may have been larger in some industries in California than elsewhere. As such, we focus our analysis on the quarters proceeding the great recession excluding data after Q1 2008.

Tables 8 and 9 present the results from running equation 9 above for wages and employment respectively. To account for the possibility that our results are biased due to incomplete coverage of agricultural workers - a well-documented feature of the QCEW data - we present results including (excluding) agriculture in columns 1-3 (4-6). The coefficients on the triple interaction term in Table 8 suggest that the policy had a modest negative effect on wages of approximately 2-4 percent: approximately 0.025 log points (affected and unregulated, column 3) and 0.037 log points (affected and regulated, column 2). These effects are robust to alternative clustering of standard errors, and the exclusion of agricultural workers.

The corresponding coefficients in Table 9 suggest that the policy appears to have had a zero or mildly positive affect on employment. Specifically, the results indicate that regulated industries experienced a significant relative employment increase of between 0.028 and 0.041 log points, whereas the effects on affected and unregulated industries is positive (0.01 to 0.012 log points) but statistically insignificant.[33] To gain more insight into employment consequences, we conduct a similar set of analyses using data from the CPS on the number of hours worked in the week prior to the date of the CPS survey, and find no evidence of significant changes in hours resulting from the policy.[34]

[33]In the appendix, we present the results including years after the great recession. These results suggest similar negative wage impacts of between 0.02 and 0.03 log points, but a different pattern for employment, with a large negative employment impact on regulated and a large positive employment impact on unregulated industries. While we cannot verify this, such findings would be consistent with the Great Recession having affected certain industries in California – notably, agriculture, construction, mining, and other services — particularly adversely. Is also consistent with the fact that the coefficient on the CAxPOST term is negative, suggesting that the recession had a differential impact on affected industries in California relative to other states.

[34]We estimate the same triple difference specification but replacing employment and wage data from the QCEW with the

Wage and employment impacts of this direction and magnitude are consistent with Lee and Taylor (2019), who find using plant-level data from US manufacturing that randomized safety inspections led to significantly improved safety (a 45 percent reduction in fatality rates), a 2 to 3 percent reduction in hourly wages, and an 8 to 10 percent increase in the number of employees per establishment. Notably, they find that employment increases for both production and non-production workers, the latter being consistent with the addition of safety and process managers. Levine et al. (2012) and Johnson (forthcoming) also find that randomized inspections and their subsequent publicizing led to a reduction in injuries without measurable impacts on firm sales and turnover. Our results build on these findings by providing evidence on the effects of government regulation on the health and safety impacts of extreme temperature.

If these estimates are unbiased, the implication would be that the policy was valued by workers at an amount equal to or greater than the cost to firms. This would suggest that, absent such a policy, workers and firms may not have been operating at the Pareto adaptation frontier. We estimate that the policy prevented on average 1,800 heat induced injuries per year in California, mainly for workers in agriculture, construction, warehousing, manufacturing and other services. The reduction in injury risk, along with possible improvements in thermal comfort, appear to have been valued by workers at more than the cost to employers.

7 Conclusion

Environmental conditions such as pollution or extreme temperature can impose large costs on workers and firms. This is true even when marginal impacts are small given the broad base of working-age individuals and the number of workers whose occupations involve exposure to the elements. Understanding the effects of extreme temperature may be of particular welfare and policy relevance given the expected increases in temperature extremes due to climate change. Measuring the true impact of such working conditions is difficult, however, because both workers and firms can in principle engage in avoidance behaviors to mitigate these costs.

log of hours worked in the previous week from the CPS as the outcome. We present results of this CPS analysis in table 10. We find no evidence that hours worked decline in either regulated or unregulated affected industries. The estimated coefficients are negative and statistically insignificant, ranging from -0.0028 log points (affected, unregulated) to -0.0069 log points (affected, regulated). These findings are consistent with reduced wages, or downwardly rigid nominal wages combined with a reduction in hours (resulting in reduced wages per worker, as above).

These choices are not always directly observed, and may be influenced by underlying labor market frictions. In this paper, we assess the consequences for workers and firms of extreme temperature on the job, in a setting that allows us to also examine how adaptation decisions may both reduce these consequences and be distorted by underlying labor market conditions.

We find that hot temperature substantially elevates workplace injury risk. A day with high temperatures between 90 and 95°F leads to a 6 to 9 percent increase in same-day injuries, relative to a day in the 60's. A day with highs in the 100 to 105°F range leads to a nearly 15 percent increase. These effects do not appear to be driven entirely by endogenous changes in labor inputs, either on the extensive (employment) or intensive (weekly hours) margin. Nor are the impacts limited to heat-illnesses. On hotter days, workers are substantially more likely to be injured in a variety of ways not directly related to heat. We estimate there are an of average 4,500 annual injuries in California caused by extreme heat but not reported as a heat injury. This implies heat related injuries are at least 500 percent more frequent than current estimates, which focus on heat-illnesses such as heat-exhaustion or heat-syncope.

Many of these injuries appear to be preventable, suggesting significant scope for adaptation to future climate change. But for reasons that are as yet unclear, many such adaptations do not appear to take place in private equilibrium. One possibility is the presence of labor market frictions. California's mandated workplace heat safety regulation appears to have substantially reduced the heat-sensitivity of workplace injuries. We estimate that hotter temperature caused approximately 1,800 fewer injuries per year in California since 2006, or approximately 22,000 injuries in the 13 years following policy implementation. Valued at an NPV of $45,0000 per injury in 2020 dollars Leigh (2011), this comes out to approximately $81,000,000 per year in estimated social benefits. At the same time, the policy appears to have reduced wages modestly but with zero or even positive employment effects, consistent with the investments having been valued by workers at more than the cost to firms. These results suggest that the policy may have solved important frictions preventing workers and firms from operating at the Pareto adaptation frontier ex ante.

Our findings are consistent with extreme temperature affecting worker physiology, cognition, and decision-making (Deschênes and Greenstone, 2011; Graff Zivin et al., 2017; Park, forthcoming; Heyes and Saberian, 2019), which has been shown in other settings to affect realized injury risk (Dillender, 2019). They are also consistent with extreme temperature reducing labor and total factor productivity (Colmer, 2018; Somanathan et al., 2018; Zhang et al., 2018), or simply increasing marginal costs due to extreme temperature, which leads profit-maximizing firms to reduce safety investment. Our findings are broadly consistent with Barreca et al. (2016), Carleton et al. (2018), and Park et al. (2020), who find that adaptation investments including air conditioning can reduce direct impacts of heat on health and human capital outcomes, and build on Garg et al. (2019), who study the effect of cash-transfer programs on the temperature-violence relationship in Mexico, and find that cash infusion substantially reduces this relationship. Our paper is the first to our knowledge to show the e ect of a targeted adaptation policy on labor market outcomes, and one of the first to empirically estimate labor market adaptation.

One immediate policy implication of these findings is that estimates of the social cost of carbon that do not incorporate temperature's effects on workplace safety may understate the magnitude of the carbon externality. These estimates also suggest that climate change may further exacerbate trends in total compensation inequality – not only across but also within countries, given the higher likelihood of lower-skilled workers to work in occupations that involve exposure to the elements (Maestas et al., 2017). However, our results also underscore the importance of considering the scope for adaptation in projecting damages from climate change, and the empirical challenges of doing so. To the extent that the California policy reduced the marginal impact of hot temperature on injury risk without significant impacts on wages and employment, this would imply that firms and workers were not operating at the Pareto Frontier of adaptation investment. Labor market frictions may be an important reason why, which highlights the importance of investigating these and other potential constraints to adaptation to climate change or other environmental externalities.

Our results indicate workplace heat exposure constitutes an important workplace disamenity, particularly for those who work in exposed industries such as construction and mining. From a welfare standpoint, workplace injuries are especially important for at least two reasons. First, to the extent that they affect working-age adults, the social costs of morbidity and lost work time are likely to be higher than for the elderly who drive the majority of mortality estimates. Dobkin et al. (2018) for instance finds that workplace injuries can not only have large direct health care costs, but lead to persistent wage impacts that affect injured worker's entire subsequent earnings trajectories. Second, the relationship between climatic variables and workplace safety carries important distributional implications. If demand for amenities such as workplace safety is lower in low wage jobs (Hamermesh, 1999; Pierce, 2001), then even if labor markets are perfectly competitive, the effects of more extreme temperatures will be regressive. Given that many workers in exposed occupations have low levels of formal education – a recent RAND survey finds that over 78 percent of men without a bachelor's degree report routine exposure to extreme environmental conditions at work, compared to 36 percent of those with a bachelor's degree (Maestas et al., 2017) – it may be important to better understand the potential distributional implications of occupational temperature exposure.

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Tables and Figures

Table 1: Summary Statistics

Notes: Table 1 presents key summary statistics of the working data set, which collapses injury and temperature information by zip code and day over the period Jan 1 2001 to Dec 31 2018. *Panel A* provides information on workplace injuries. *Panel B* provides information on temperature.

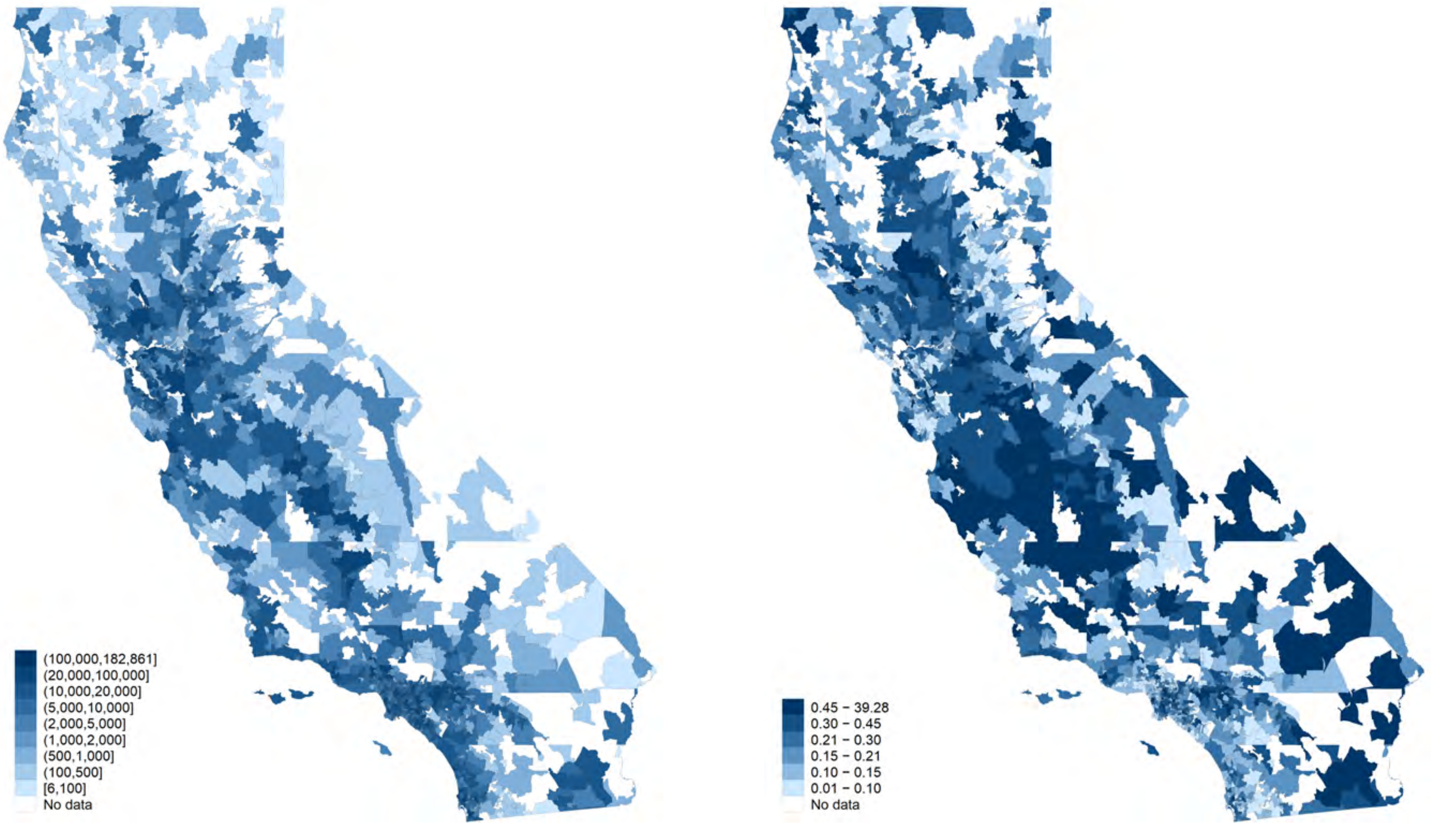
Panel A: Injuries

Variable	Mean	Median	S.D.	25th	75th	Observations
Injuries	1.01	0.00	2.07	0.00	1.00	11,596,536
Injuries (T=60-65F)	1.20	0.00	2.38	0.00	2.00	1,004,586
Injuries - Cause: Extreme Temperatures	0.00	0.00	0.04	0.00	0.00	11,596,536
Injuries - Cause: All Other Causes	1.01	0.00	2.06	0.00	1.00	11,596,536
Injuries - Body Part: Core Body	0.19	0.00	0.74	0.00	0.00	11,596,536
Injuries - Body Part: All Other	0.81	0.00	1.63	0.00	1.00	11,596,536

Panel B: Temperatures

Variable	Mean	Median	S.D.	25th	75th	Observations
% Days 60-65F (Omitted Bin)	0.12	0.00	0.30	0.00	0.00	11,596,536
% Days 80-85F	0.10	0.00	0.27	0.00	0.00	11,596,536
% Days 85-90F	0.08	0.00	0.24	0.00	0.00	11,596,536
% Days 90-95F	0.06	0.00	0.22	0.00	0.00	11,596,536
% Days 95-100F	0.04	0.00	0.18	0.00	0.00	11,596,536
% Days 100-105F	0.02	0.00	0.13	0.00	0.00	11,596,536
% Days Above 105F	0.01	0.00	0.08	0.00	0.00	11,596,536
Days/Year 60-65F (Omitted Bin)	25.00	23.00	16.64	14.38	32.18	11,596,536
Days/Year 80-85F	15.85	12.00	15.66	1.84	26.00	11,596,536
Days/Year 85-90F	12.28	6.00	14.08	0.00	22.00	11,596,536
Days/Year 90-95F	9.76	2.00	13.54	0.00	16.00	11,596,536
Days/Year 95-100F	6.53	0.08	11.16	0.00	8.43	11,596,536
Days/Year 100-105F	3.10	0.00	7.11	0.00	2.00	11,596,536
Days/Year Above 105F	1.29	0.00	6.47	0.00	0.00	11,596,536

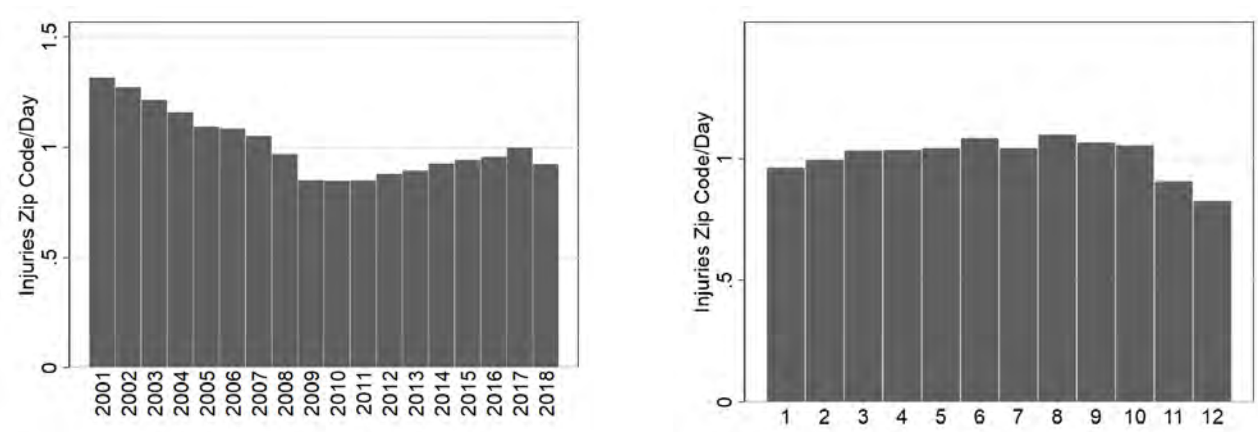
Figure 1: Injuries in California



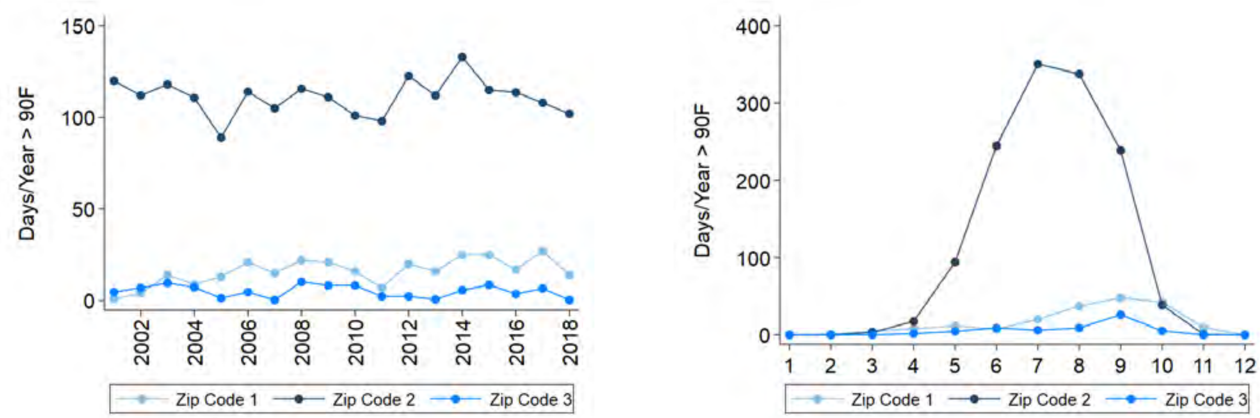
Notes: Figure 1 depicts the number of injury claims over the study period (2001-2018) by zip code, taking location information for the reported work-site of injury. The *left* panel presents raw counts per zip code; the panel on the *right* provides the number of injuries per establishment..

Figure 2: Injuries and Temperatures Over Time

Panel A: Injuries

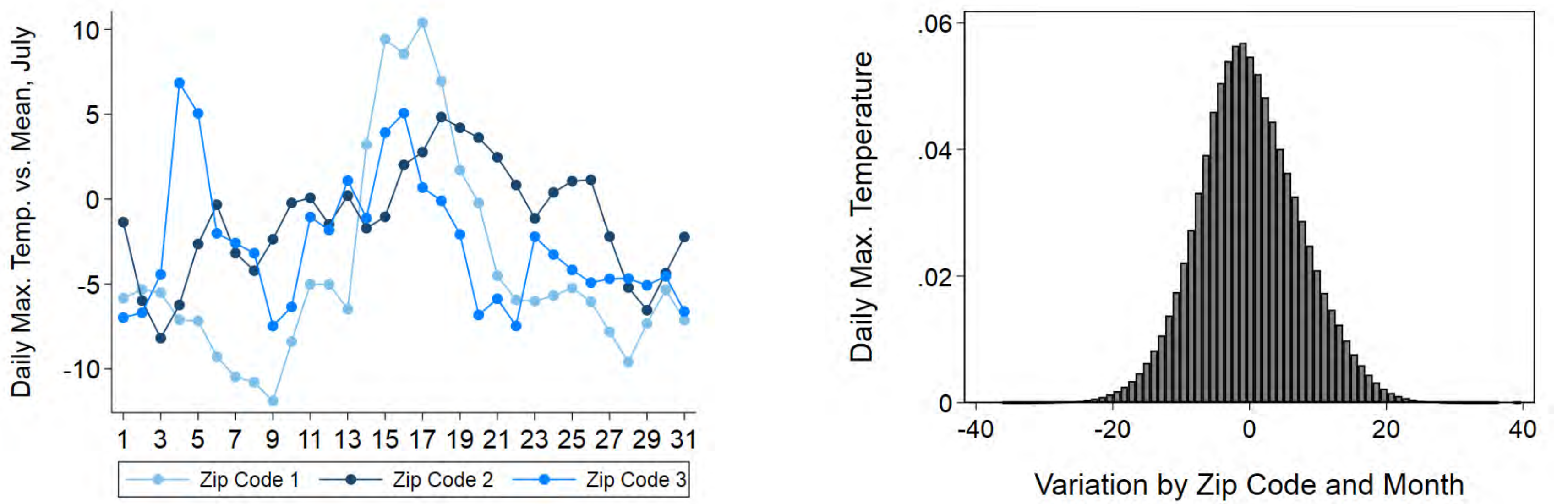


Panel B: Temperatures



Notes: Figure 2 presents trends in injuries and temperatures over the years in our sample (*left*), as well as seasonality in each across months (*right*). The histograms in *Panel A* show counts of injuries occurring in California-based work sites during the period 2000-2018. *Panel B* depicts the number of 90° F days per year (*left*) and per month (*right*) for three representative zip codes: Los Angeles *(Zip Code 1)*, Bakersfield *(Zip Code 2)*, and San Francisco *(Zip Code 3)*.

Figure 3: Identifying Variation in Temperatures



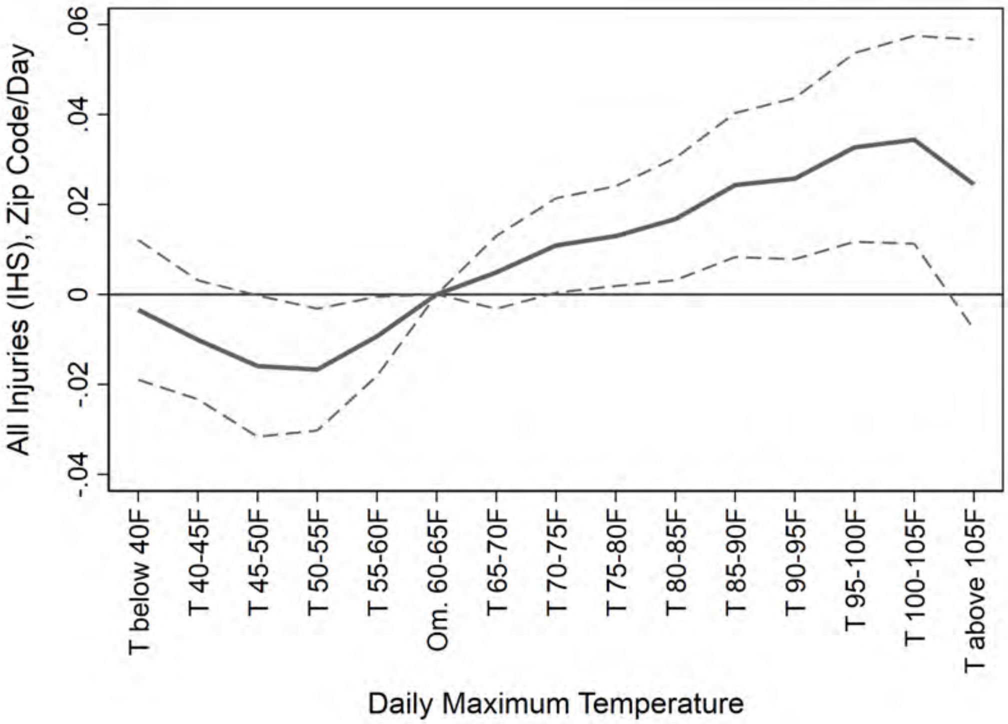
Notes: The *left* panel illustrates the identifying variation in daily maximum temperatures for three representative zip codes across days of the month in July, plotting deviations from zip-code-specific monthly means for zip codes in Los Angeles (*Zip Code 1*), Bakersfield (*Zip Code 2*), and San Francisco (*Zip Code 3*). The panel on the *right* shows residualized variation in daily maximum temperatures in degree Fahrenheit, and the x-axis refers to the deviation in °F, plotting the deviation from zip code-and month-specific means.

Table 2: Temperature and Injuries – Main Effect (IHS)

	(1) IHS	(2) IHS	(3) IHS	(4) IHS	(5) IHS
T above 105F	0.00497	0.0249	0.0249	0.0220	0.0245
	(0.0126)	(0.0150)	(0.0150)	(0.0156)	(0.0161)
T 100-105F	0.0317***	0.0360**	0.0360**	0.0325**	0.0344**
	(0.00911)	(0.0105)	(0.0105)	(0.0111)	(0.0115)
T 95-100F	0.0342***	0.0352***	0.0352***	0.0315**	0.0327**
	(0.00821)	(0.00938)	(0.00938)	(0.00993)	(0.0105)
T 90-95F	0.0259***	0.0277**	0.0277**	0.0250**	0.0257**
	(0.00679)	(0.00815)	(0.00815)	(0.00858)	(0.00894)
T 85-90F	0.0238***	0.0262***	0.0262***	0.0242**	0.0243**
	(0.00667)	(0.00747)	(0.00747)	(0.00778)	(0.00800)
T 80-85F	0.0178**	0.0192**	0.0192**	0.0169*	0.0168*
	(0.00551)	(0.00621)	(0.00621)	(0.00649)	(0.00678)
N	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00
Injuries Zip/Day (60-65F)	0.67	0.67	0.67	0.67	0.67
Injuries Zip/Year (60-65F)	245.40	245.40	245.40	245.40	245.40
Injuries Sample/Year	38,113.66	38,113.66	38,113.66	38,113.66	38,113.66
Injuries Sample/01-18	675,410.38	675,410.38	675,410.38	675,410.38	675,410.38
Zip Code FE	Yes	No	No	No	No
Month FE	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	No	No
Zipcode × Month FE	No	Yes	Yes	Yes	Yes
Precipitation	No	No	Yes	Yes	Yes
Month × Year FE	No	No	No	Yes	No
County × Month × Year FE	No	No	No	No	Yes

Notes: Table 2 shows the effect of temperature on injury claims for California-based work sites over the period 2001 to 2018. All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day on indicator variables representing each of 15 temperature bins, as well as controls for precipitation and the fixed effects noted above. The results of the main specification corresponding to equation 5 are shown in column 5. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month and presented in parentheses (* p<.10 **p<.05 ***p<.01).

Figure 4: Temperature and Injuries – Main Specification



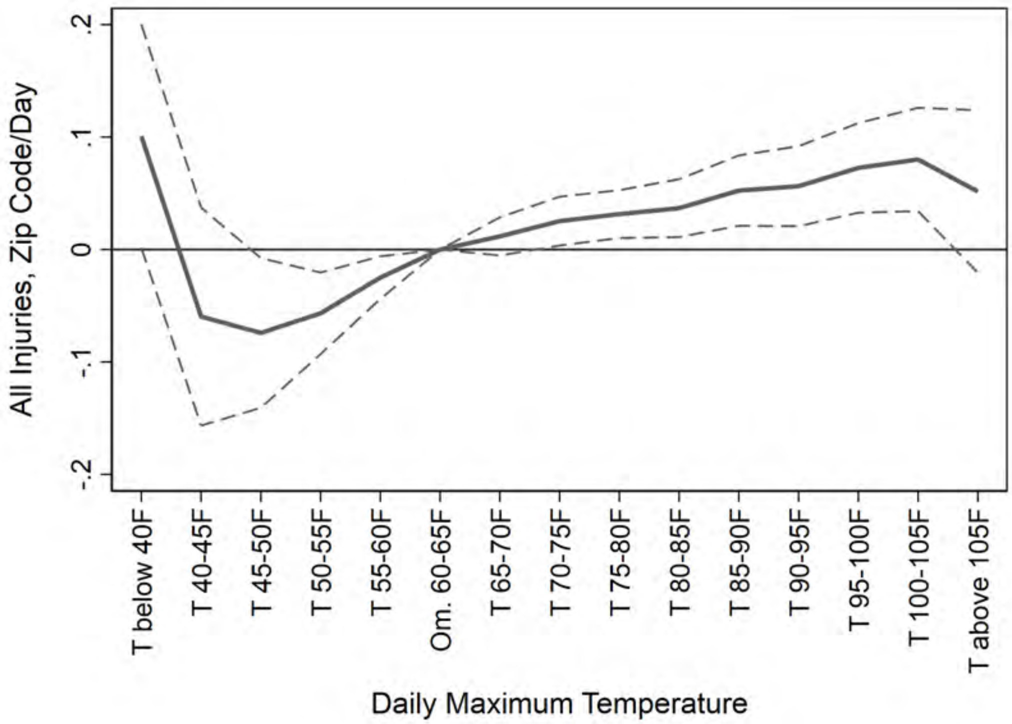
Notes: Figure 4 plots the full set of temperature coefficients obtained from regressions specified in equation 5 (point estimates from column 5 of Table 2). All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. They reflect residual variation in injuries after regressing on zip code × month and county × year × month fixed effects, as well as controls for precipitation. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month, and 95 percent confidence intervals are denoted by dashed lines.

Table 3: Temperature and Injuries – Main Effect (Poisson)

	(1) poisson	(2) poisson	(3) poisson	(4) poisson	(5) poisson
T above 105F	0.0385	0.0663	0.0664	0.0624	0.0516
	(0.0301)	(0.0348)	(0.0348)	(0.0357)	(0.0369)
T 100-105F	0.0957***	0.0945***	0.0945***	0.0891***	0.0802***
	(0.0189)	(0.0215)	(0.0214)	(0.0225)	(0.0235)
T 95-100F	0.0935***	0.0877***	0.0877***	0.0819***	0.0726***
	(0.0172)	(0.0190)	(0.0190)	(0.0201)	(0.0203)
T 90-95F	0.0717***	0.0680***	0.0680***	0.0643***	0.0564**
	(0.0158)	(0.0176)	(0.0176)	(0.0182)	(0.0182)
T 85-90F	0.0638***	0.0626***	0.0626***	0.0602***	0.0524**
	(0.0147)	(0.0157)	(0.0157)	(0.0160)	(0.0160)
T 80-85F	0.0477***	0.0472***	0.0472***	0.0447***	0.0368**
	(0.0121)	(0.0130)	(0.0130)	(0.0133)	(0.0131)
N	11,596,536.00	11,502,250.00	11,502,250.00	11,502,250.00	11,497,394.00
Injuries Zip/Day (60-65F)	0.67	0.67	0.67	0.67	0.67
Injuries Zip/Year (60-65F)	245.40	245.40	245.40	245.40	245.40
Injuries Sample/Year	38,113.66	38,113.66	38,113.66	38,113.66	38,113.66
Injuries Sample/01-18	675,410.38	675,410.38	675,410.38	675,410.38	675,410.38
Zip Code FE	Yes	No	No	No	No
Month FE	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	No	No
Zipcode × Month FE	No	Yes	Yes	Yes	Yes
Precipitation	No	No	Yes	Yes	Yes
Month × Year FE	No	No	No	Yes	No
County × Month × Year FE	No	No	No	No	Yes

Notes: Table 3 shows the effect of temperature on injury claims for California-based work sites over the period 2001 to 2018. All coefficients are obtained from poisson regressions of injury counts per zip code and day on indicator variables representing each of 15 temperature bins, as well as controls for precipitation and the fixed effects noted above. The results of the main specification corresponding to equation 5 are shown in column 5. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month and presented in parentheses (* p<.10 **p<.05 ***p<.01).

Figure 5: Temperature and Injuries – Main Specification (Poisson)



Notes: Figure 5 plots the full set of temperature coefficients obtained from regressions specified in equation 5 (point estimates from column 5 of Table 3). All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. They reflect residual variation in injuries after regressing on zip code × month and county × year × month fixed effects, as well as controls for precipitation. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month, and 95 percent confidence intervals are denoted by dashed lines.

Table 4: Extreme Temperature and (100x) Log Employment

	(1)	(2)	(3)	(4)	(5)
Days above 100 (°F)	0.020	0.018	0.018	0.013	0.024
	(0.032)	(0.031)	(0.031)	(0.033)	(0.021)
Days in 90s (°F)	0.001	0.001	0.001	-0.002	0.003
	(0.013)	(0.012)	(0.012)	(0.015)	(0.013)
Days in 80s (°F)	-0.001	-0.000	-0.000	-0.003	0.003
	(0.012)	(0.011)	(0.011)	(0.011)	(0.009)
Days below 30 (°F)	-0.104***	-0.099***	-0.099***	-0.095***	-0.087***
	(0.027)	(0.025)	(0.025)	(0.024)	(0.021)
Average monthly precip		-1.748	-1.748	-1.733	-1.763*
		(1.163)	(1.163)	(1.164)	(0.994)
N	1,865,016	1,865,016	1,865,016	1,865,016	1,864,224
County FE's	Yes	Yes	Yes	Yes	Yes
Quarter FE's	Yes	Yes	Yes	Yes	Yes
Year FE's	Yes	Yes	Yes	Yes	Yes
Industry FE's	Yes	Yes	Yes	Yes	Yes
Precipitation	No	Yes	Yes	Yes	Yes
County X Industry FE's	No	No	Yes	Yes	Yes
Industry X Year FE's	No	No	No	Yes	Yes
Regional trends	No	No	No	No	Yes

Notes: Heteroskedasticity robust standard errors clustered by state and quarter-year are in parentheses (* $p<.10$ ** $p<.05$ *** $p<.01$). Coefficients in each column come from a regression of 100 times log total employment in a given county-industry-quarter on the variables shown.The sample is restricted to county-industries for which quarterly employment information is available for the entire time period (2000-2017). Temperature denotes daily maximum temperature. Precipitation includes average daily rainfall in inches as well as controls for snow (omitted). All regressions include controls for days in 30's, 40's, and 50's with days in the 60's and 70's as the omitted category. Column 2 adds controls for county-year average precipitation and snowfall. Column 3 adds county-industry fixed effects. Column 4 adds industry-year fixed effects. Column 5 adds linear time trends by census region.

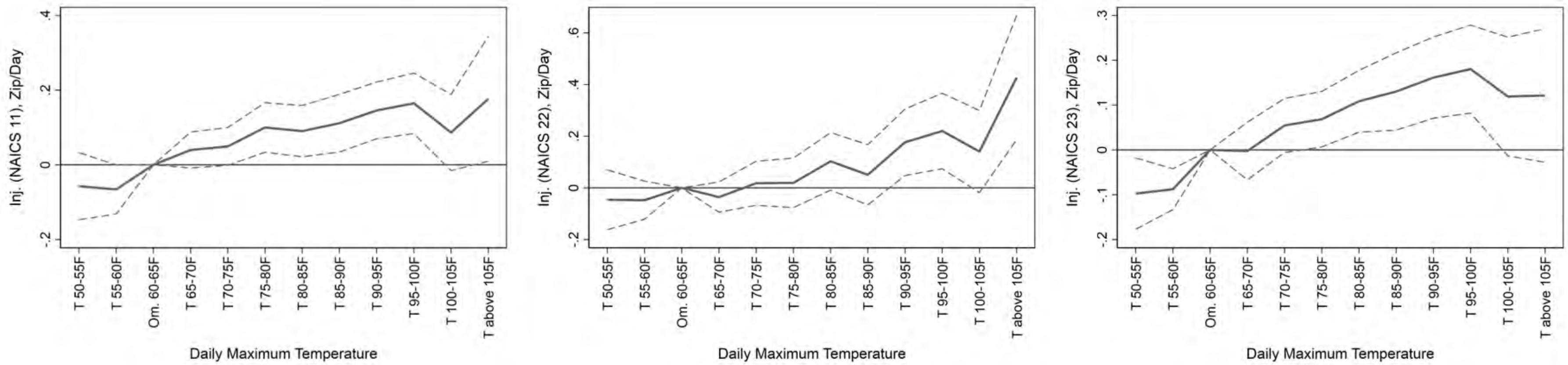
Table 5: Impact of Heat on Hours worked

	All Workers			HE Workers		
T above 105F	-0.0027	-0.0028	-0.0004	-0.0051	-0.0070	-0.0037
	(0.0028)	(0.0027)	(0.0035)	(0.0042)	(0.0048)	(0.0050)
T 100-105F	-0.0019	-0.0019	-0.0005	0.0005	-0.0005	-0.0011
	(0.0020)	(0.0020)	(0.0023)	(0.0027)	(0.0025)	(0.0038)
T 95-100F	0.0000	0.0003	0.0004	0.0010	0.0002	-0.0002
	(0.0015)	(0.0014)	(0.0019)	(0.0020)	(0.0020)	(0.0026)
T 90-95F	-0.0004	-0.0004	0.0004	0.0012	0.0001	0.0002
	(0.0012)	(0.0012)	(0.0015)	(0.0016)	(0.0016)	(0.0020)
T 85-90F	-0.0002	-0.0000	0.0006	0.0016	0.0010	0.0016
	(0.0011)	(0.0011)	(0.0013)	(0.0014)	(0.0014)	(0.0018)
T 80-85F	0.0003	0.0004	0.0002	0.0012	0.0007	0.0002
	(0.0011)	(0.0011)	(0.0013)	(0.0014)	(0.0015)	(0.0018)
T 75-80F	0.0006	0.0005	0.0006	0.0013	0.0010	0.0005
	(0.0010)	(0.0010)	(0.0012)	(0.0012)	(0.0013)	(0.0017)
N	793,613	793,613	793,597	398,510	398,510	398,440
MSA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes		Yes	Yes	
MSA $\times$ Month FEs			Yes			Yes
Year FEs	Yes			Yes		
MSA $\times$ Year FEs		Yes	Yes		Yes	Yes

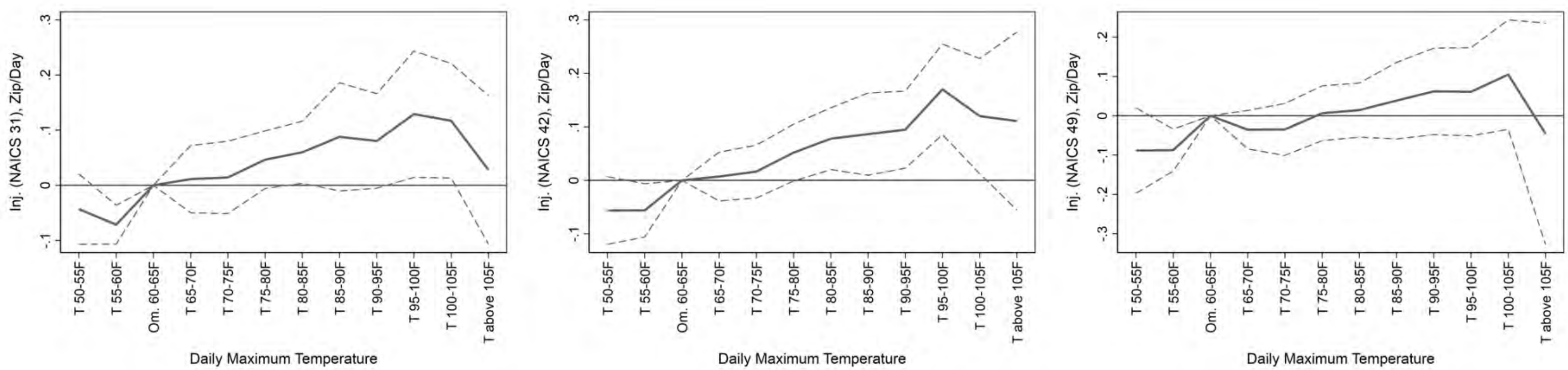
Notes: High exposure workers are those with time outside above the median. All regressions weighted by CPS provided link weights.

Figure 6: Indoor vs Outdoor Workplaces (By Industry)

Panel A: Outdoor Industries



Panel B: Indoor Industries



Notes: Figure 6 In all of the above, the dependent variable is the inverse hyperbolic sine transformed count of injuries per zip code and day. Daily maximum temperatures are assigned to a vector of 15 temperature bins ranging from 40°F and below to temperatures greater than 105°F. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. *Panel A* plots coefficients obtained from regressions of the inverse hyperbolic sine of injuries in outdoor industries: notably, agriculture (NAICS==11), construction (23) and utilities (22). *Panel B* plots the coefficients from the same regressions for claims occurring in industries where work is done predominantly indoors: namely, manufacturing (31-33), wholesale trade (42), and transportation and warehousing (48-49). Heteroskedasticity robust standard errors are clustered two-way by county and year-month, and 95 percent confidence intervals are denoted by dashed lines.

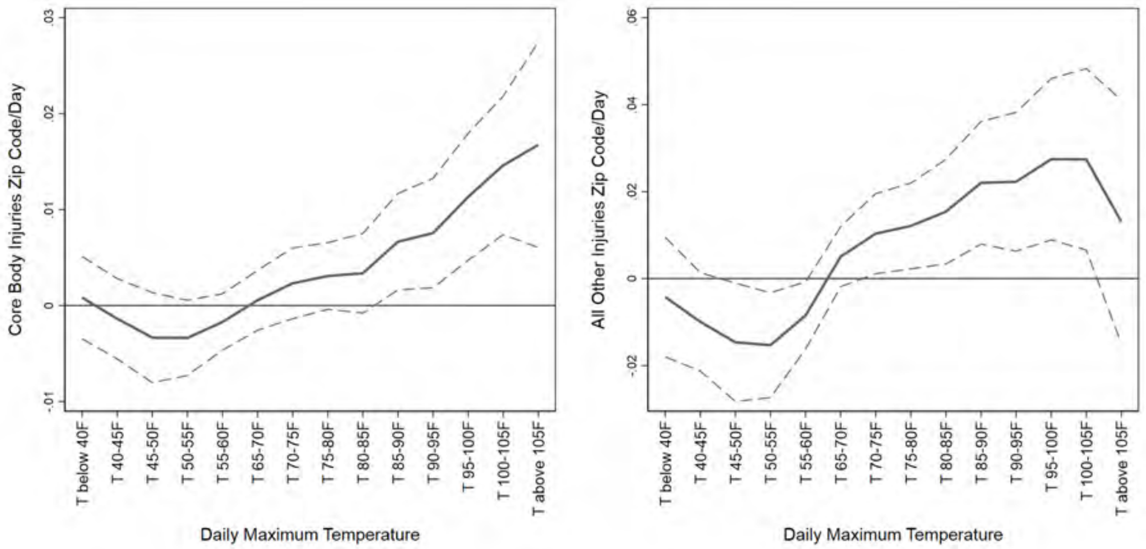
Table 6: Heat-Illness and All Other Injuries

	(1) Extreme Temp	(2) All Other	(3) Core Body	(4) All Other
T above 105F	0.00654***	0.0212	0.0168**	0.0130
	(0.000968)	(0.0159)	(0.00535)	(0.0140)
T 100-105F	0.00385***	0.0327**	0.0146***	0.0274*
	(0.000334)	(0.0116)	(0.00360)	(0.0104)
T 95-100F	0.00192***	0.0318**	0.0113**	0.0275**
	(0.000152)	(0.0105)	(0.00331)	(0.00927)
T 90-95F	0.00117***	0.0252**	0.00756*	0.0223**
	(0.000129)	(0.00894)	(0.00285)	(0.00797)
T 85-90F	0.000595***	0.0241**	0.00666*	0.0220**
	(0.0000978)	(0.00799)	(0.00251)	(0.00704)
T 80-85F	0.000272**	0.0167*	0.00337	0.0154*
	(0.0000902)	(0.00677)	(0.00207)	(0.00601)
N	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00
Injuries Zip/Day (60-65F)	0.00	0.67	0.17	0.57
Injuries Zip/Year (60-65F)	0.36	245.25	63.19	209.48
Injuries Sample/Year	743.91	370,612.45	93,384.10	316,935.24
Injuries Sample/01-18	13,391.21	6,671,056.50	1,680,923.75	5,704,872.00
Zipcode × Month FE	Yes	Yes	Yes	Yes
County × Month × Year FE	Yes	Yes	Yes	No
Precipitation	Yes	Yes	Yes	Yes

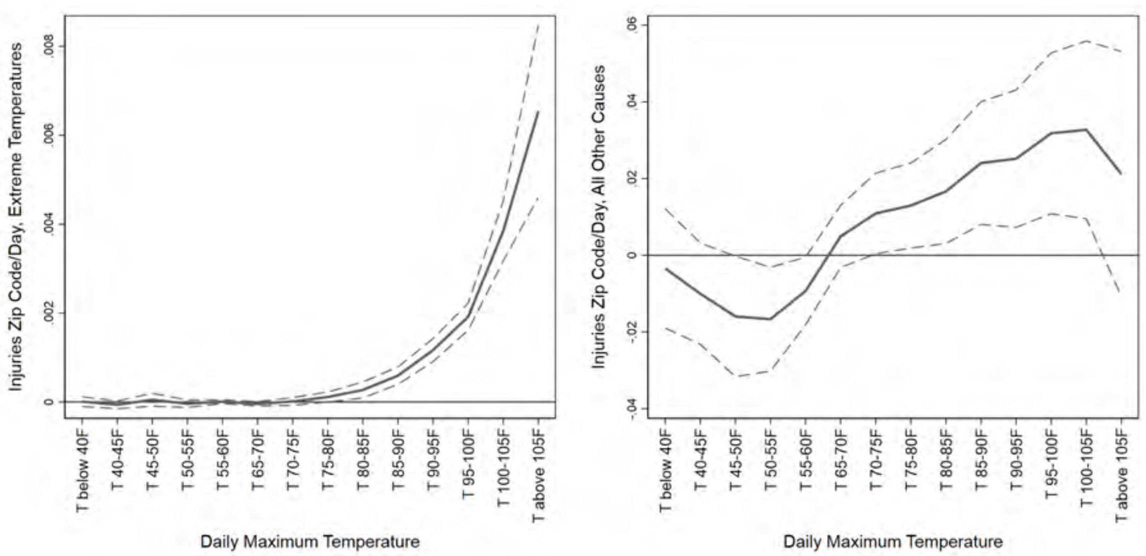
Notes: Table 6 shows the sensitivity of injury claims to temperature for different categories of injuries. All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. They reflect residual variation in injuries after regressing on zip code × month and county × year × month fixed effects, as well as controls for precipitation. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. In columns 1 and 3, the dependent variables are the count of IHS transformed injury claims officially categorized as being caused by extreme temperature and involving core body organs respectively. In columns 2 and 4, injuries are limited to all other injuries – by official cause (2) and body part affected (4). Heteroskedasticity robust standard errors clustered by county and year-month are noted in parentheses (* p<.10 **p<.05 ***p<.01).

Figure 7: Heat Illness and All Other Injuries

Panel A: Official Classification

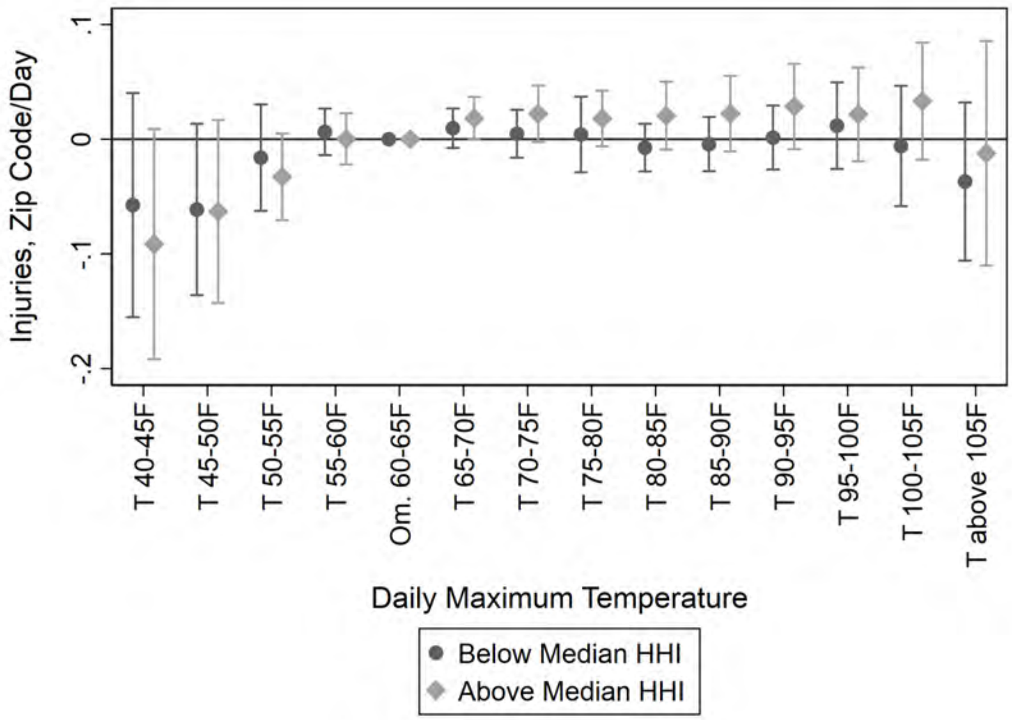


Panel B: Affected Body Parts



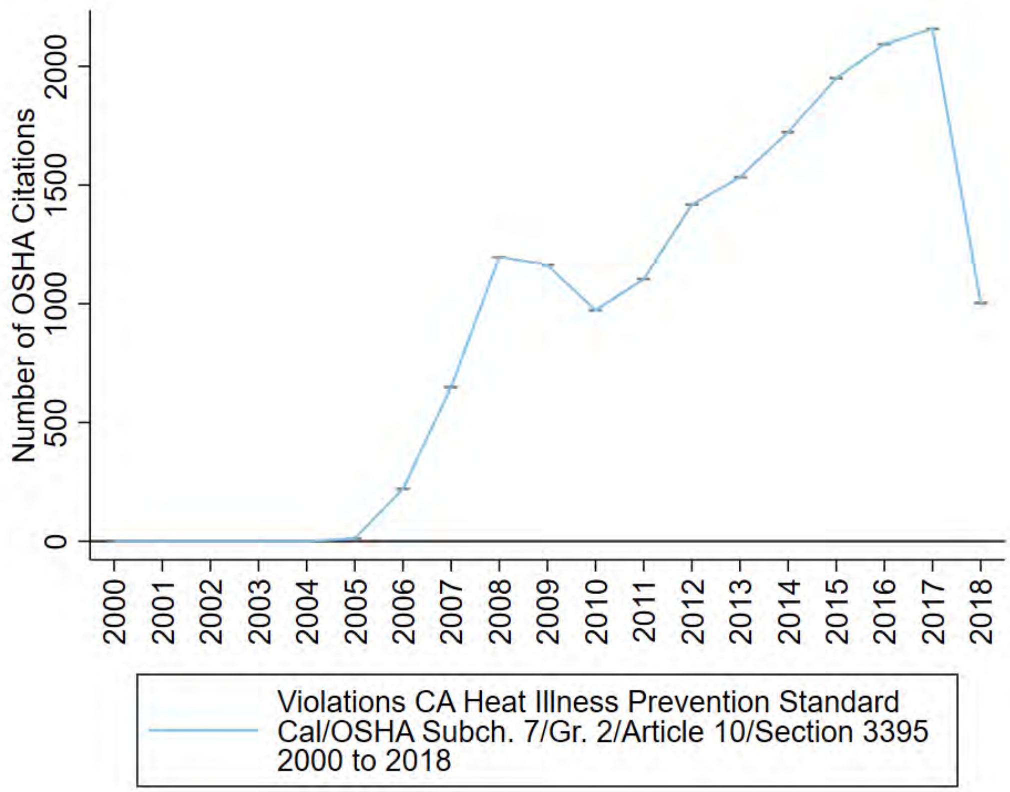
Notes: Figure 7 depicts the full set of temperature coefficients from the regressions presented in table 6. *Panel A* plots coefficients obtained from regressions of the counts of heat-related injuries according to the DWC injury classification as the dependent variable *(left)* and the counts of all other injuries as the dependent variable in column 2 *(right)*. All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. They reflect residual variation in injuries after regressing on zip code × month and county × year × month fixed effects, as well as controls for precipitation. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered two-way by county and year-month, and the 95 percent confidence intervals are marked by the dashed lines.

Figure 8: Labor Market Concentration and Temperature-Injury Relationship



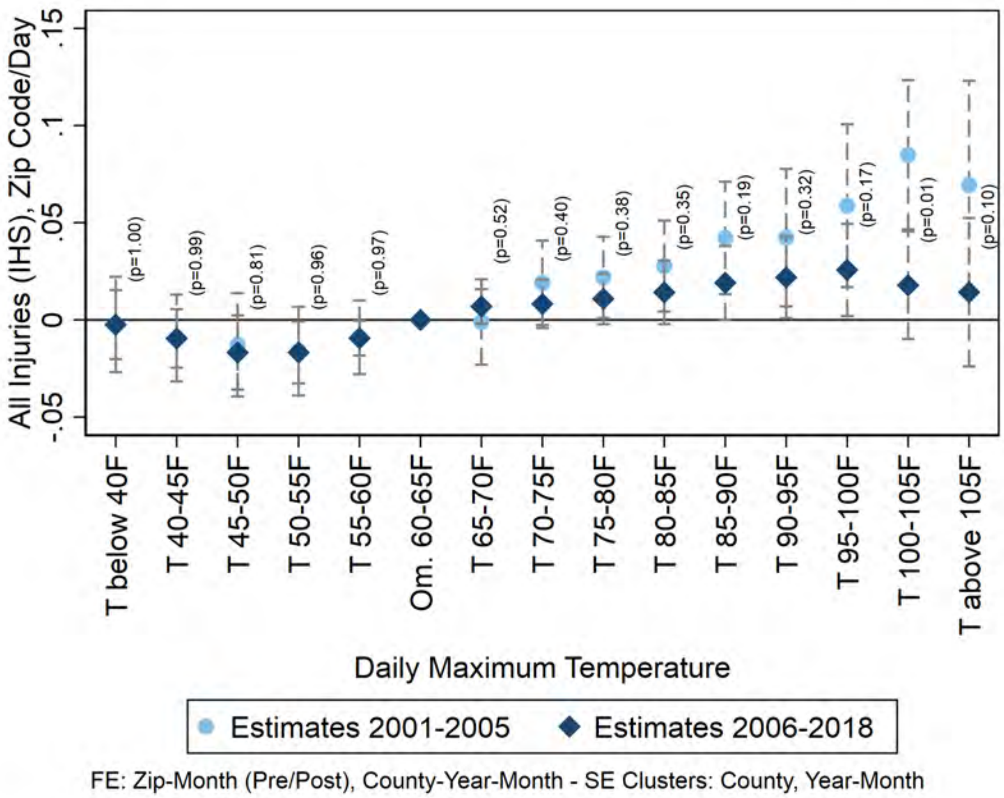
Notes: Figure 8 plots the temperature-injury relationship by local labor market concentration, using information on occupation-CZ-level Herfindahl-Hirschman Indices (HHI) from Azar et al. (2020), depicting coefficients from separate regressions for below and above median values of the national HHI distribution (in 2016). The light grey bars indicate injuries in occupation-CZs with above-median HHI's (measured in 2016); the dark grey bars indicate below median. The dependent variable in both cases is the inverse hyperbolic sine transformed count of injuries per zip code and day, across all California-based work sites over the period 2001-2018. Daily maximum temperatures are assigned to a vector of 15 temperature bins ranging from 40°F and below to temperatures greater than 105°F. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered two-way by county and year-month, and 95 percent confidence intervals are denoted by whiskers.

Figure 9: Cal OSHA Citations for Heat Standard Over Time



Notes: Figure 9 plots Cal-OSHA citations for violations of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395) for all California-based establishments by year.

Figure 10: Temperatures and Injuries Before and After the Introduction of the Heat Illness Prevention Standard



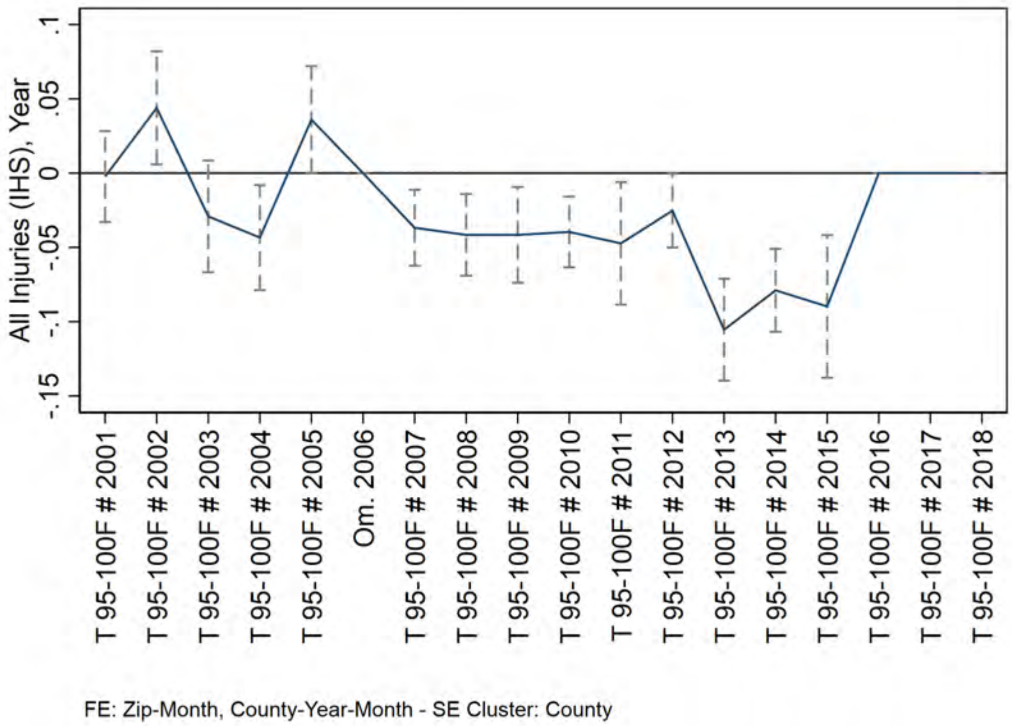
Notes: Figure 10 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls before and after the introduction of the policy. Both regressions include zip code × month, and county × year × month fixed effects, allowing zip code × month fixed effects to vary before and after the policy. Estimates for the period after (before) the introduction of the standard are plotted in dark blue (light blue). Heteroskedasticity robust standard errors are clustered by county and year-month, and 95 percent confidence intervals are plotted as dashed lines. The p-values of tests of statistical significance of the difference in the sensitivity of injuries to temperatures before and after the policy are shown in parentheses.

Table 7: Temperatures and Injuries Before and After the Introduction of the Heat Illness Prevention Standard – Table

	below 40	40-45F	45-50F	50-55F	55-60F	65-70F	70-75F	75-80F	80-85F	85-90F	90-95F	95-100F	100-105F	above 105F
Pre														
b	-.0023	-.0093	-.0128	-.016	-.0090	-.0011	.0190	.0218	.0277	.0421	.0423	.0587	.0849	.0693
p	.8462	.4063	.3376	.1636	.3451	.9210	.0841	.0417	.0211	.0050	.0199	.0068	.0001	.0121
	below 40	40-45F	45-50F	50-55F	55-60F	65-70F	70-75F	75-80F	80-85F	85-90F	90-95F	95-100F	100-105F	above 105F
Post														
b	-.0025	-.0095	-.0168	-.0167	-.0094	.0069	.0081	.0108	.0141	.0191	.0218	.0256	.0178	.0142
p	.7812	.2101	.0833	.0393	.0389	.1270	.1896	.1031	.0889	.0487	.0406	.0344	.2028	.4581
p Dif	(p=1.00)	(p=0.99)	(p=0.81)	(p=0.96)	(p=0.97)	(p=0.52)	(p=0.40)	(p=0.38)	(p=0.35)	(p=0.19)	(p=0.32)	(p=0.17)	(p=0.01)	(p=0.10)

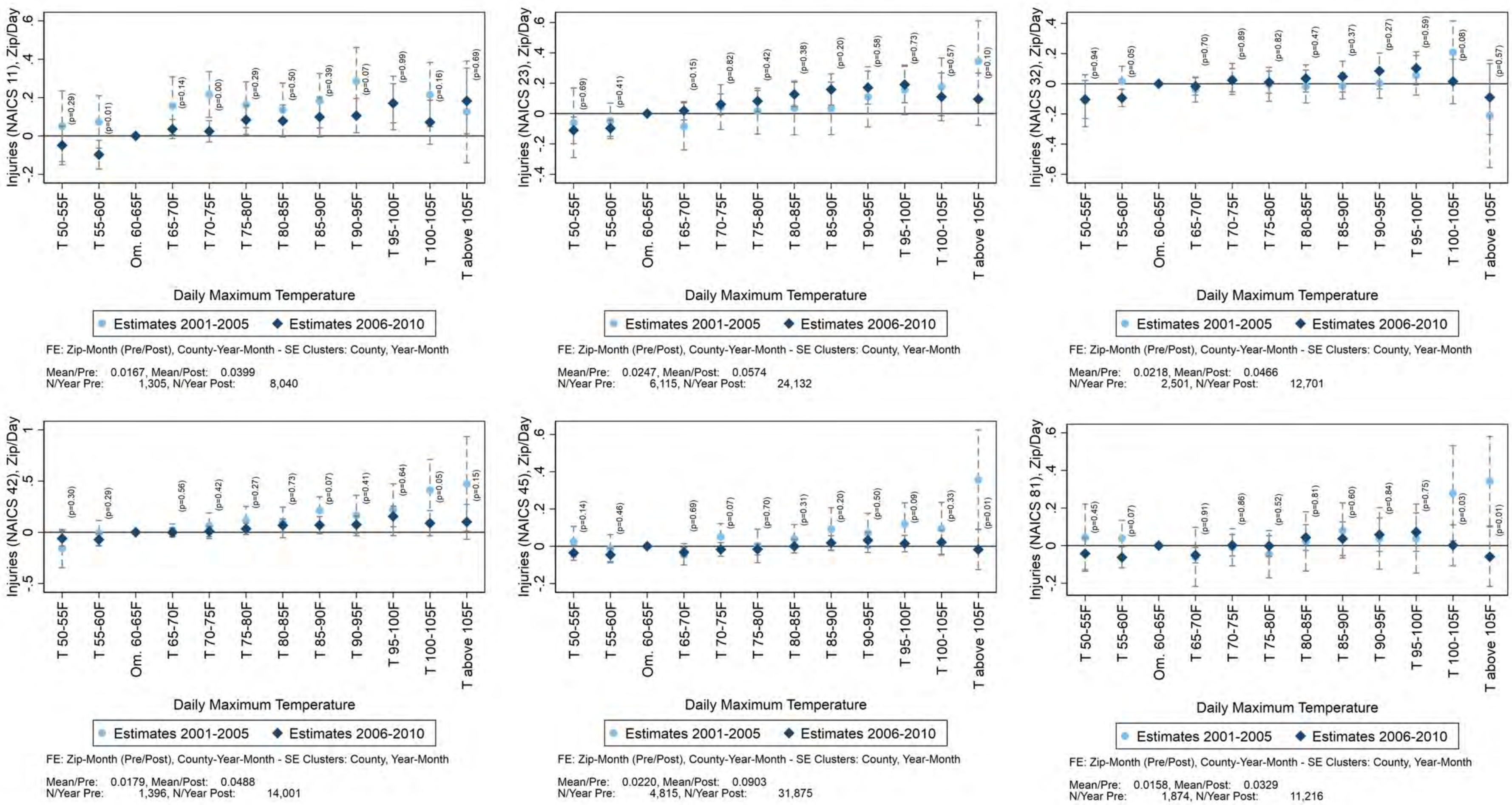
Notes: Table 7 provides point estimates and standard errors from estimating the effect of temperature on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). Coefficients *(b)* and p-values *(p)* are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls before and after the introduction of the policy. Both regressions include zip code $\times$ month, and county $\times$ year $\times$ month fixed effects, while we allow zip code $\times$ month fixed effects to vary by zip-code before and after the policy. Estimates for the period after (before) introduction of the policy are labelled *Post (Pre)*. Heteroskedasticity robust standard errors are clustered by county code and year-month, with 95 percent confidence intervals plotted as dashed lines. Heteroskedasticity robust standard errors are clustered by county and year-month. The p-values of tests of statistical significance of the difference in the sensitivity of injuries to temperatures before and after the policy are shown in parentheses.

Figure 11: Change in Heat-Sensitivity of Injury Over Time



Notes: Figure 11 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls for each year of our sample, showing the coefficients for days with highs between 95°F and 100°F. All regressions include zip code × month, and county × year × month fixed effects, while we allow zip code × month fixed effects to vary by year. Heteroskedasticity robust standard errors are clustered by county and year-month, the 95 pecent confidence intervals are plotted as dashed lines.

Figure 12: Effect of Policy on Temperature-Injury Relationship (Affected Industries)



Notes: Figure 12 In all of the above, the dependent variable is the inverse hyperbolic sine transformed count of injuries per zip code and day. Daily maximum temperatures are assigned to a vector of 15 temperature bins ranging from 40°F and below to temperatures greater than 105°F. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Each panel plots coefficients obtained from regressions of the inverse hyperbolic sine of injuries on the temperature bins shown for periods before (2001-2005, light blue) and after (2006-2010, dark blue) the policy, showing industries where at least one temperature bin appears to show a significant difference in injuries. These include: agriculture (11), construction (23), a subset of manufacturing (32), a subset of wholesale (42), a subset of retail (45), and other services (81). Heteroskedasticity robust standard errors are clustered by county and year-month, and 95 percent confidence intervals are denoted by box and whisker plots.

Table 8: Differences in Differences: Log Wage Level (Pre-Recession Only)

	(1) All Affected	(2) Reg.	(3) Unreg.	(4) All Affected	(5) Reg.	(6) Unreg.
CAxPOST	0.031***	0.024***	0.021***	0.031***	0.024***	0.021***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
CAxTREATxPOST	-0.040***	-0.037***	-0.025***	-0.040***	-0.038***	-0.026***
	(0.002)	(0.004)	(0.000)	(0.002)	(0.004)	(0.000)
N	871,629	871,629	871,629	851,961	851,961	851,961
Δ Treated	-0.009	-0.014	-0.004	-0.009	-0.014	-0.004
	0.004	0.005	0.004	0.004	0.006	0.004
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-way interactions	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	No	No	No

Notes: Heteroskedasticity robust standard errors clustered by state and year are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column come from a regression of log total employment in a given county-industry-quarter (NAICS 2-digit) on the variables shown, as well as all two-way interactions between a dummy for California, Treated industry, and Post-2005 (Q3). $\Delta Treated$ reports the sum of the reported coeffiencts, with standard errors calculated using the delta method. The sample is restricted to county-industries for which quarterly employment and wage information are available for the entire time period (2000-2017). Affected industries include agriculture, construction, wholesale, transportation and warehousing, retail, real estate and rental/leasing, professional, scientific and technical services, administrative support and waste management, and other services (except Public Administration), and are selected on the basis of industry-specific analyses of the change in temperature-injury relationships pre- and post-2005. Among these, regulated industries include agriculture, construction, wholesale, transportation and warehousing, and administrative support and waste management. Columns (4)-(6) omit agriculture, based on the observation that QCEW measures agricultural employment relatively poorly, and minimum wages may be more likely to bind.

Table 9: Differences in Differences: Log Employment Level (Pre-Recession Only)

	(1) All Affected	(2) Reg.	(3) Unreg.	(4) All Affected	(5) Reg.	(6) Unreg.
CAxPOST	-0.018**	-0.012*	-0.010	-0.018*	-0.012	-0.009
	(0.008)	(0.006)	(0.008)	(0.009)	(0.006)	(0.008)
CAxTREATxPOST	0.031***	0.028***	0.012	0.036***	0.041***	0.010
	(0.003)	(0.003)	(0.012)	(0.000)	(0.003)	(0.013)
N	871,629	871,629	871,629	851,961	851,961	851,961
Δ Treated	0.012	0.017	0.001	0.018	0.029	0.001
	0.007	0.008	0.010	0.009	0.009	0.010
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-way interactions	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	No	No	No

Notes: Heteroskedasticity robust standard errors clustered by state and year are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column come from a regression of log total employment in a given county-industry-quarter (NAICS 2-digit) on the variables shown, as well as all two-way interactions between a dummy for California, Treated industry, and Post-2005 (Q3). $\Delta Treated$ reports the sum of the reported coeffiencts, with standard errors calculated using the delta method. The sample is restricted to county-industries for which quarterly employment and wage information are available for the entire time period (2000-2017). Affected industries include agriculture, construction, wholesale, transportation and warehousing, retail, real estate and rental/leasing, professional, scientific and technical services, administrative support and waste management, and other services (except Public Administration), and are selected on the basis of industry-specific analyses of the change in temperature-injury relationships pre- and post-2005. Among these, regulated industries include agriculture, construction, wholesale, transportation and warehousing, and administrative support and waste management. Columns (4)-(6) omit agriculture, based on the observation that QCEW measures agricultural employment relatively poorly, and minimum wages may be more likely to bind.

Table 10: Triple Difference CPS Hours

	(1) All Affected	(2) Regulated	(3) Unregulated
CAxPOST	-0.0143	-0.0143*	-0.0152*
	(0.0097)	(0.0086)	(0.0082)
CAxTREATxPOST	-0.0039	-0.0069	-0.0028
	(0.0144)	(0.0154)	(0.0124)
MSA FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes
Quarter x Year FE	Yes	Yes	Yes
Two-way interactions	Yes	Yes	Yes

Notes: Heteroskedasticity robust standard errors clustered by MSA are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column come from a regression of log hours worked in the last week in a MSA-industry-quarter (NAICS 2-digit) on the variables shown, as well as all two-way interactions between a dummy for California, Treated industry, and Post-2005 (Q3). Affected industries include agriculture, construction, wholesale, transportation and warehousing, retail, real estate and rental/leasing, professional, scientific and technical services, administrative support and waste management, and other services (except Public Administration), and are selected on the basis of industry-specific analyses of the change in temperature-injury relationships pre- and post-2005. Among these, regulated industries include agriculture, construction, wholesale, transportation and warehousing, and administrative support and waste management.

A Appendix A: Theory and Data Notes

Model of Equalizing Differences in Workplace Safety

Here, we build upon the seminal equalizing differences model of Rosen (1974) to examine the particular case of temperature changes to reflect the fact that extreme temperature may influence the level of optimal safety investment mutually agreed to by workers and employers. As a benchmark, we will consider the consequences of temperature shocks in settings where extreme temperature raises the overall costs – pecuniary or non-pecuniary – of providing a given level of safety.

Setup

We model decisions by N identical firms producing output Q under perfect competition.[35] L represents labor inputs, and production functions exhibit the usual diminishing returns: $Q = f(L)$, $f_L > 0, f_{LL} < 0$.

Let $R(T, S)$ represent injury risk, where the level of risk depends on both ambient temperature T and firm safety investments S. We assume that $\frac{\partial R}{\partial S} \leq 0$, and $\frac{\partial R}{\partial T} \geq 0$, and that the second derivatives in both cases are non-negative; that is, risk is increasing in temperature, possibly non-linearly, and the effectiveness of safety investments is diminishing in the level of investment.[36]

Workplace injury risk is a disamenity for workers, but firms must incur a cost to reduce it. Unlike in the stylized model above, we model compensating differentials and other costs of providing safety separately. Let c denote firms' direct per unit cost of providing an additional increment of workplace safety, and $w(R(T, S))$ the wage that firms must pay, conditional on a given level of realized workplace risk. The wage rate is a function of R since, in equilibrium, it will depend on the level of compensating differential offered. Note that we are assuming workers have full information regarding the safety risks associated with working in a given firm or occupation. In practice, there may be information problems which drive a wedge between perceived and actual injury risk.

Workers face a trade off between additional consumption from wage income and added workplace safety: $U = U(C, R)$, where $U_C > 0, U_{CC} < 0$, $\frac{\partial U}{\partial R} < 0, \frac{\partial^2 U}{\partial R^2 < 0}$. For simplicity, we assume that each of M identical workers provides a unit measure of labor and set unearned income to zero, so that $C = w(R)$.[37] Note that if workers derive direct utility from more pleasant temperature conditions (and find extreme temperature to be unpleasant, aside from any injury risk), this can be folded into the parameter R.

Comparative Statics

Firms choose optimal labor and safety inputs to maximize profits $\Pi = pf(L) - w(R(T, S))L - c_s S$. Workers choose a wage-safety bundle to maximize utility $U = U(w(R), R)$. For ease of exposition, we focus on short-run avoidance behaviors and defensive investments, but the same logic applies to long-run investments, including decisions regarding the production technology or the location of production and employment. Specifically, we will consider the impact of short-run (e.g. day-to-day) fluctuations in temperature on firms' short-run production

[35] As is standard, we will assume that capital investments are fixed in the short run, and firms are price takers in product and labor markets.

[36] For simplicity, we will set aside the possibility that temperature directly affects labor productivity, separate from its effects on injury risk. Allowing for additional impacts on productivity does not affect the main predictions.

[37] Note that in doing so we abstract from extensive and intensive margin labor supply decisions.

decisions, assuming that workers have the option to switch firms if they aren't being paid the market-clearing compensating differential.[38]

The first order conditions $\frac{d\Pi}{dL} = 0$, $\frac{d\Pi}{dS} = 0$, and $\frac{dU}{dR} = 0$ jointly determine equilibrium L^*, S^* and $w^*(R^*)$ given parameters, and can be re-arranged to obtain the following equations:

$$c_s = -w_R R_S L \psi \tag{10}$$

$$p f_L(L) = w(R(T, S)) \tag{11}$$

$$w_R = -\frac{\frac{\partial U}{\partial R}}{U_C} \tag{12}$$

Together, these conditions define firms' optimal labor inputs and level of safety investment given workers' preferences, product and input prices, and production parameters. Equation 10 shows that firms invest in safety to the point where the marginal cost equals the marginal benefit, the latter being in terms of reduced compensating differentials required to induce workers to take on such work.[39] Equation 11 shows that perfectly competitive firms will pay workers their marginal revenue product.Equation 12 shows that workers demand a bundle of wages and risk such that the slope of the compensating differential (the relative price of safety) equals the ratio of marginal utility of consumption and the marginal utility of safety.

In equilibrium, utility-maximizing workers and profit-maximizing firms will agree to a bundle of wages and safety investments specific to a given labor market (e.g. the market for landscapers with no previous experience).[40] Intuitively, we would expect that as the cost of safety goes up, firms re-optimize their input mix (L^*, S^*), and that workers respond to new wage-safety offers by choosing a new bundle of consumption and safety $(w^*(R^*), 1 - R^*)$, provided that wages and employment are sufficiently flexible, if only in expectation.

Appealing to the implicit function theorem to define all choice variables as implicit functions of T, we can totally differentiate the first order conditions with respect to T. With a bit of algebra, we arrive at the following equation representing the expected change in labor inputs as a function of T:

$$\frac{dL^*}{dT\psi} = \frac{C_S R_{ST}}{W_R R_S^2} \tag{13}$$

Since C_S, W_R and R_S^2 are positive, the sign of $\frac{dL^*}{dT}$ depends on the sign of R_{ST}, which represents the change in the risk-reducing effect of safety investment with respect to increased temperature. If a given safety investment is more effective at more extreme temperatures (R_S is more negative), this term would be negative, implying that firm labor demand L^* decreases with extreme temperature. On the other hand, if a given safety investment is less effective at more extreme temperatures, then we would expect firms' labor demand to increase with extreme temperature. At least for safety investments that are designed to reduce temperature-related risks in particular, it seems likely that the former holds, implying $\frac{dL^*}{dT} < 0$.

[38]We will assume that, in equilibrium, firms have invested in the fixed investments necessary to allow for a market-clearing (w^*, R^*) bundle for a given average climate $\bar{T}$, such that any changes with respect to short-run weather shocks T are net of such longer-term adaptations to a given climate as in Deschênes and Greenstone (2011); Carleton et al. (2018).

[39]Note that, since we are assuming firms to be price-takers in both product and labor markets, the wage offer curve (W_R) is considered to be exogenous to any individual firm's decision.

[40]Note that this is the outcome of a labor market equilibrium where idential workers and firms agree to one optimal wage-risk bundle that is standard across the specific labor market of interest (w^*, R^*). One could of course generalize to allow for heterogeneous workers and firms as in Rosen (1974), which would lead to a schedule of $(w^*_{i,j}, R^*_{i,j})$ for worker i and firm j (i.e. a wage-offer *curve*). But given the focus of the model, we assume identical workers and firms for the time being.

Similarly, we can express the change in equilibrium injury risk as a function of T as follows:

$$\frac{dR^*}{dT\psi} = \frac{pf_{LL}\frac{dL^*}{dT}}{W_R} \tag{14}$$

Since $p\psi$and W_R are positive and f_{LL} is negative, the above equation implies that the sign of $\frac{dR^*}{dT}$ depends on the sign of $\frac{dL^*}{dT}$. If $\frac{dL^*}{dT}$ is negative, then $\frac{dR^*}{dT}$ is positive, implying that realized injury risk will increase in response to hotter temperature. On the other hand, in states of the world where $\frac{dL^*}{dT}$ is positive, we might expect the net change in injury risk per worker to be negative. This reflects the fact that, if parameters are such that firms' optimal labor input response to hotter temperature is positive, it must also be the case that, per unit of labor input, injury risk is lower.

Finally, $\frac{dS^*}{dT}$ can be expressed as:

$$\frac{dS^*}{dT\psi} = \frac{\frac{pf_{LL}\frac{dL^*}{dT}}{W_R} - \frac{\partial R}{\partial T}}{\frac{\partial R}{\partial S}} \tag{15}$$

Note that the sign of $\frac{dS^*}{dT}$ depends on the sign of $\frac{dL^*}{dT}$: namely, optimal safety investment decreases in response to temperature shocks if the optimal labor input response is positive, and vice versa. This suggests that, if cost, utility, and productivity parameters are such that the firm's optimal response to increased temperature is to increase labor inputs, it must be the case that they do so while reducing overall safety investment per worker. The intuition here is that perfectly competitive firms cannot respond to adverse cost shocks by increasing all inputs. At the same time, this expression also suggests that firms may, over some parameter space, simultaneously reduce labor inputs *and* reduce safety inputs.

These expressions illustrate the central intuition that perfectly competitive firms respond to adverse cost shocks through some combination of reducing safety investment ($\frac{dS^*}{dT} >\psi 0$) and/or reducing labor demand ($\frac{dL^*}{dT} <\psi 0$), at least when a set of reasonable conditions are met.

Imperfect Information

Some have suggested that information problems may prevent workers from being fully aware of the risks associated with temperature extremes (Viscusi and Moore, 1991). This would mean that workers would in general require less compensating differentials to take on more safety risk, since there would a wedge between real and perceived risks on the job. We can model this as a reduction in the $\frac{dw^*}{dT}$ and w^* terms. This means that, *ceteris paribus*, firms are more likely to reduce safety investment in response to extreme temperature, since lower overall labor costs and lower compensating differentials make it less likely that firms respond by reducing labor demand.

Alternative Explanations

Endogenous Incident Reporting

It is also possible that, for any given level of underlying injury risk, the realized level of reporting may be endogenous to temperature. Ex ante, it is unclear in which direction the resulting bias would go. For instance, it may be more likely that workers report injuries on very hot days, especially if they believe that they have the backing of legal mandates. This bias may vary with the level of salience of any given temperature event. Suppose firms engage in some trade off between reputation risk associated with higher workplace accident rates (from reporting an injury) and the risk of being fined by OSHA (from failing to report an injury that has occurred).[41] In this case, the relative effect of temperatures at the higher end of the distribution may be biased upwards due to this reporting effect, but the absolute magnitude of all temperature coefficients would under-represent the true increase in injury risk.

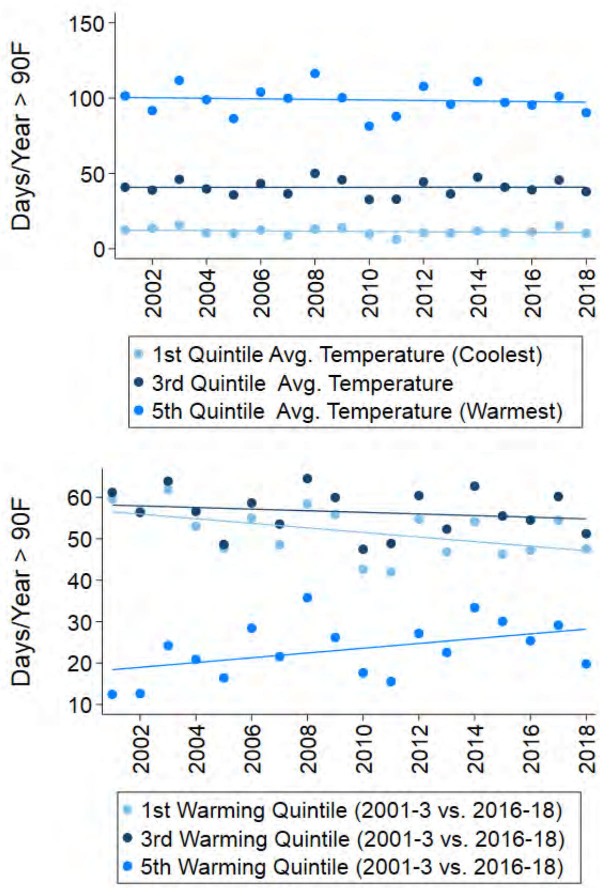
Alternatively, workers and employers may be less likely to report on hot days if they are more fatigued or less likely to be interacting with each other to begin with. There is some evidence that the functioning of institutions can be sensitive to temperature (e.g. police arrests, judge decisions, as in Obradovich et al. (2018)), and that the effort levels of surveyors is also temperature-dependent (LoPalo, 2019). In this case, our estimates would likely understate the increase in risk associated with extreme temperature.

It is likely difficult to control for these possibilities directly in this setting. We nevertheless attempt to further explore robustness to potential endogenous reporting by leveraging information on reported cause of injury below.

[41] It seems plausible that the latter risk is elevated in the vicinity of an extreme heat event (e.g. 100°F) relative to a less uncommon heat event (e.g. 85°F), since risks associated with extreme heat events are often publicized by the media and local public health officials, and since OSHA agencies often engage in targeted inspections.

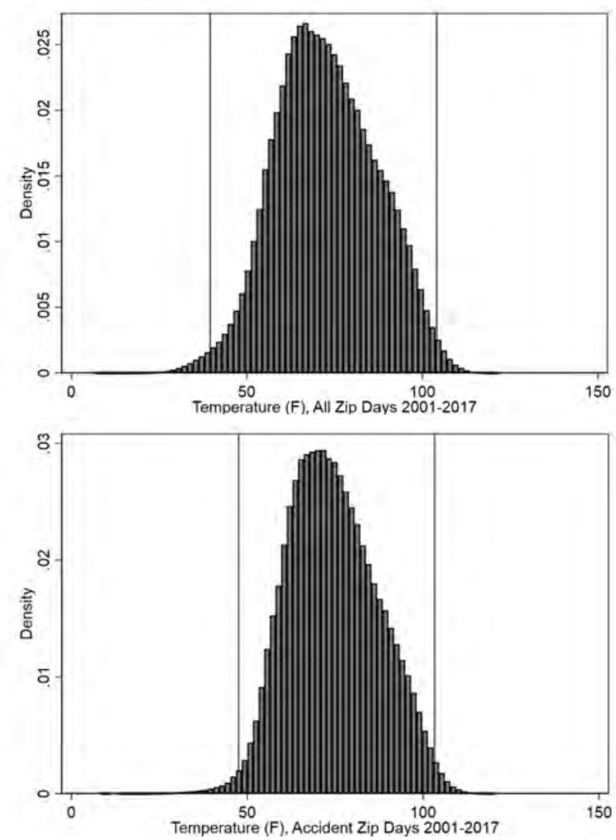
B Additional Tables, Figures, and Robustness Tests

Figure B1: Injuries and Temperatures Over Time



Notes: Figure B1 shows the number of days with temperatures over 90°F over time. The upper panel shows trends in the first, third, and fifth quintiles of the average temperature distribution within California. The lower panel shows similar trends over time, but grouping locations by quintile of the average realized warming distribution (2001-2003 to 2016-2018).

Figure B2: Distribution of Temperatures in California



Notes: Figure B2 shows the distribution of daily maximum temperatures for all zip code days from 2001 to 2018 in California (upper panel) as well as on days on which injuries occur (lower panel). The vertical lines mark the 1st and 99th percentiles of the temperature distributions respectively.

Table B1: Distribution of Injuries

Notes: Table B1 provides information on the number of injury claims in California by body part (panel A) and injury description (panel B) over the period 2000 to 2018.

Panel A: Details on the Injury – Affected Body Part

	N	Percent	Sum
No Information	4,911,029	44%	44%
Low Back Area	1,315,420	12%	56%
Multiple Body Parts	1,176,573	11%	66%
Finger	950,806	9%	75%
Hand	661,532	6%	81%
Shoulder	579,700	5%	86%
Eye	409,725	4%	90%
Upper Back Area	189,197	2%	91%
Abdomen incl. Groin	168,629	2%	93%
Upper Arm	147,520	1%	94%
Chest	143,982	1%	96%
Wrist	105,305	1%	97%
Lumbar and/or Sacral Vertebrae	77,809	1%	97%
Toe	70,158	1%	98%
Internal Organs	54,557	0%	98%
Disc	53,723	0%	99%
Ear	45,802	0%	99%
Facial Bones	43,938	0%	100%
Mouth	30,554	0%	100%
Spinal Cord	10,953	0%	100%
Total	11,146,912	100%	100%

Panel B: Description of the Injury

	N	Percent	Sum
Strain or Tear	3,377,724	30%	30%
Contusion	1,235,237	11%	41%
Laceration	1,187,723	11%	52%
Sprain or Tear	1,077,774	10%	62%
All Other Specific Injuries, NOC	950,443	9%	70%
All Other Cumulative Injuries	547,983	5%	75%
Puncture	364,373	3%	78%
Multiple Physical Injuries Only	314,734	3%	81%
Inflammation	304,112	3%	84%
Fracture	285,617	3%	87%
Foreign Body	260,527	2%	89%
Burn	169,258	2%	90%
Mental Stress	160,116	1%	92%
Crushing	97,190	1%	93%
Carpal Tunnel Syndrome	89,245	1%	93%

No Physical Injury	80,005	1%	94%
Dermatitis	72,469	1%	95%
Hernia	63,792	1%	95%
Dislocation	51,056	0%	96%
Multiple Injuries Including Both Physical and Psychological	45,856	0%	96%
All Other Occupational Disease Injury, NOC	43,507	0%	97%
Infection	43,432	0%	97%
Contagious Diseases	39,239	0%	97%
Respiratory Disorders (Gases, Fumes, Chemicals, etc.)	37,012	0%	98%
Concussion	31,791	0%	98%
Myocardial Infarction (Heart Attack)	23,751	0%	98%
Mental Disorder	20,555	0%	98%
No Information	19,683	0%	99%
Syncope	18,556	0%	99%
Amputation	14,022	0%	99%
Rupture	13,641	0%	99%
Hearing Loss or Impairment	11,326	0%	99%
Heat Prostration	11,097	0%	99%
Poisoning-Chemical (Other than Metals)	10,290	0%	99%
Electric Shock	9,803	0%	99%
Loss of Hearing	8,499	0%	100%
Poisoning-General (Not OD or Cumulative Injury)	8,484	0%	100%
Cancer	7,342	0%	100%
Vascular	6,133	0%	100%
Asbestosis	6,050	0%	100%
Angina Pectoris	5,075	0%	100%
Severance	5,067	0%	100%
Vision Loss	4,821	0%	100%
Dust Disease, NOC (All other Pneumoconiosis)	3,385	0%	100%
VDT-Related Diseases	2,602	0%	100%
Asphyxiation	1,656	0%	100%
Freezing	1,259	0%	100%
AIDS	1,019	0%	100%
Poisoning-Metal	623	0%	100%
Enucleation	586	0%	100%
Radiation	535	0%	100%
Black Lung	297	0%	100%
Hepatitis C	287	0%	100%
Silicosis	194	0%	100%
Byssinosis	59	0%	100%
Total	11,146,912	100%	100%

Table B4: Temperatures and Injuries – OLS

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
T above 105F	-0.00742	0.0458	0.0458	0.0362	0.0514
	(0.0300)	(0.0325)	(0.0325)	(0.0337)	(0.0342)
T 100-105F	0.0630**	0.0803**	0.0803**	0.0692**	0.0821**
	(0.0222)	(0.0239)	(0.0239)	(0.0251)	(0.0257)
T 95-100F	0.0667**	0.0758***	0.0758***	0.0651**	0.0742**
	(0.0193)	(0.0209)	(0.0209)	(0.0221)	(0.0230)
T 90-95F	0.0469**	0.0569**	0.0568**	0.0488*	0.0561**
	(0.0165)	(0.0186)	(0.0186)	(0.0195)	(0.0198)
T 85-90F	0.0456**	0.0556**	0.0556**	0.0492**	0.0549**
	(0.0155)	(0.0169)	(0.0169)	(0.0176)	(0.0174)
T 80-85F	0.0313*	0.0376**	0.0376**	0.0312*	0.0358*
	(0.0126)	(0.0140)	(0.0140)	(0.0145)	(0.0145)
N	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00
Injuries Zip/Day (60-65F)	1.20	1.20	1.20	1.20	1.20
Injuries Zip/Year (60-65F)	439.69	439.69	439.69	439.69	439.69
Injuries Sample/Year	652,245.57	652,245.57	652,245.57	652,245.57	652,245.57
Injuries Sample/01-18	11,740,558.00	11,740,558.00	11,740,558.00	11,740,558.00	11,740,558.00
Zip Code FE	Yes	No	No	No	No
Month FE	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	No	No
Zipcode × Month FE	No	Yes	Yes	Yes	Yes
Precipitation	No	No	Yes	Yes	Yes
Month × Year FE	No	No	No	Yes	No
County × Month × Year FE	No	No	No	No	Yes

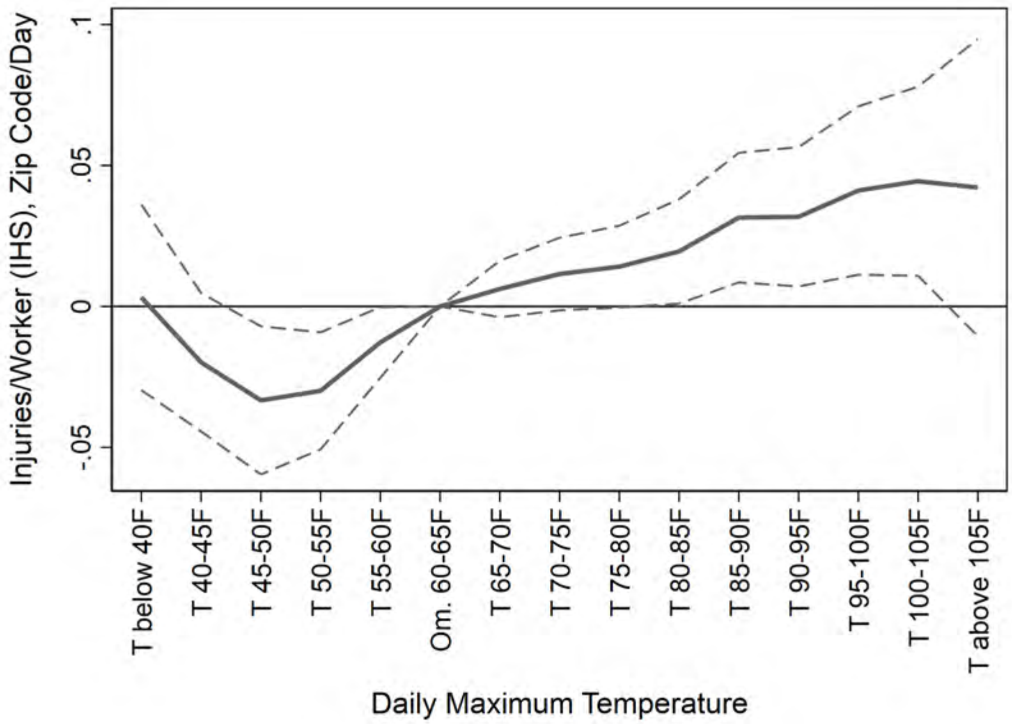
Notes: Table B4 shows the effect of temperature on injury claims for California-based work sites over the period 2001 to 2018. All coefficients are obtained from regressions of injury counts per zip code and day on indicator variables representing each of 15 temperature bins, as well as controls for precipitation and the fixed effects noted above. The results of the main specification corresponding to equation 5 are shown in column 5. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month and presented in parentheses (* p<.10 **p<.05 ***p<.01).

Table B5: Temperatures and Injuries – All Temperature Bins

	(1) IHS	(2) IHS	(3) IHS	(4) IHS	(5) IHS
T above 105F	0.00497	0.0249	0.0249	0.0220	0.0245
	(0.0126)	(0.0150)	(0.0150)	(0.0156)	(0.0161)
T 100-105F	0.0317***	0.0360**	0.0360**	0.0325**	0.0344**
	(0.00911)	(0.0105)	(0.0105)	(0.0111)	(0.0115)
T 95-100F	0.0342***	0.0352***	0.0352***	0.0315**	0.0327**
	(0.00821)	(0.00938)	(0.00938)	(0.00993)	(0.0105)
T 90-95F	0.0259***	0.0277**	0.0277**	0.0250**	0.0257**
	(0.00679)	(0.00815)	(0.00815)	(0.00858)	(0.00894)
T 85-90F	0.0238***	0.0262***	0.0262***	0.0242**	0.0243**
	(0.00667)	(0.00747)	(0.00747)	(0.00778)	(0.00800)
T 80-85F	0.0178**	0.0192**	0.0192**	0.0169*	0.0168*
	(0.00551)	(0.00621)	(0.00621)	(0.00649)	(0.00678)
T 75-80F	0.0139**	0.0144**	0.0144**	0.0129*	0.0130*
	(0.00463)	(0.00503)	(0.00503)	(0.00530)	(0.00554)
T 70-75F	0.0116*	0.0111*	0.0111*	0.0105*	0.0109*
	(0.00468)	(0.00488)	(0.00488)	(0.00511)	(0.00525)
T 65-70F	0.00415	0.00400	0.00400	0.00434	0.00491
	(0.00389)	(0.00395)	(0.00395)	(0.00401)	(0.00404)
T 55-60F	-0.00520	-0.00780	-0.00780	-0.00714	-0.00930*
	(0.00373)	(0.00412)	(0.00412)	(0.00432)	(0.00440)
T 50-55F	-0.00288	-0.0129*	-0.0129*	-0.0135*	-0.0167*
	(0.00656)	(0.00633)	(0.00633)	(0.00660)	(0.00676)
T 45-50F	0.0129	-0.0109	-0.0109	-0.0132	-0.0159*
	(0.00862)	(0.00771)	(0.00771)	(0.00761)	(0.00784)
T 40-45F	0.0294***	-0.00624	-0.00624	-0.00713	-0.0101
	(0.00822)	(0.00631)	(0.00631)	(0.00650)	(0.00660)
T below 40F	0.0595***	0.00151	0.00151	-0.000501	-0.00342
	(0.0113)	(0.00792)	(0.00792)	(0.00823)	(0.00776)
N	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00
Injuries Zip/Day (60-65F)	0.67	0.67	0.67	0.67	0.67
Injuries Zip/Year (60-65F)	245.40	245.40	245.40	245.40	245.40
Injuries Sample/Year	38,113.66	38,113.66	38,113.66	38,113.66	38,113.66
Injuries Sample/01-18	675,410.38	675,410.38	675,410.38	675,410.38	675,410.38
Zip Code FE	Yes	No	No	No	No
Month FE	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	No	No
Zipcode × Month FE	No	Yes	Yes	Yes	Yes
Precipitation	No	No	Yes	Yes	Yes
Month × Year FE	No	No	No	Yes	No
County × Month × Year FE	No	No	No	No	Yes

Notes: Table B5 shows the effect of temperature on injury claims for California-based work sites (2001 to 2018). It differs from Table 2 in that listing the estimated coefficients for all temperature bins. All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day on indicator variables representing each of 15 temperature bins, as well as controls for precipitation and the fixed effects noted above. The results of the main specification corresponding to equation 5 are shown in column 5. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month and presented in parentheses (* p<.10 **p<.05 ***p<.01).

Figure B3: Temperature and Injuries – Injuries per Worker



Notes: Figure B3 plots the coefficients obtained from regressions specified in equation 5, with point estimates shown in Table 2, column 5, but where the dependent variable is the inverse hyperbolic sine transformed injury count per zip code and day divided by the number of workers in that zip code-quarter, where we assign employment by county. All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. They reflect residual variation in injuries after regressing on zip code × month and county × year × month fixed e ects, as well as controls for precipitation. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month, and 95 percent confidence intervals are denoted by dashed lines.

Table B6: Temperatures and Injuries - Alternative Fixed Effect Specifications

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
T above 105F	0.0220	0.0242	0.00196	0.0116	0.0311**	0.00711	0.0174
	(0.0156)	(0.0192)	(0.0130)	(0.0149)	(0.00916)	(0.0100)	(0.00943)
T 100-105F	0.0325**	0.0338*	0.0283**	0.0312**	0.0344***	0.0289***	0.0316***
	(0.0111)	(0.0139)	(0.00942)	(0.0102)	(0.00618)	(0.00745)	(0.00616)
T 95-100F	0.0315**	0.0321*	0.0307***	0.0324**	0.0296***	0.0284***	0.0298***
	(0.00993)	(0.0127)	(0.00858)	(0.00953)	(0.00477)	(0.00572)	(0.00494)
T 90-95F	0.0250**	0.0253*	0.0233**	0.0256**	0.0252***	0.0234***	0.0255***
	(0.00858)	(0.0112)	(0.00706)	(0.00812)	(0.00409)	(0.00437)	(0.00425)
T 85-90F	0.0242**	0.0244*	0.0217**	0.0239**	0.0251***	0.0225***	0.0247***
	(0.00778)	(0.0104)	(0.00686)	(0.00748)	(0.00376)	(0.00399)	(0.00380)
T 80-85F	0.0169*	0.0170*	0.0152**	0.0168*	0.0184***	0.0167***	0.0183***
	(0.00649)	(0.00782)	(0.00565)	(0.00636)	(0.00327)	(0.00340)	(0.00327)
N	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00
Zip Code FE	No	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	Yes	No	Yes	Yes
Zipcode × Month FE	No	No	Yes	Yes	Yes	Yes	No
Month × Year FE	Yes	Yes	Yes	No	No	Yes	No
County Linear Trends	No	No	Yes	No	Yes	No	No
County × Month × Year FE	No	No	No	Yes	No	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the Week FE	No	No	No	No	Yes	Yes	Yes

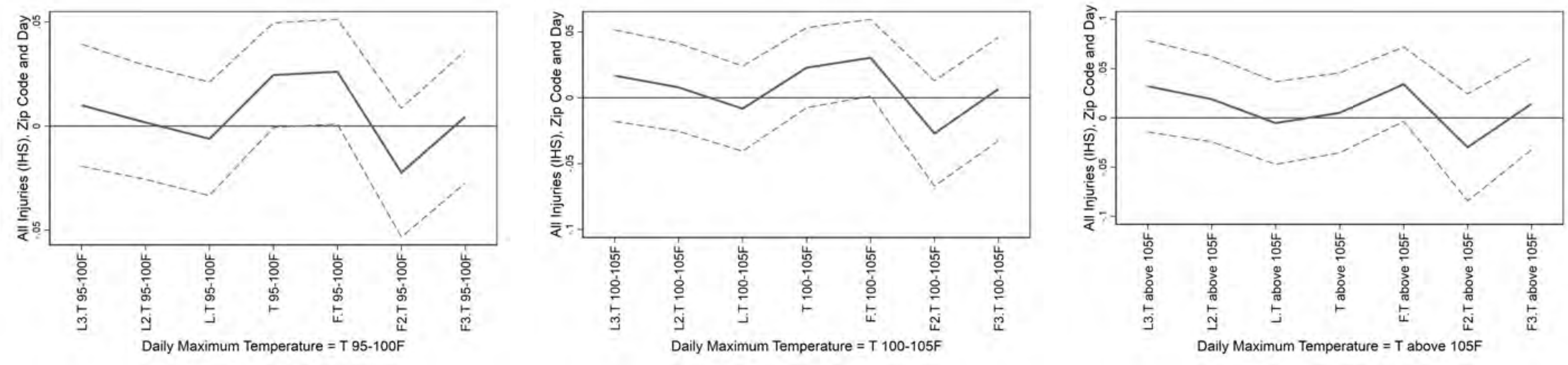
Notes: Table B6 shows the effect of temperatures on injury counts in California from 2001 to 2018, and shows alternative fixed effect specifications not included in Table 2. The dependent variables in each regression is the IHS transformation of injuries by zip code-day. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month and depicted in parentheses (* p<.10 **p<.05 ***p<.01).

Table B7: Temperatures and Injuries - Alternative Clustering of Standard Errors

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
T above 105F	0.0245	0.0245	0.0245	0.0245	0.0245***	0.0245***
	(0.0161)	(0.0118)	(0.0172)	(0.0127)	(0.00308)	(0.00450)
T 100-105F	0.0344**	0.0344**	0.0344**	0.0344**	0.0344***	0.0344***
	(0.0115)	(0.0107)	(0.0121)	(0.0110)	(0.00191)	(0.00365)
T 95-100F	0.0327**	0.0327**	0.0327**	0.0327**	0.0327***	0.0327***
	(0.0105)	(0.0101)	(0.0108)	(0.0101)	(0.00150)	(0.00357)
T 90-95F	0.0257**	0.0257**	0.0257**	0.0257*	0.0257***	0.0257***
	(0.00894)	(0.00849)	(0.00950)	(0.00900)	(0.00125)	(0.00230)
T 85-90F	0.0243**	0.0243**	0.0243**	0.0243**	0.0243***	0.0243***
	(0.00800)	(0.00732)	(0.00856)	(0.00794)	(0.00115)	(0.00190)
T 80-85F	0.0168*	0.0168*	0.0168*	0.0168*	0.0168***	0.0168***
	(0.00678)	(0.00621)	(0.00716)	(0.00656)	(0.00102)	(0.00211)
N	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00	11,596,536.00
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SE County Cluster	Yes	Yes	No	No	No	Yes
SE Zip Code Cluster	No	No	Yes	Yes	Yes	No
SE Year-Month Cluster	Yes	No	Yes	No	No	No
SE Year Cluster	No	Yes	No	Yes	No	No

Notes: This table probes the robustness of the main effect of temperature on injuries to alternative clustering of standard errors. The dependent variables in each regression is the IHS transformation of injuries by zip code-day. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month and depicted in parentheses (* p<.10 **p<.05 ***p<.01).

Figure B4: Temperatures and Injuries - Lags and Leads



Notes: Figure B4 plots coefficients from a dynamic distributed lags variant of equation 5, with three leads and lags of daily maximum temperatures. The dependent variable in each regression is the IHS transform of injury counts per zip code and day. Each regression includes the full set of 15 temperature bins, ranging from below 40°F to above 105°F, as well as controls for precipitation, zip code × month and county × year × month fixed effects. We plot lead-lag dynamics for the three hottest temperature bins. The omitted category is days with maximum temperatures between 60 and 65°F. The unit of analysis is zip code-days. Heteroskedasticity robust standard errors are clustered by county and year-month and 95 percent confidence intervals plotted as dashed lines.

Figure B5: Temperatures and Injuries - Rolling Window Estimations

Panel A: 3-Day Rolling Window

	p(Diff.)	All	RW(3) All
T above 105F	0.00	0.0243	0.0453*
		(0.0161)	(0.0176)
T 100-105F	0.00	0.0342**	0.0463***
		(0.0115)	(0.0122)
T 95-100F	0.00	0.0325**	0.0442***
		(0.0105)	(0.0107)
T 90-95F	0.00	0.0256**	0.0359***
		(0.00893)	(0.00935)
T 85-90F	0.00	0.0242**	0.0342***
		(0.00799)	(0.00818)
T 80-85F	0.01	0.0166*	0.0246***
		(0.00676)	(0.00705)
N		11,593,008.00	11,593,008.00
Zipcode × Month FE		Yes	Yes
County × Month × Year FE		Yes	Yes
Precipitation		Yes	Yes

Panel B: 5-Day Rolling Window

	p(Diff.)	All	RW(5) All
T above 105F	0.04	0.0241	0.0513***
		(0.0161)	(0.0139)
T 100-105F	0.05	0.0340**	0.0455***
		(0.0115)	(0.00837)
T 95-100F	0.05	0.0323**	0.0418***
		(0.0104)	(0.00697)
T 90-95F	0.17	0.0254**	0.0370***
		(0.00892)	(0.00612)
T 85-90F	0.15	0.0240**	0.0348***
		(0.00799)	(0.00560)
T 80-85F	0.04	0.0164*	0.0264***
		(0.00674)	(0.00488)
N		11,589,480.00	11,589,480.00
Zipcode × Month FE		Yes	Yes
County × Month × Year FE		Yes	Yes
Precipitation		Yes	Yes

Notes: Panel A and B of Table B5 show the effect of temperature on injury counts in California (2001-2018), and differs from the results shown in Table 2 in that injury counts as the dependent variable are summed over a rolling window of 3 (5) days in *Panel A* (*Panel B*). Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 105°F in 5° increments. Temperature bins below 80°F are suppressed in this table, but included as controls in all estimations. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered by county and year-month and depicted in parentheses (* p<.10 **p<.05 ***p<.01). The first column shows the p-statistic obtained by testing the difference between coefficients from regressions on daily injury counts *(column 2)* and rolling window injury counts *(column 3)*.

Table B8: Extreme Temperature and (100x) Log Employment - By Industry

	(1) Agr	(2) Min	(3) Uti	(4) Con	(5) Man	(6) Tra
Days above 100 (°F)	-0.057	-0.002	-0.015	0.154***	0.060*	0.046
	(0.109)	(0.107)	(0.020)	(0.048)	(0.031)	(0.032)
Days in 90s (°F)	0.007	-0.084	-0.021	0.047	0.026	0.000
	(0.082)	(0.058)	(0.029)	(0.048)	(0.025)	(0.026)
Days in 80s (°F)	0.040	-0.021	-0.019	0.038	0.026	-0.021
	(0.080)	(0.030)	(0.017)	(0.031)	(0.021)	(0.026)
Days below 30 (°F)	-0.049	-0.325***	-0.018	-0.456***	0.020	-0.077*
	(0.106)	(0.105)	(0.037)	(0.075)	(0.032)	(0.044)
Average monthly precip	-14.115**	-17.503***	-2.741	-7.273**	-3.023	-5.355***
	(6.585)	(6.468)	(1.845)	(3.286)	(1.919)	(1.609)
N	41,544	32,328	34,848	153,072	171,288	66,672
County FE's	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE's	Yes	Yes	Yes	Yes	Yes	Yes
Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE's	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
Regional trends	Yes	Yes	Yes	Yes	Yes	Yes

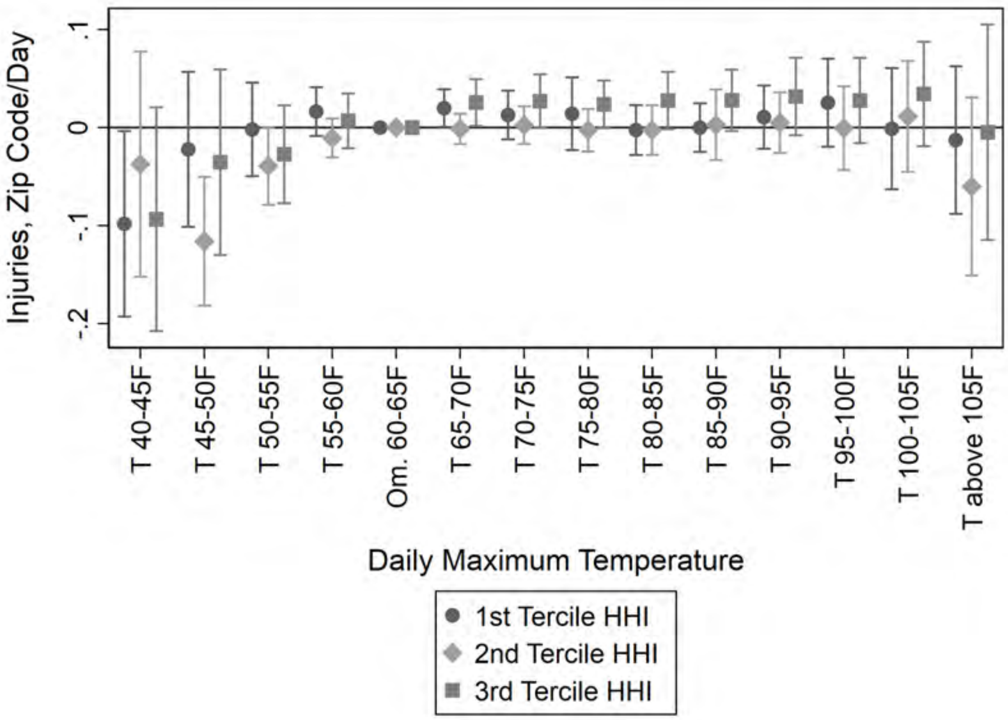
Notes: Heteroskedasticity robust standard errors clustered by state and quarter-year are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column and panel come from a regression of 100 times log total employment in a given county-industry-quarter on the variables shown, limiting the analysis to the industries listed. The sample is restricted to county-industries for which quarterly employment information is available for the entire time period (2000-2017). Temperature denotes daily maximum temperature and daily total precipitation is measured in inches. All regressions include controls for snow, as well as days in 30's, 40's, and 50's with days in the 60's and 70's as the omitted category.

Table B9: Extreme Temperature and (100x) Log Employment - By Industry

	(1) Who	(2) Ret	(3) Fin	(4) Edu	(5) Hea	(6) Acc
Days above 100 (°F)	0.030	0.031**	0.038***	-0.037	0.016	-0.114**
	(0.040)	(0.014)	(0.009)	(0.058)	(0.018)	(0.046)
Days in 90s (°F)	0.037	0.017	0.005	0.019	0.011	-0.103***
	(0.024)	(0.014)	(0.013)	(0.036)	(0.014)	(0.032)
Days in 80s (°F)	0.003	-0.001	0.005	-0.006	-0.004	-0.090**
	(0.016)	(0.011)	(0.006)	(0.034)	(0.010)	(0.035)
Days below 30 (°F)	-0.072*	-0.022	0.013	-0.002	-0.024**	-0.068*
	(0.036)	(0.019)	(0.013)	(0.036)	(0.011)	(0.036)
Average monthly precip	0.002	-1.169	-0.435	1.518	-0.619	-5.776***
	(2.361)	(0.976)	(0.721)	(2.635)	(1.063)	(1.915)
N	108,864	210,384	145,296	57,384	72,360	108,288
County FE's	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE's	Yes	Yes	Yes	Yes	Yes	Yes
Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE's	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
Regional trends	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Heteroskedasticity robust standard errors clustered by state and quarter-year are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column and panel come from a regression of 100 times log total employment in a given county-industry-quarter on the variables shown, limiting the analysis to the industries listed. The sample is restricted to county-industries for which quarterly employment information is available for the entire time period (2000-2017). Temperature denotes daily maximum temperature and daily total precipitation is measured in inches. All regressions include controls for snow, as well as days in 30's, 40's, and 50's with days in the 60's and 70's as the omitted category.

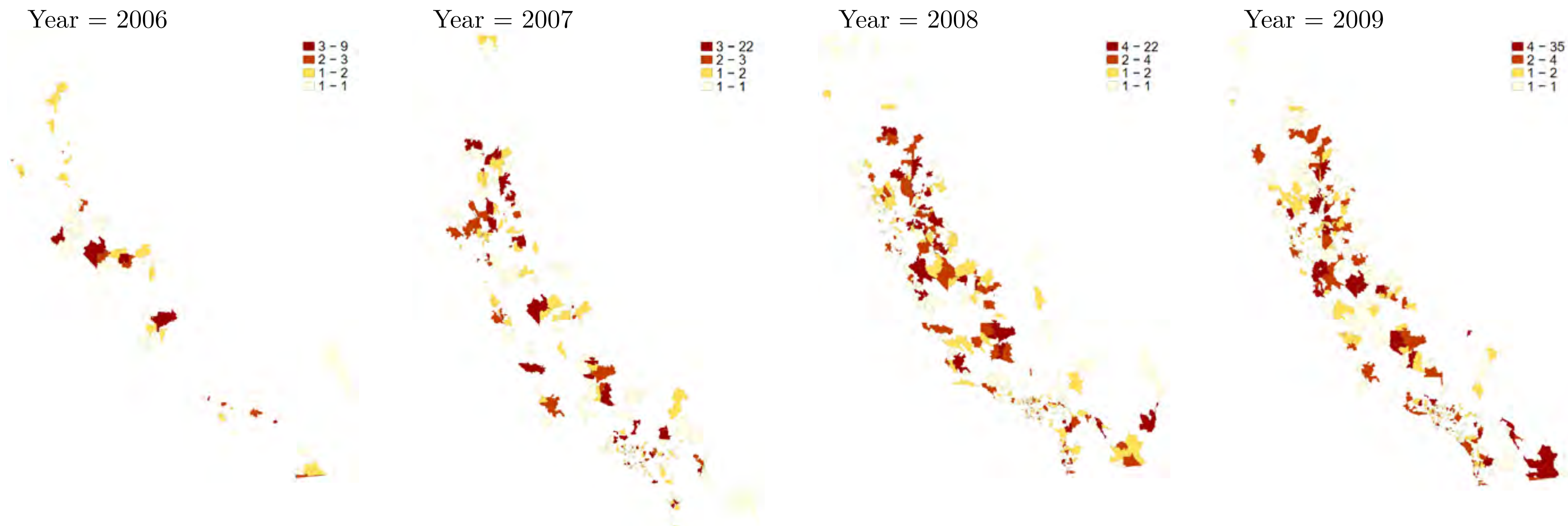
Figure B6: Labor Market Concentration and Temperature-Injury Relationship (Terciles)

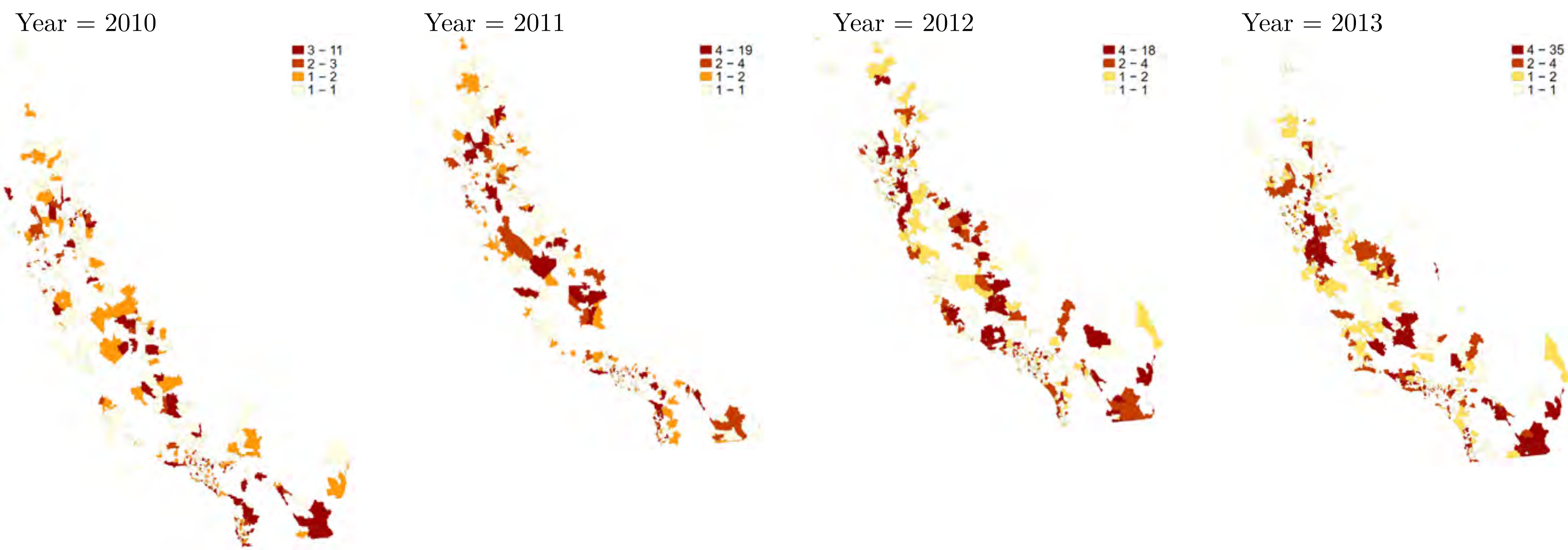


Notes: Figure B6 plots the temperature-injury relationship by local labor market concentration, using information on occupation-CZ-level Herfindahl-Hirschman Indices (HHI) from Azar et al. (2020), and depicting coefficients from separate regressions for each tercile of the national HHI distribution (in 2016). The dependent variable in both cases is the inverse hyperbolic sine transformed count of injuries per zip code and day, across all California-based work sites over the period 2001-2018. Daily maximum temperatures are assigned to a vector of 15 temperature bins ranging from 40°F and below to temperatures greater than 105°F. The omitted category is the temperature bin with daily maximum temperatures between 60 and 65°F. Heteroskedasticity robust standard errors are clustered two-way by county and year-month, and 95 percent confidence intervals are denoted by whiskers.

Figure B7: Enforcement of Workplace Safety Mandate - OSHA

Notes: Figure B7 maps a total of approx. 18,000 violations of the heat illness prevention standards (HIP, Cal/OSHA subchapter 7, group 2, article 10, section 3395) revealed through OSHA inspections of approx. 12,000 establishments in California from 2006 to 2018 (with increasing enforcement frequencies from 2006 to 2013 shown here). The standard was first filed on August 8th 2005 as an emergency legislation, which means that the policy could be implemented within 17 days and was initially effective for 180 days. After two re-adoption periods, the HIP was permanently implemented on July 7, 2006.

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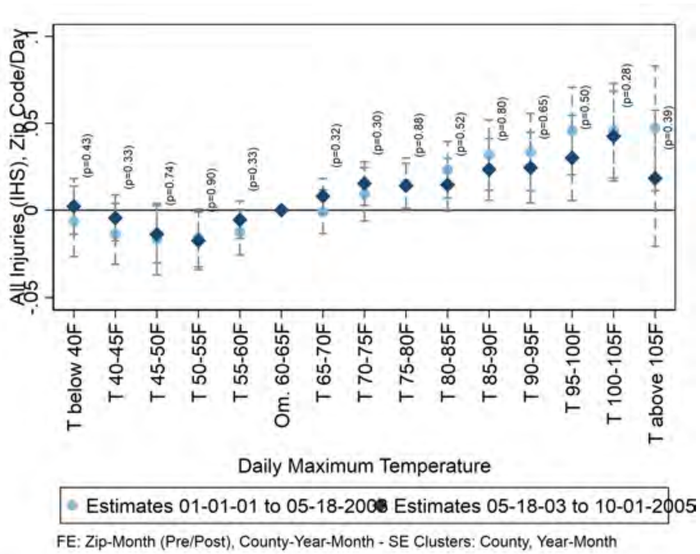
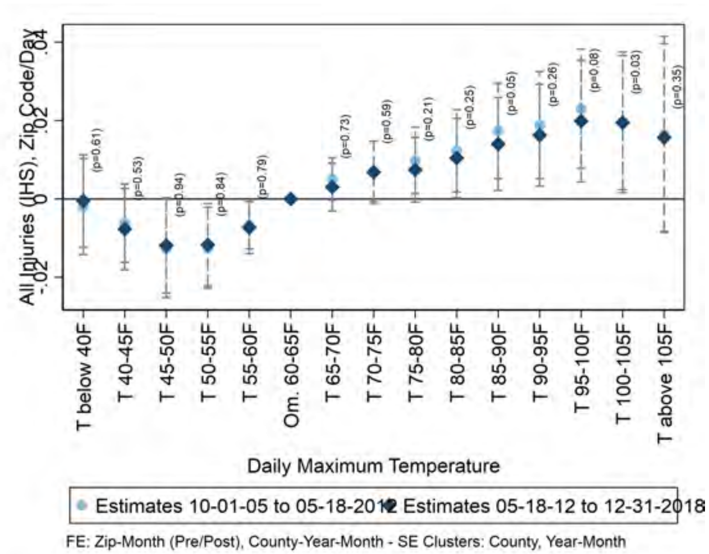
3 - 11
2 - 3
1 - 2
1 - 1
Year = 2011
4 - 19
2 - 4
1 - 2
1 - 1
Year = 2012
4 - 18
2 - 4
1 - 2
1 - 1
Year = 2013
4 - 35
2 - 4
1 - 2
1 - 1

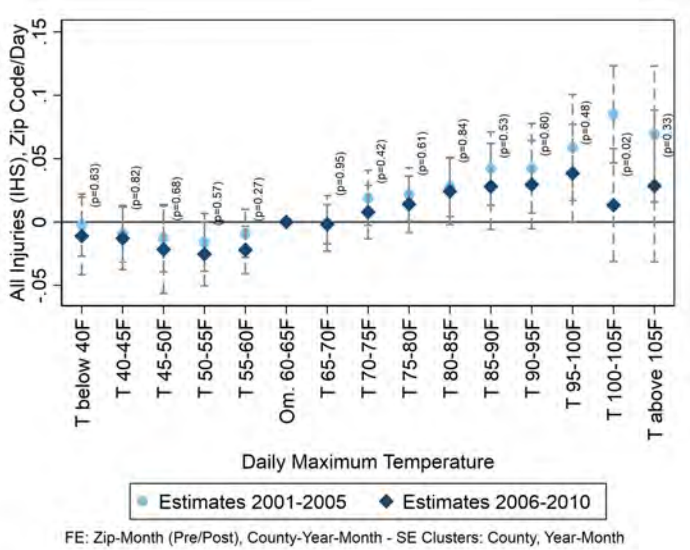
Figure B8: Temperatures and Injuries Before and After the Introduction of the Heat Illness Prevention Standard – Robustness Tests

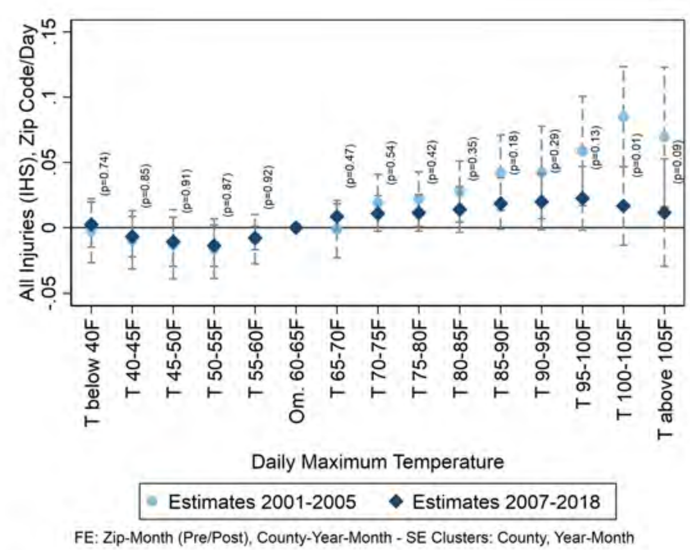




Notes: Figure B8 shows placebo tests of the effect of temperatures on workplace injuries using two different placebo treatments. ON the left we split the period prior to the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395) into a placebo pre and post period and compare effects. On the right we do the same with the post-period. In both cases we compare temperature-injury coefficients from running equation 5 in each placebo period. The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls before and after the introduction of the policy. Regressions include zip code × month, and county × year × month fixed effects, while we allow zip code × month fixed effects to vary by zip-code before and after the policy. The estimates for the period after (before) the introduction of the standard are plotted in dark blue (light blue). Heteroskedasticity robust standard errors are clustered by county code and year-month, with 95 percent confidence intervals plotted as dashed lines. P-values from tests of the statistical significance of the difference in the sensitivity of injuries to temperatures before and after the policy implementation are shown in parentheses.

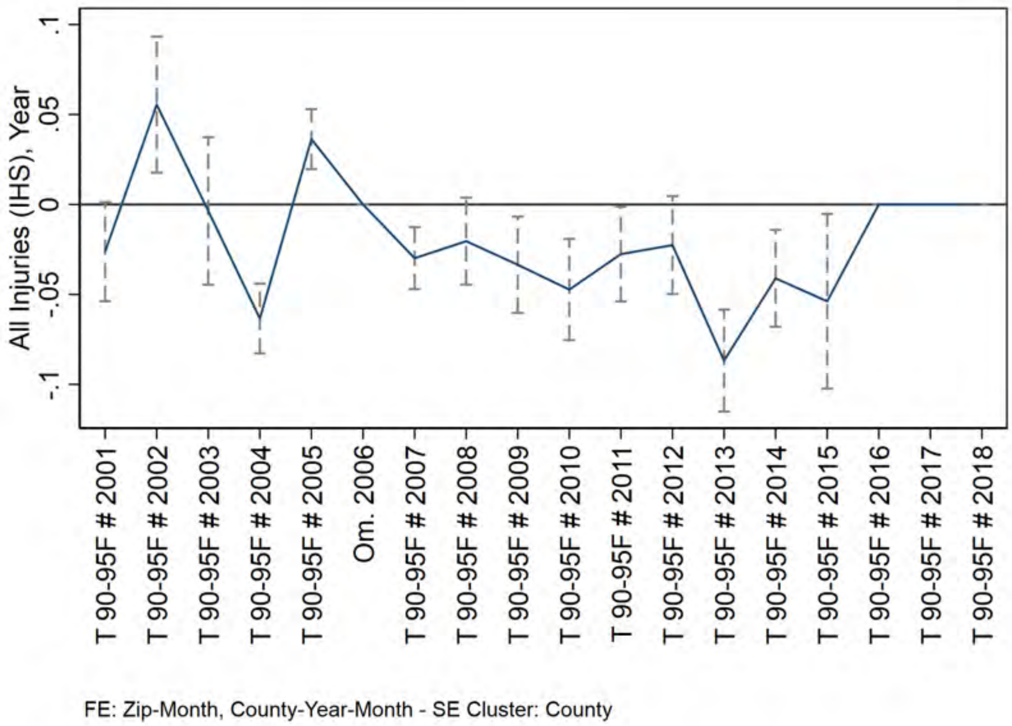
Figure B9: Temperatures and Injuries Before and After the Introduction of the Heat Illness Prevention Standard – Robustness Tests





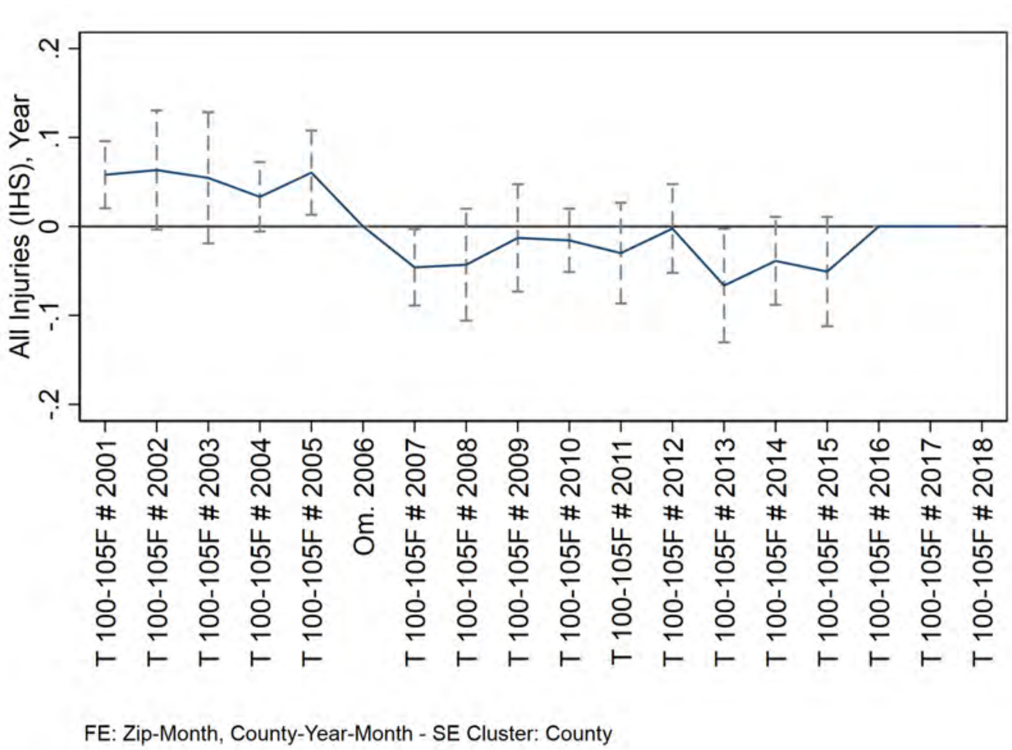
Notes: Figure 11 shows two robustness tests of the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). In the first robustness test, we limit pre- and post-policy periods to equal lengths of five years *(left)*. In the second test, we exclude the year (2006) in which the policy was adopted as a permanent statute *(right)*. The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls before and after the introduction of the policy. Regressions include zip code × month, and county × year × month fixed effects, while we allow zip code × month fixed effects to vary by zip-code before and after the policy. The estimates for the period after (before) the introduction of the standard are plotted in dark blue (light blue). Heteroskedasticity robust standard errors are clustered by county code and year-month, with 95 percent confidence intervals plotted as dashed lines. P-values from tests of the statistical significance of the difference in the sensitivity of injuries to temperatures before and after the policy implementation are shown in parentheses.

Figure B10: Change in Heat-Sensitivity of Injury Over Time



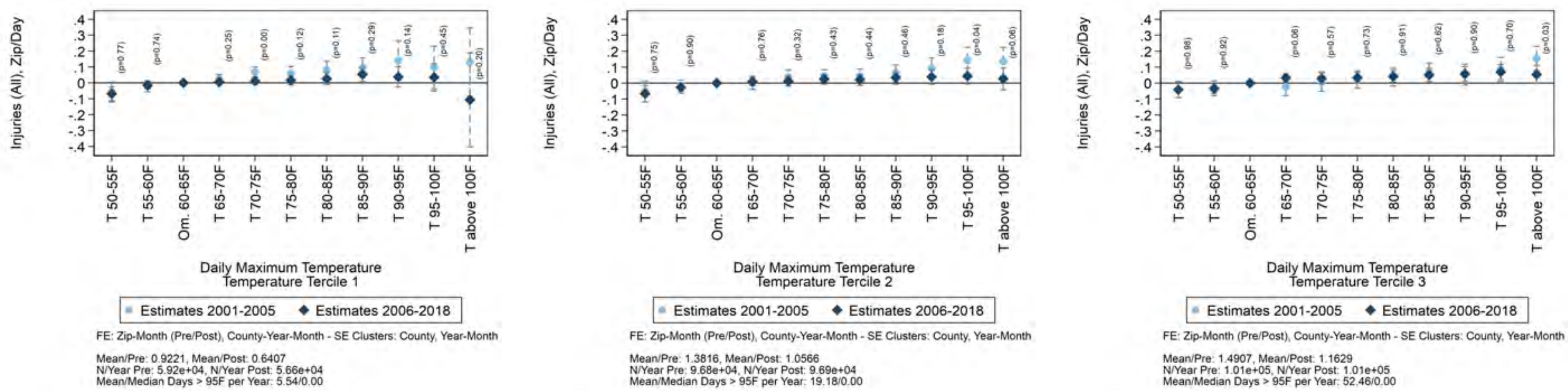
Notes: Figure B10 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls for each year of our sample, showing the coefficients for days with highs between 90°F and 95°F. All regressions include zip code × month, and county × year × month fixed effects, while we allow zip code × month fixed effects to vary by zip-code before and after the policy. Heteroskedasticity robust standard errors are clustered by county and year-month, with 95 percent confidence intervals plotted as dashed lines.

Figure B11: Change in Heat-Sensitivity of Injury Over Time



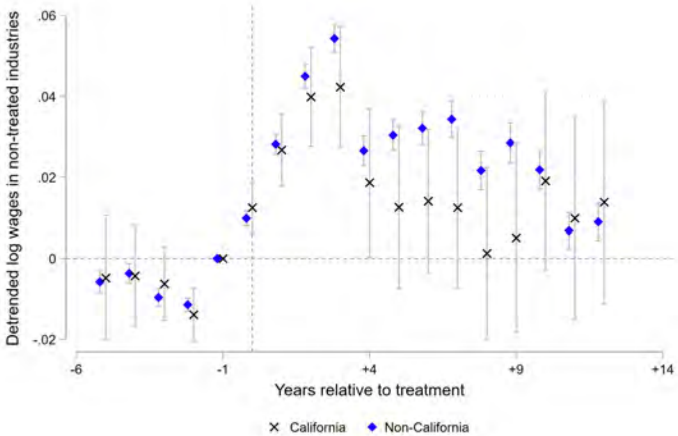
Notes: Figure B11 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls for each year of our sample, showing the coefficients for days with highs between 100°F and 105°F. All regressions include zip code × month, and county × year × month fixed effects, while we allow zip code × month fixed effects to vary by zip-code before and after the policy. Heteroskedasticity robust standard errors are clustered by county and year-month, with 95 percent confidence intervals plotted as dashed lines.

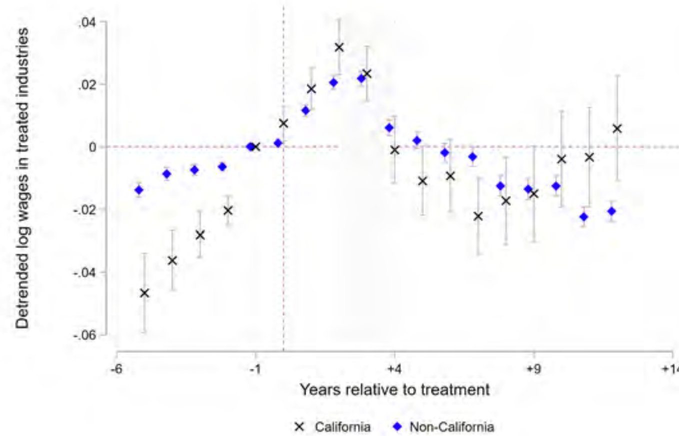
Figure B12: Change in Heat-Sensitivity of Injury Over Time – By Climate Tercile



Notes: Figure B12 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395), by tercile of the California climate distribution, where climate is measured in terms of the average number of days anove 95°F per year over the study period. The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 5) on temperature bins and precipitation controls for each year of our sample. All regressions include zip code × month, and county × year × month fixed effects, while we allow zip code × month fixed effects to vary by zip-code before and after the policy. Heteroskedasticity robust standard errors are clustered by county and year-month, with 95 percent confidence intervals plotted as dashed lines. P-values from tests of the statistical significance of the difference in the sensitivity of injuries to temperatures before and after the policy implementation are shown in parentheses.

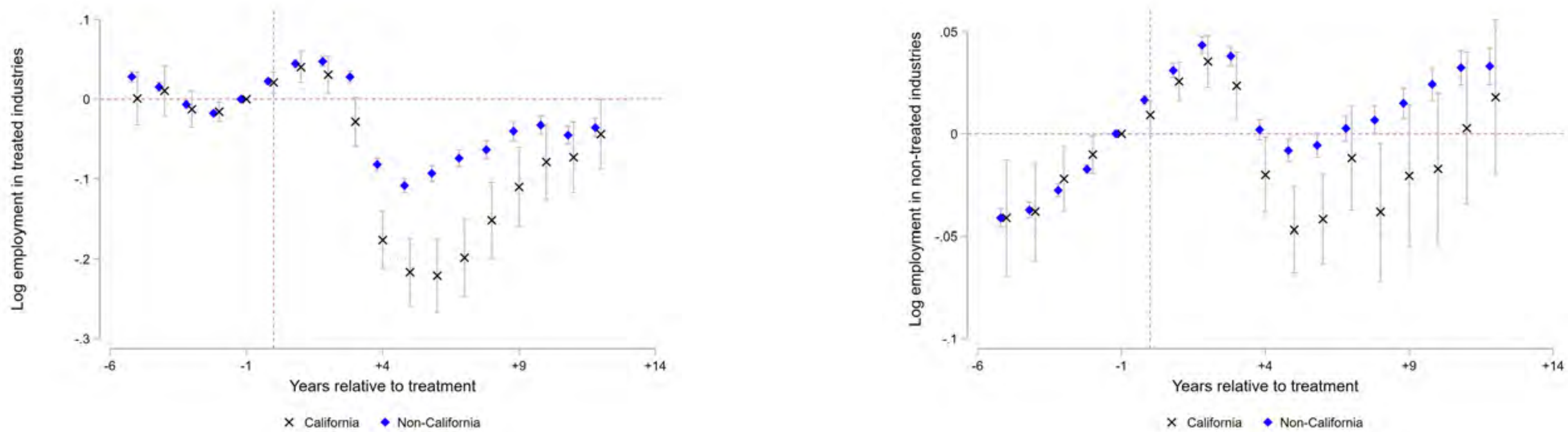
Figure B13: Trends in QCEW Wages by Treated Industries





Notes: Figure B13 shows the event study of the HIPS policy implementation on log QCEW wage levels in California and non-California counties by Treated and non-Treated industries with a linear year trend removed . The impacted in Treated industries is shown in the left panel while non-Treated industries are shown in the right panel. Coefficients are estimated relative to employment levels in the year prior to the implementation of the policy. Regressions include county and industry by quarter fixed effects. Standard errors are clustered at the county level and shown in light grey bars.

Figure B14: Trends in QCEW Employment by Treated Industries



Notes: Figure B14 shows the event study of the HIPS policy implementation on log QCEW employment levels in California and non-California counties by Treated and non-Treated industries. The impacted in Treated industries is shown in the left panel while non-Treated industries are shown in the right panel. Coefficients are estimated relative to employment levels in the year prior to the implementation of the policy. Regressions include county and industry by quarter fixed effects. Standard errors are clustered at the county level and shown in light grey bars.

Table B10: Differences in Differences: Log Wages per Worker

	(1) All Affected	(2) Reg.	(3) Unreg.	(4) All Affected	(5) Reg.	(6) Unreg.
CAxPOST	0.020**	0.014**	0.013*	0.020**	0.014**	0.014**
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
CAxTREATxPOST	-0.027***	-0.021***	-0.022***	-0.027***	-0.020***	-0.023***
	(0.004)	(0.006)	(0.002)	(0.004)	(0.007)	(0.001)
N	1,901,736	1,901,736	1,901,736	1,858,824	1,858,824	1,858,824
Δ Treated	-0.007	-0.007	-0.009	-0.007	-0.006	-0.009
	0.008	0.010	0.007	0.008	0.012	0.007
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-way interactions	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	No	No	No

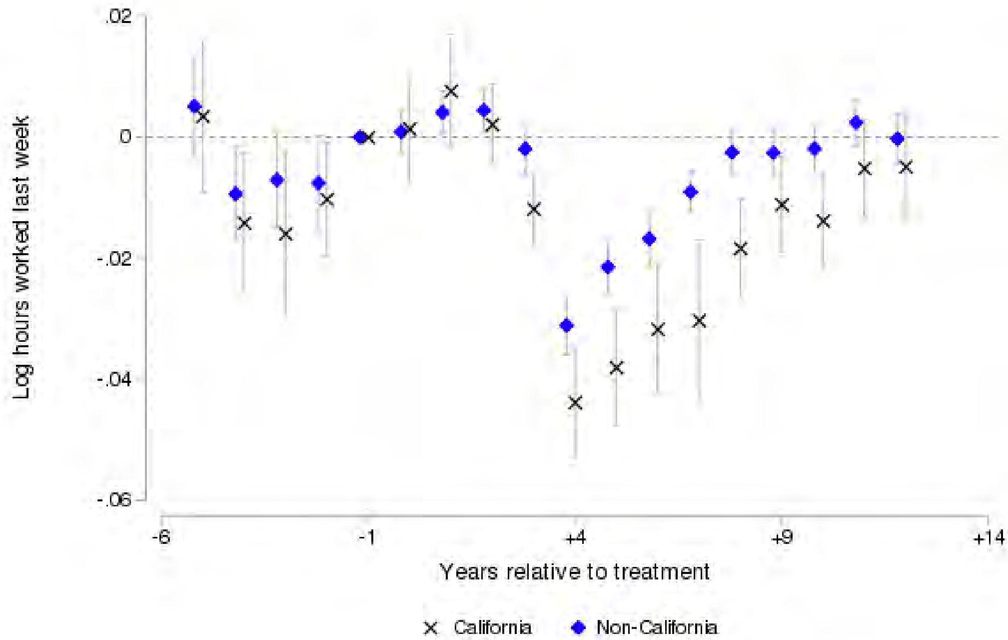
Notes: Heteroskedasticity robust standard errors clustered by state and year are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column come from a regression of log total employment in a given county-industry-quarter (NAICS 2-digit) on the variables shown, as well as all two-way interactions between a dummy for California, Treated industry, and Post-2005 (Q3). $\Delta Treated$ reports the sum of the reported coeffiencts, with standard errors calculated using the delta method. The sample is restricted to county-industries for which quarterly employment and wage information are available for the entire time period (2000-2017). Affected industries include agriculture, construction, wholesale, transportation and warehousing, retail, real estate and rental/leasing, professional, scientific and technical services, administrative support and waste management, and other services (except Public Administration), and are selected on the basis of industry-specific analyses of the change in temperature-injury relationships pre- and post-2005. Among these, regulated industries include agriculture, construction, wholesale, transportation and warehousing, and administrative support and waste management. Columns (4)-(6) omit agriculture, based on the observation that QCEW measures agricultural employment relatively poorly, and minimum wages may be more likely to bind.

Table B11: Differences in Di erences: Log Employment Level

	(1) All Affected	(2) Reg.	(3) Unreg.	(4) All Affected	(5) Reg.	(6) Unreg.
CAxPOST	-0.024**	-0.013	-0.042***	-0.024**	-0.013	-0.040***
	(0.009)	(0.013)	(0.013)	(0.009)	(0.013)	(0.013)
CAxTREATxPOST	-0.029**	-0.094***	0.050**	-0.027**	-0.097***	0.049**
	(0.010)	(0.014)	(0.018)	(0.012)	(0.018)	(0.018)
N	1,901,736	1,901,736	1,901,736	1,858,824	1,858,824	1,858,824
Δ Treated	-0.053***	-0.107***	0.009	-0.051	-0.110***	0.009
	0.018	0.017	0.017	0.019	0.021	0.018
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-way interactions	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture	Yes	Yes	Yes	No	No	No

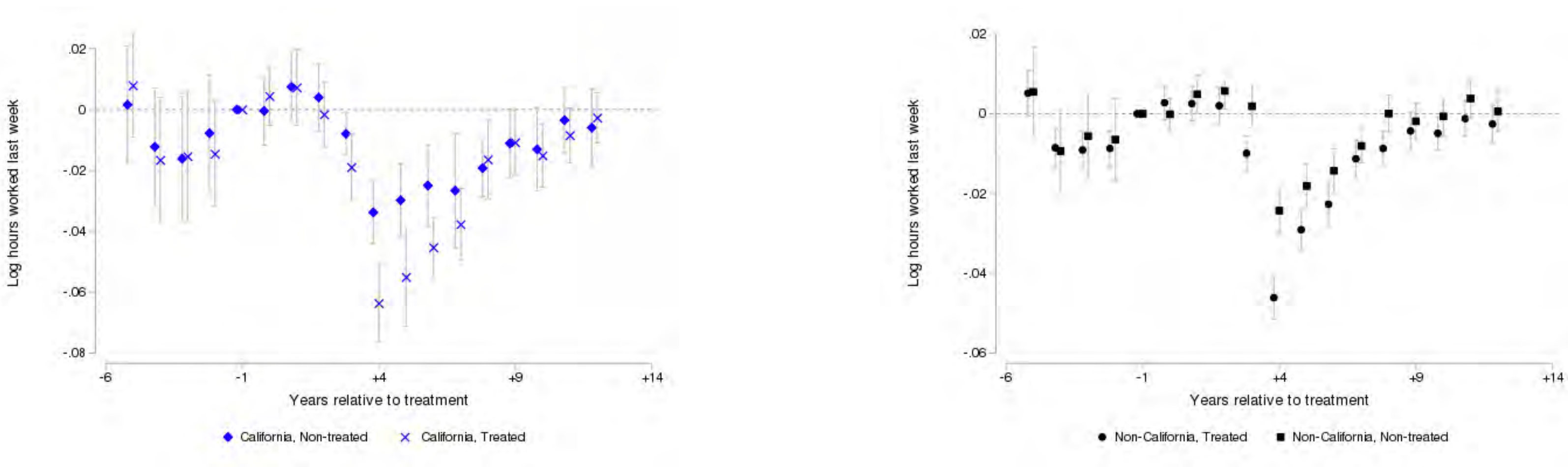
Notes: Heteroskedasticity robust standard errors clustered by state and year are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column come from a regression of log total employment in a given county-industry-quarter (NAICS 2-digit) on the variables shown, as well as all two-way interactions between a dummy for California, Treated industry, and Post-2005 (Q3). $\Delta Treated$ reports the sum of the reported coeffiencts, with standard errors calculated using the delta method. The sample is restricted to county-industries for which quarterly employment and wage information are available for the entire time period (2000-2017). Affected industries include agriculture, construction, wholesale, transportation and warehousing, retail, real estate and rental/leasing, professional, scientific and technical services, administrative support and waste management, and other services (except Public Administration), and are selected on the basis of industry-specific analyses of the change in temperature-injury relationships pre- and post-2005. Among these, regulated industries include agriculture, construction, wholesale, transportation and warehousing, and administrative support and waste management. Columns (4)-(6) omit agriculture, based on the observation that QCEW measures agricultural employment relatively poorly, and minimum wages may be more likely to bind.

Figure B15: Trends in CPS Employment



Notes: Figure B15 shows the event study of the HIPS policy implementation on CPS employment levels in California and non-California MSAs. Coefficents are estimated relative to employment levels in the year prior to the implementation of the policy. Regressions include MSA and industry by quarter fixed effects. The sample covers the full CPS period from 2000 to 2017. Standard errors are clustered at the MSA level and shown in light grey bars.

Figure B16: Trends in CPS Employment by Treated Industries



Notes: Figure B16 shows the event study of the HIPS policy implementation on CPS employment levels in California and non-California MSAs by Treated and non-Treated industries. California is show in the left panel while non-California MSAs are shown in the right panel. Coefficents are estimated relative to employment levels in the year prior to the implementation of the policy. Regressions include MSA and industry by quarter fixed effects. The sample covers the full CPS period from 2000 to 2017. Standard errors are clustered at the MSA level and shown in light grey bars.