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ABSTRACT

Temperature, Workplace Safety, and Labor Market Inequality*

Using data covering the universe of injury claims from the nation's largest worker's compensation system (2001-2018), we explore the relationship between temperature and workplace safety and its implications for labor market inequality. Hotter temperature increases workplace injuries significantly, causing approximately 20,000 injuries per year. The effects persist in both outdoor and indoor settings (e.g. manufacturing, warehousing), and for injury types ostensibly unrelated to temperature (e.g. falling from heights), consistent with cognitive or cost-related channels. The risks are substantially larger for men versus women; for younger versus older workers; and for workers at the lower end of the income distribution, suggesting that accounting for workplace heat exposure may exacerbate total compensation inequality. We document a decline in the heat-sensitivity of injuries over the study period, suggesting significant scope for adaptation using existing technologies.

JEL Classification: J20, J32, I18, Q50

Keywords: temperature, workplace safety, labor, inequality, climate change, adaptation

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1 Introduction

Wage inequality between workers with and without a college degree has risen sharply in the decades since 1990, both in the United States and many other OECD countries (Autor, 2014; Goos et al., 2009). But job quality is about more than headline wages, and may depend on non-wage characteristics such as flexibility or workplace health risks. One determinant of working conditions that has received relatively little attention to date is the physical environment in which work occurs. In this paper, we study how exposure to environmental externalities on the job may affect realized labor market inequality, focusing on the relationship between temperature and workplace safety using confidential microdata on worker injuries.

Workplace safety may be an important component of non-wage compensation, especially for those at the lower end of the income distribution. For instance, the average injury rate in warehousing is 4 times that in real estate, and 18 times that in finance (BLS, 2019). The welfare impacts of such injuries and illnesses can be considerable, individually and in aggregate, as the costs are not limited to medical expenses but also include costs of foregone earnings for workers and costs of recruiting and training replacements for firms (Broten et al., 2019). In the U.S., upwards of 4 million workers are injured on the job each year, a substantial fraction of whom experience permanent disabilities (Leigh, 2011; BLS, 2019).[1]

According to the first nationally representative survey of working conditions, 78 percent of the roughly 105 million U.S. workers without a bachelor's degree report routine exposure to harsh environmental conditions such as extreme temperature or poor air quality at work (Maestas et al., 2017). Recent evidence suggests that hotter temperature in particular can adversely affect health (Deschênes and Greenstone, 2011; Barreca et al., 2016), cognition (Graff Zivin et al., 2017), and decision-making (Heyes and Saberian, 2019), which could in turn have important implications for worker productivity and safety. However, little is known regarding the effects of temperature on workplace safety and their implications for economic inequality.

Understanding the labor market consequences of temperature shocks may be particularly important given anthropogenic climate change. 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] The overall welfare implications of such warming

[1] Leigh (2011) estimates that, accounting for potential under-reporting, there were 8.5 million non-fatal workplace injuries in 2007, of which 1 million resulted in temporary total disability, and half a million of which resulted in permanent disability. The social cost of workplace injuries resulting in permanent disability has been estimated at $650,000 per incident (Leigh and Robbins, 2004).

[2] While some parts of the U.S. will benefit from a reduction in extreme cold days, many are expected to experience

will depend in part on how the damages associated with a given amount of warming are distributed (Anthoff and Emmerling, 2019), as well as the scope for adaptation to such adverse effects (Kahn, 2016). Whether the realized damages will be generally progressive or regressive remains unsettled (see Hsiang et al. (2018)), as is the question of how firms and workers will adapt.[3]

Here, we provide what is to our knowledge one of the most comprehensive assessments to date of the effect of temperature on workplace health and safety, and the first assessment of potential implications for labor market inequality. We leverage claims-level injury data from the California Worker's Compensation System over the period 2001-2018, which we link to spatially and temporally granular weather data at the zip code-day level, as well as information on occupation and industry characteristics. This data represents a more comprehensive picture of workplace injuries than most publicly available data sets, which helps us to overcome reporting and measurement challenges present in much earlier work, and allows for a richer characterization of potential distributional implications.[4] Our findings build on seminal work by Dillender (2019), who provides some of the first evidence of temperature's effect on workplace injuries using data from Texas, and finds that hot and cold days exert positive impacts on injuries on average, but suggests limited scope for adaptation to such risks.

We present three main findings. First, we find that hotter temperature significantly increases the likelihood of injury on the job. A day with high temperatures between 85 and 90°F leads to a 5 to 7 percent increase in same-day injury risk, relative to a day in the 60's. A day above 100°F leads to a 10 to 15 percent increase. Causal identification relies on the premise that idiosyncratic variation in daily temperature within a given zip code-month is plausibly exogenous, and that the resulting effect on injuries is not driven by potential endogenous changes in labor inputs, assumptions which we interrogate in further detail below.

We find that hotter temperature increases workplace accidents in both indoor and outdoor settings, and for many injury types not directly related to heat. As one might expect, hotter temperature significantly increases injuries in predominantly outdoor industries such as agriculture, utilities and construction. But higher temperatures also

a net increase in extreme temperature days, often defined as days with high temperature above 90°F or below 32°F. 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 (Reidmiller et al., 2018).

[3]As Hsiang et al. (2018) discusses in greater detail, the distribution of environmental damages within countries is as yet largely unknown. In particular, while there is some evidence of spatial heterogeneity in climate damages (Hsiang et al., 2017), there is relatively little evidence regarding differences in impacts across individuals within countries, which may be important in understanding potential adaptation responses and implications for inequality.

[4]For instance, publicly available measures of workplace safety tend to either be highly aggregated (e.g. by industry or state), and/or feature high reporting thresholds (e.g. only including very serious incidents such as the death of a worker or hospitalization of three or more workers).

increase injuries in 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. We also find that claims for many injuries not typically considered heat-related rise on hotter days. These include injuries caused by falling from heights, being struck by a moving vehicle, or mishandling dangerous machinery. The increase in injuries affects a wide range of body parts, suggesting that the mechanisms may not be limited to heat-illnesses such as heat stroke or heat syncope.

These are previously undocumented facts with possibly significant policy implications, given the nearly exclusive attention to date on outdoor workers and heat illnesses: i.e. incidents that are medically coded as due to heat exposure. All told, we estimate hotter temperature to have caused approximately 360,000 additional injuries in California over the period 2001-2018, or roughly 20,000 per year relative to a hypothetical benchmark in which all workers experience only optimal temperatures. For perspective, this is roughly eleven times the number of workplace concussions, and at least nineteen times the annual number of workplace injuries the worker compensation microdata records as caused by extreme temperature.[5]

To help interpret our empirical findings, we outline a simple model of safety investment in the presence of temperature shocks. One explanation is that heat's impact on cognition and concentration (e.g. (Graff Zivin et al., 2017)) lead to deleterious health outcomes when coupled with baseline hazardous work environments. Another is that temperature affects the costs of maintaining a given level of safety, due to pecuniary costs such as higher energy expenditures (Auffhammer, 2017), or increased opportunity costs of shift time given reduced labor productivity (Somanathan et al., 2018).[6] Our model suggests that, under reasonable assumptions, hotter temperature should increase workplace injuries net of optimizing responses by workers and employers, even in indoor settings and for injury types ostensibly unrelated to heat exposure. The model also suggests that, due to potential compensating differentials and income effects operating in opposite directions, the distribution of heat-related injuries is ambiguous a

[5]Our estimate is over 300 times the number of medically diagnosed, work-related heat illnesses recorded by Cal-OSHA: approximately 60 per year. The National Institutes of Occupational Safety and Health (NIOSH) estimates that there were approximately 4,000 heat-related injuries and illnesses in the entire United States in 2016 (Jacklitsch et al., 2016).

[6]This motivates a model in which injury risk is a function of both direct physiological risk (e.g. heat stroke) and adaptation investments that improve overall safety but at a cost (e.g. incremental effort/attention, air conditioning, construction of shade structures). 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 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.

priori, which motivates our second set of analyses.

Our second finding is that temperature exposure at work may exacerbate trends in labor market inequality. We show using occupation- and zip-code level aggregates that average incomes and injury rates tend to be negatively correlated, such that lower wage workers tend to experience greater baseline injury rates.[7] We then explore potential distributional implications of hotter temperature on the job. First, we assess whether the effect of daily temperature has different incremental effects on low- vs high-income workers within a given location. For instance, a day with hot outdoor temperature may have very different implications for telephone pole repairmen versus lawyers working in the same zip code. We then combine this with information on the level of exposure – proxied using the number of dangerously hot days (above 90°F) experienced at work – which the theory of residential sorting suggests will be negatively correlated with income (Banzhaf and Walsh, 2008; Albouy et al., 2016).

Due to the fact that lower wage workers are more likely to work in dangerous occupations, more likely to live and work in places with greater heat exposure, and experience larger marginal increases in risk on hotter days, the *net* effect on injuries is far greater for low income groups. We estimate that, for someone from the bottom quintile of the zip-code level residential income distribution, the annual effect is approximately 5 times larger than for someone from the top quintile of the residential income distribution. We also find that the effect of heat on injuries is significantly larger for men relative to women, and for younger workers relative to older ones. Our results are consistent with the well-documented general decline in overall labor market prospects of prime-aged men with lower levels of education (Binder and Bound, 2019), but at odds with the temperature-mortality literature (Carleton et al., 2018), which finds larger effects for the elderly. They also suggest that the distribution of climate damages may not only be regressive across countries, as is well-documented (Dell et al., 2012), but also across individuals within countries and depend in particular on occupation and industry.

Finally, we provide a series of analyses that shed light on the potential for adaptation to climate-related workplace risks. A natural question is whether such hazards are mostly unavoidable features of exposed work, or whether workers and firms can adapt: for instance, through changes in production technology or safety investments such as shade or cooling structures. Existing research suggests physical limits to adaptation in the context of labor (Kjellstrom et al., 2016; Dillender, 2019), in contrast to evidence for significant adaptation potential in the context of mortality (Barreca et al., 2016; Carleton et al., 2018), agricultural yield (Mendelsohn et al., 1994; Burke et al., 2015),

[7]This extends seminal work by Hamermesh (1998), who shows using industry-level injury and time use data that, during the period 1979 to 1995, rising wage inequality tended to correlate with rising disamenity inequality.

and learning (Park et al., 2020b).[8]

We find evidence of significant adaptation potential. The effect of temperature on injuries falls significantly during our study period. For instance, the effect of a day above 90°F falls by roughly a third between 2000 and 2018, and the effect of days above 100°F is statistically indistinguishable from zero after 2005. We note that the temporal profile of heat's effects on injuries coincides with the introduction of what was at the time the nation's first heat safety mandate, the California Heat Illness Prevention Standard (Q3 2005), which applied only to outdoor workplaces.[9] Our findings are consistent with the policy having been binding for a subset of firms, though it may also be driven by correlated secular trends in workplace safety or contemporaneous policies at the state or Federal level. While we remain agnostic to the source of the decline in heat-related injuries, our findings are consistent more broadly with the possibility of adaptation using existing technologies.

Our paper contributes to multiple literatures. First, we extend a literature examining the causes and consequences of economic inequality, particularly in the labor market. While previous work documents growing wage inequality in the United States and other OECD countries, whether trends in non-wage compensation inequality mitigate or exacerbate such trends in wage inequality remains poorly understood, particularly for the period after 2000.[10] Our contribution is to shed light on a particular non-wage aspect of compensation that might affect our understanding labor market inequality. We are the first to show how an environmental externality affects realized total compensation inequality, and the first to assess the distributional implications of workplace safety using administrative microdata.

We also contribute to a growing literature that uses micro-economic variables to estimate marginal damages due to climate change. Previous quasi-experimental analyses estimate the causal impact of temperature on health (Deschênes and Greenstone, 2011; Barreca et al., 2016; Carleton et al., 2018), labor supply (Graff Zivin and Neidell, 2014), learning and cognitive performance (Graff Zivin et al., 2017; Park et al., 2020b,a), and energy demand (Auffhammer, 2017). We augment these studies by providing one of the first assessments of the potential impacts of temperature on workplace safety, with the notable exception of Dillender (2019). Like Barreca et al. (2016) and Carleton

[8]For instance, Dillender (2019) uses mining injury data to show that heat causes similar injuries in historically hot as well as cooler climates, which is taken as evidence of limits to adaptation. In contrast, Barreca et al. (2016) and Carleton et al. (2018) find that the mortality response to hotter temperature varies significantly by average climate, and can be largely explained by variation in residential AC penetration.

[9]The policy required employers to invest in employee training regarding heat illness, shade structures, and free water and paid rest breaks on days with temperatures above 95°F, and was coupled with a vigorous enforcement regime that featured over 18,000 inspections in the ensuing years.

[10]An expansive literature documents rising wage inequality, particularly along lines of educational attainment. For instance, see Autor et al. (2003); Autor (2014) or Katz and Krueger (2017).

et al. (2018), we empirically estimate the potential for adaptation to such shocks, which is vital in estimating a credible mapping from such short-run weather-economy relationships to a longer-run climate-economy response function.[11]

Finally, we augment the literature on the determinants of working conditions, including workplace safety. Previous work explores the effects of government health and safety regulations (Levine et al., 2012; Johnson, forthcoming), workers' compensation insurance premiums (Viscusi and Moore, 1991), and changes in product market demand (Charles et al., 2019) on workplace safety. Our contribution is in assessing how changes in environmental conditions may affect workplace safety. Our findings are consistent with Charles et al. (2019), who show that both demand and supply side conditions can jointly affect workplace injury risk.

Two recent papers are particularly in the spirit of ours. Dillender (2019) finds using data from Texas and the U.S. mining industry that extreme temperature raises injury risk, and that adaptation to such risks may be limited. Marinescu et al. (2021) use data on labor rights violations to show that increases in wages tend to be correlated with fewer labor rights violations. Our analysis differs from Dillender in that we explore implications for labor market inequality, assess changes over time, and explore heterogeneity by industry, occupation, age, and gender. Moreover, Dillender's setting represents the only state wherein worker's compensation insurance is *not* required, unlike our setting and many OECD contexts. Our analysis builds on Marinescu et al. (2021) by exploring the potential contribution of non-wage aspects of work to labor market inequality, but differs in the emphasis on environmental externalities and in using administrative data on injuries as opposed to labor rights violations, which may miss important subsets of injuries and cases where no outright labor violations occurred but workers were injured nevertheless.

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 and explores potential mechanisms and the overall magnitude of the effect in light of previous studies. Section 5 assesses heterogeneity by wage, age, gender, and labor market concentration. Section 6 explores the potential for adaptation. Section 7 discusses and concludes.

[11] Given space constraints, we eschew a formal assessment of potential impacts of future climate change on workplace safety, and note simply that few if any existing integrated assessment models (IAMs) include occupational morbidity effects, leaving such analyses for future research.

2 Background and Conceptual Framework

2.1 Working Conditions and Labor Market Inequality

Our motivation for exploring inequality in physical working conditions is two-fold: to better understand the contribution of working conditions to total compensation inequality, and to explore the potential distributional implications of climate change, which can be thought of as an environmental externality that results in rising ambient temperatures. To our knowledge, there exists to date little empirical work exploring either dimension of labor market inequality.

Economists typically model non-wage amenities such as safety in a Rosen equalizing differences framework, which suggests potential compensating differentials and thus a positive relationship between wages and injuries. However, as noted by Hamermesh (1999), to the extent that workplace safety is a normal good, secular increases in total compensation inequality would lead to increases in disamenity-inequality such that wage-inequality understates total compensation inequality. In addition, as noted in Mortensen (2003) and Sorkin (2018), allowing for imperfectly competitive labor markets and utility dispersion across job matches implies that higher paying jobs might also have more desirable non-wage characteristics. A further dimension relevant to this setting is the potential for spatial sorting on local climate amenities, as documented in hedonic studies such as Albouy et al. (2016) and Sinha et al. (2017). To the extent that thermal comfort at home or at work is a normal good, higher income individuals would sort into more pleasant (milder) local climates, and be willing to pay a higher premium to avoid temperature extremes. Thus, it is unclear whether non-wage characteristics such as harsh physical working conditions are compensating or augmenting on net, making the distributional implications of rising temperatures at work ambiguous a priori.

2.2 Temperature and Workplace Safety

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. While the epidemiological and occupational health literature has long noted the potential links between extreme temperature and safety, many of these studies are either cross-sectional in nature or follow time-series analyses for an individual plant or city, making causal inference challenging (Ramsey et al., 1983; Ramsey, 1995; Adam-Poupart et al., 2014; Kjellstrom et al., 2016).

Extreme temperature 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).[12] Recent evidence 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 influencing injury risk through a number of channels, including but not limited to direct physiological effects and cost-related changes in safety investment.[13]

2.3 Conceptual Framework

We develop a simple conceptual framework that fixes ideas and guides our empirical analysis. We present a formal model in the Appendix, and present a stylized version here for ease of exposition. 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 workplace safety such as training workers regarding safety hazards, upgrading capital equipment, and monitoring production processes. Utility-maximizing workers weigh the benefits of such occupational characteristics as workplace safety against the prospects of working with lower pay (Rosen, 1974; Jones-Lee, 1974).

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

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

Safety investments may entail pecuniary and non-pecuniary costs to the firm.[14]

[12] 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.

[13] Estimates of the productivity impacts of temperature vary significantly by study setting (Cachon et al., 2012; Somanathan et al., 2018). One possibility is that, depending on the work incentives and adaptation investments in place, smaller productivity effects may mask larger unmeasured welfare impacts in the form of worker health or disutility. On one extreme is a stylized scenario in which workplaces mandate significant rest breaks on hotter days, and large labor productivity effects partially reflect increased leisure time, thus overstating net welfare impacts. On the opposite extreme, small or zero labor productivity effects may reflect compensatory effort on part of workers to meet strict production quotas, the health and safety consequences of which may have gone largely unobserved in studies of output or wages.

[14] 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,

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 $w_R \geq 0$. 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.[15]

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:

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

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 defensive investments in determining safety more broadly.

How might firms respond 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 $w_R > 0$.[16] 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 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.

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

2019).

[15] 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.

[16] 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.

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. In particular, we expect 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.

3 Data and Summary Statistics

3.1 Worker's Compensation Microdata

We combine confidential records of workplace injuries in California from the Department of Workers' Compensation (DWC) over the period 2001 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 injuries still go unreported. California legally obliges employers to maintain worker's compensation insurance, regardless of the number of employees or size of establishment. This allows us to provide a far more comprehensive account of workplace safety risks than many publicly available datasets, including OSHA records.

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). Our data also includes for each claim the medically determined cause (e.g. fall), type (e.g. strain), and body parts affected (e.g. knee) by the incident, as well as some limited demographic information including age and gender. The data also includes information on zip code of residence for the injured workers, which allows us to assign zip code-level average income information using data from the IRS Individual Tax Statistics database. For our primarily analyses, 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 Industry, Occupation, and Labor Market Concentration

Unlike many previous analyses of workplace safety, we are able to incorporate claims-level information on worker occupation and industry. We generate industry (NAICS) and occupation (SOC) codes for a subset of the injury claims in our data set 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). 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". The median match probability is 89 percent. This allows us to assign SOC codes to approximately 7.1m observations.[17]

We combine this information with data on employment and wages by occupation (6 digit SOC), city, and year using data from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics database. For analyses of labor market inequality, we combine this information local Herfindahl-Hirschman Indices (HHI) information by occupation and commuting zone (CZ) from Azar et al. (2020), and zip code level residential income data from the Internal Revenue Service (IRS) Individual Income Tax Statistics.

3.3 Local Weather Data

We combine 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 2000 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, which captures the distribution of observed temperatures in California (Figure 3). To control for potential effects of rainfall on workplace safety, we link each zip code-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 pre-

[17] Industry codes are reported to the DWC as either NAICS or SIC codes. To assign injuries to industries, we convert four-digit industry codes and codes labeled as SIC codes from SIC to NAICS, and remove erroneous codes which cannot be mapped to NAICS sectors. Subsequently, we obtain occupation (SOC) codes by parsing the combinations of job descriptions and NAICS codes using the NIOSH tool, available here: https://wwwn.cdc.gov/nioccs3/

cipitation, days with half an inch to one inch, and days with more than one inch of precipitation.

3.4 Employment, Wages, Hours

To better understand potential endogenous labor input responses, as well as the possibility of compensating differentials, we take information on employment and wages by county, 2-digit industry, and quarter from the QCEW for the period 2001 to 2018. 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 also collect monthly data on hours worked from the U.S. Current Population Survey (CPS) from 2000 to 2018 (Flood et al., 2020). Using the merged PRISM data we calculate the number of days in the reference week in each temperature and precipitation bin.

3.5 Summary Statistics

Table 1 presents summary statistics for injuries (Panel A) and temperatures (Panel B). On average, there are 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. As shown in Appendix D, 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%).

Figure 1 shows the spatial distribution of injuries across California. 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.

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, 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. On a given day, the high temperature may vary by over 25°F across zip codes within Los Angeles County alone.

4 Temperature and Injuries

4.1 Empirical Strategy

In our first empirical examination we exploit variation in local temperatures across days within a zip code and month (Figure 2 and 3), and rely on the fact that this variation is plausibly exogenous net of location-specific seasonality in potential determinants of workplace safety. Specifically, we examine whether realized injuries are higher on a hotter-than-average day within a given zip code-month-year cell. We implement this empirical strategy with regressions of the form:

$$F(Inj_{icdmy}) = \Sigma_{k=1}^{K} \beta^k Temp_{icdmy} + \Sigma_{p=1}^{P} \delta^p Precip_{icdmy} + \eta_{im} + \gamma_{my} + \epsilon_{icdmy} \qquad (3)$$

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 more 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. distance to central business district), as well as zip code-specific seasonality in injury risk (e.g. regional differences in construction or agricultural harvest seasons). γ_{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 γ_{my} with γ_{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. 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 Appendix D.

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 $\Sigma_{k=1}^{K}\beta^{k}Temp_{icdmy}$ coefficients. In particular, we are interested in the effect of days with especially cold or hot temperatures, where the β'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 effects 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. The main threat to identification comes from potential endogenous changes in labor inputs, a possibility we discuss in greater detail below.[18]

4.2 Main Effect

The main results from running equation 3 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.[19]

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 Dillender (2019), we find no evidence for significant impacts of extreme cold, though the point estimates on colder bins is positive. These estimates are

[18]It is also possible for other meteorological variables to co-vary with temperature within zip code-months. For instance: daylight hours, which may affect sleep duration, or some air pollutants such as ozone, the formation of which may be affected by temperature. We note that in principle our estimates may be partially driven by such residual co-variation. We leave an assessment of separate effects of daylight, pollution, as well as their interaction with temperature for future work.

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

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.

4.2.1 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 3 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 significant at the 1 percent level, apart from the noisier 105°F bin. The implied magnitudes are 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 4 in Appendix D), and ones that divide injuries by the number of workers in each county-quarter (Figure 4 in Appendix D). 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 3 that include day of week and day of month fixed effects (Table 6 of Appendix D). The results are essentially unchanged. Table 8 of Appendix D 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 some 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 3 that heat increases injury risk in a two-day window spanning the reported date of injury on the claim (Figure 5 of Appendix D). 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 above, even when expressed relative to the 'optimal' 50 to 55°F bin, may understate the true, error-in-recall-adjusted effect of heat (Figure 6 of Appendix D).

4.2.2 Accounting for Potential Labor Input Responses

As we describe in our analytic 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.[20] 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, 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, the details of which are presented in Appendix B.

We find no evidence of significant employment responses to hot temperature. As shown in Table 8 of Appendix D, 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.[21] This finding holds across a range of

[20] 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.

[21] 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

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.

Table 9 of Appendix D provides results from running similar regressions using data on hours worked from the CPS. 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.

These results indicate that high temperatures increase overall safety risk on the job. 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.

4.3 Assessment of Potential Mechanisms

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: i.e. the "biological risk" in our model. This is important because in examining the impact of heat on workplace injuries the existing 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 be related to temperature. In addition, energy expenditures have been shown to increase on hotter days (Auffhammer, 2017). This could suggest relative reductions in safety

interval of -0.022 percent to +0.026 percent.

investment on hotter days by optimizing firms, even in the presence of compensating differentials.

4.3.1 Heterogeneity by Injury Type

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 ($\frac{\partial R}{\partial T}$), but also increases overall injury risk. For instance, injuries in our data are classified as being caused by a "Fall, Slip, or Trip","Moving part of Machine", or "Crash of Vehicle". There is also a separate variable that records the body part(s) affected, including such entries as "Ear", "Eye", "Back" or "Cardiovascular system".

Table 4 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 panel of Figure 7 presents the resulting coefficients graphically. 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 such claims.

Replacing the outcome variable with all other injuries, we also find a positive relationship. The magnitude of this relationship is 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 ostensibly unrelated claims comprise the vast majority of residual injury burden associated with extreme heat. Over the period 2001-2018, there were on average 618,000 such claims per year in California, compared to 850 injuries caused by "Extreme Temperature" per year.

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 4). 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.

4.3.2 Outdoor vs Indoor Work Settings

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 3 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) and accommodation and food services (72, e.g. hotels, restaurants, drinking establishments). Within manufacturing, the industries with the largest impacts appear to include food processing, textiles, and apparel manufacturing. 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).

4.4 Magnitude of Heat-Related Safety Burden

One important implication of these estimates is that workplace safety risks due to hotter temperature may be a more pervasive phenomenon than official statistics suggest. To provide an illustration of the magnitude of the additional injury burden associated with hotter temperature on the job, we take the $\Sigma_{k=1}^{K}\beta^{k}Temp_{idmy}$ coefficients from the main (IHS) specification above (column 5 of Table 2, taking the 50 to 55°F bin as the "optimal" reference bin) and multiply the percentage increase in injury risk for each temperature bin above 70° Fahrenheit with the average number of days in each temperature bin observed in California over the study period and then multiply the implied total percentage change in injuries by the baseline injury rate in the omitted bin. This provides an estimate of the number of additional injuries, relative to the omitted bin, that are attributable to experiencing the average number of days with temperatures in each bin. Aggregating across bins, we obtain an estimate of 14,800 injuries caused by hotter temperatures per year in California, or approximately 266,000 over the study period. We note that, using the Poisson specification, the estimate is approximately 24,800 additional injuries per year, or 446,000 total. These estimates suggest that injuries and illnesses caused by hotter temperature constitute approximately 2.5 to 4 percent of all incidents serious enough to be reported to worker's comp in California.

These figures are estimated relative to a counter-factual in which all days above 70° Fahrenheit are replaced by days in the optimal temperature bin for all workers, and so should be interpreted with caution. Nevertheless, they illustrate the non-trivial magnitude of heat's effects on workplace safety, and suggest that official statistics may understate the injury/illness burden associated with hotter temperature substantially. 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).[22]

5 Labor Market Inequality

As discussed in section 2 whether or not we would expect temperature-related safety risks to be associated with lower incomes is ambiguous a priori. Here, we provide an assessment of the distributional implications of changes in extreme temperature, using information on the workers' zip codes of residence and workplace, as well as information on gender, age, and labor market concentration by occupation.

5.1 Distribution of Baseline Health and Safety Risk

We begin by documenting some descriptive facts regarding the distribution of workplace health and safety risks, extending work by Hamermesh (1998). As shown in Figure 8, which present binned scatterplots of the relationship between annual injury claims per tax return across the zip code-level residential income distribution, lower income individuals experience substantially more injuries on the job. This is true both for the subset of claims officially designated as being caused by extreme temperature as well as for all injury types.

[22]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."

Table 5 presents average injury rates, income, and temperatures by quintile of the residential income distribution. Those living in the bottom quintile of the residential income distribution experience approximately 5.2 injuries (WC claims) per 100 taxpayers, compared to 2.2 per 100 taxpayers in the top quintile.[23]

We find evidence consistent with geographic sorting on climate (dis-)amenities, whereby higher income individuals live and work in parts of the state that feature milder climates. For instance, those in the bottom quintile live in zip codes that experience 70 days per year above 90°F on average, compared to 26.2 days per year for those in the top quintile. The gradient across workplaces, which we proxy for using information on the site of the injury, appears to be substantial as well. Workers in the bottom quintile of the income distribution work in parts of the state that experience 53.8 days above 90°F on average; those in the top income quintile work in places that experience 33.8 such days. These patterns are consistent with existing hedonic analyses, including Albouy et al. (2016), Sinha et al. (2017), and Maddison and Bigano (2003) who find that individuals are willing to pay a considerable housing premium to locate in areas that have fewer extreme temperature days, particularly days above 90°F.

These differences in *average* injuries and temperature exposure alone suggest that, unless the effect of heat on injuries is more pronounced for higher income workers, the overall welfare impact of heat-related safety risks may be larger for lower income populations.[24] In other words: that the external costs of carbon-intensive consumption may be distributed regressively, even within countries.

We next assess whether the *marginal* effect of temperature on injury risk varies across the income distribution, something many previous assessments of climate damages have been unable to do due to data limitations. Ex ante, it is unclear whether hotter temperature leads to greater relative changes in safety risk in more exposed or lower wage work environments. On the one hand, workers who are more frequently exposed to temperature extremes may be better adapted, either in terms of physiological acclimation or situational awareness. On the other hand, workers in lower-wage occupations may also have worse outside options, meaning that they are less likely to be able to demand safety-enhancing measures such as air conditioning as part of their total compensation package, or may simply have poorer underlying health.

[23] Ideally, we would deflate by number of employees. We do not have this information, and so proxy for the number of full time workers in a zip code using IRS data on tax filers.

[24] We note that there may be many other factors that give rise to these differences in injury rates, including differential reporting conditional on injury. If lower income workers are less likely to report injuries to their employers or to file for worker's compensation, then these comparisons would understate the differences across income groups. If, on the other hand, lower income workers are more likely to work in settings where reporting of injuries is more stringent – for instance, due to greater OSHA oversight – then these comparisons overstate the distributional differences.

5.2 Heterogeneity in Causal Effect of Temperature by Average Residential Income

We estimate versions of equation 3 separately for each quintile of the employee income distribution. The results from these regressions are presented in Table 8. These estimates exploit roughly the same variation in workplace temperatures as before, but for individuals with different estimated incomes. For instance,they capture potential differences in the effect of a hot day for construction day laborers, architects, and security personnel who may work at the same establishment but live in different zip codes.

As shown in columns (1)-(5) of Table 6, the effect of a day above 90°F is positive and significant across all income quintiles. The point estimates are larger at the bottom relative to the top of the residential income distribution. Our estimated coefficient for the lowest income quintile is nearly 40% larger than the estimated effect in the richest quintile. A day above 90°F results in 7.4 (se=1.8) percent more injuries for those in the bottom quintile of the income distribution, whereas the corresponding coefficient in the top quintile is 5.4 (se=2.1). These differences are not statistically significant, however; a Wald test comparing quintiles one and five suggests a p-value of 0.13. Thus, we cannot reject the null that the percentage increase in injuries is not different across workers of different residential income levels. However, when combined with the fact that lower income workers tend to be more exposed to hotter temperature on average, and to work in settings that feature elevated baseline safety risk, the implied total impact of heat on safety appears to be highly regressive, as discussed below.[25]

5.3 Heterogeneity in Causal Effect of Temperature by Age and Gender

An important feature of U.S. labor markets in recent decades has been the relative decline of employment prospects for men relative to women. In particular, prime-age men without a bachelor's degree have experienced downward trends in wages, employment and labor-force participation. While a growing literature documents the potential drivers of the decline in labor-force participation among prime-age men, few studies assess the contribution of non-wage compensation, including physical working conditions (Binder and Bound, 2019).

[25]The heterogeneity we document is based on the median zip code income. If a gradient in marginal impacts by individuals' income exists and is downward sloping, and there are low-income individuals living in high income zip codes, our estimates of the marginal effect of heat on on high income *individuals* may be biased upwards. Conversely, if there are high income individuals living in low income zip codes the estimated marginal effect on low income *individuals* will be biased downwards. Both of these biases imply that, were we able to estimate using individual rather than area income, the gradient across individuals would be steeper than the gradient we estimate here across areas.

Here, we exploit claims-level information on worker age and gender to assess potential variation in workplace safety risk arising from physical working conditions. We find that, in addition to experiencing more health risks on the job at baseline, prime-age men also appear to experience more elevated workplace safety risks due to environmental conditions such as temperature. The results of running equation 3 separately by age group are shown in Table 8, focusing on the coefficients for days above 90°F. Figure 11 shows the full range of temperature coefficients across the same-day temperature distribution for workers ages 30 and below compared to workers ages 60 and above. The marginal effect of a day above 90°F is 7.7 (se=1.4) percent and 7.2 (se=1.9) percent for workers in their 20's and 30's, compared to 4.8 (se=2.2) and a statistically insignificant 2.5 (se=2) for workers in their 50's and 60 and above respectively.

Similarly, Table 9 and Figure 12 show results of a similar analysis comparing male and female workers. Consistent with existing evidence, men tend to work in more dangerous occupations on average, with 40 percent more injury claims on average. The marginal effect of hotter temperature also appears to be larger for men. A day above 90°F increases injuries by approximately 3.6 (se=1.9) percent for female workers compared to 8.4 percent (se=1.9) for men. A Wald test suggests a statistically significant difference in coefficients (p=0.03).

5.4 Compensating Differentials

One possibility is that exposed workers receive hazard pay to compensate for increased safety risks due to hotter temperature. If such compensating differentials are large, they may offset the regressivity implied by the effect on injuries. Given data limitations, we eschew a formal estimation of compensating differentials in this analysis.

In the appendix, we outline a series of analyses that assess the potential for compensating differentials, using wage data for the United States by 2-digit industry and county from the QCEW (2001-2018). Exploiting variation in temperatures within counties over time, we find no evidence for compensating differentials within county-industries. That is, county-industry-years with more hot days (e.g. above 90°F) do not appear to exhibit higher wages per worker. If anything, hotter temperature appears to reduce quarterly wages and employment in many industries.[26] This is consistent with

[26] This of course does not rule out the possibility of compensating differentials at a more temporally granular level, or for specific occupations or sub-industries that exhibit high exposure. It is also possible that some of the cross-sectional variation in injuries over income groups described above masks heterogeneity in unobserved determinants of productivity that are consistent with some degree of compensating differentials. However, viewed in light of recent evidence, including Kim et al. (2020), who finds little evidence of compensating differentials for heat exposure in a sample of Korean workers, our results are consistent with the interpretation that exposure to extreme temperatures on the job may comprise another aspect of "bad jobs", in line with the Mortensen/Sorkin effect.

recent studies that find little evidence for compensating differentials for exposure to extreme temperature on the job in the cross-section (Kim and Lim, 2017), but at odds with Lavetti (2020), who finds in the context of deep-sea fishing that workers are paid compensating differentials for elevated mortality risk during stormier seasons.

5.5 Heterogeneity in Causal Effect of Temperature by Local Labor Market Concentration

To further investigate potential implications for labor market inequality, we assess whether labor market concentration affects the relationship between temperature and injuries. Previous literature finds evidence that more concentrated labor markets can lead to lower wages, and that low-skilled workers are more likely to work in more concentrated labor markets (Naidu et al., 2016; Azar et al., 2020; Schubert et al., 2020). All else equal, we might expect workers in more monopsonistic labor markets to tolerate greater workplace disamenities before terminating employment relationships and to have lower wages. To the extent that safety is a component of total compensation, this would imply that firms would provide less safety for a given wage ex ante, and 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. On the other hand, larger firms may be more likely to provide greater safety investments (for instance, given greater cash-on-hand), which would push in the opposite direction. Similarly, workers in more concentrated labor markets may feel less inclined to report workplace injuries given more limited outside options.

We assess heterogeneity in the main effect by level of labor market concentration, using measures of local labor market concentration from Azar et al. (2020), who provide HHI's by SOC-CZ in 2013 for a subset of occupations. We assign each injury claim in our data a dummy corresponding to the quantile of the national HHI distribution, and re-estimate equation 3 separately for each tercile of the HHI distribution, collapsing all days above 90°F for ease of exposition. Because HHI's are only available for a subset of occupations in Azar et al. (2020), and because valid occupation information is only available for a subset of injuries in our data, we are only able to assign HHI information to a subset of injury observations, resulting in substantially noisier estimates.

We fail to find evidence that workers in more concentrated labor markets experience elevated heat-related safety risks. As shown in Figure 10 and Table 7, while the point estimates on hotter temperature bins are larger in the upper tercile of concentrated labor markets, the differences are not statistically significant. The effect of a day above 90°F has a significant positive effect on injuries in the top tercile (β=0.063, se=0.019), whereas the effect is slightly smaller for the bottom tercile (β=0.056, se=0.016). A

Wald test comparing the bottom and top tercile coefficients results in a p-value of 0.39. Because our data suggests higher overall reported injury rates in less concentrated labor markets – 12.5 per 100 FTE in the bottom tercile vs 5.1 per 100 FTE in the top tercile – the implied overall injury burden associated with hotter temperature is actually smaller in more concentrated labor markets. We hesitate to draw strong conclusions from this relationship, as our measures of labor market concentration are not experimental and as such may be correlated with other unobserved worker or firm characteristics.

5.6 Implications for Labor Market Inequality

As noted above, the rate of workplace injuries varies considerably across income groups, as does average exposure. One way to characterize the net effect of heat on workers' wellbeing would be as the product of the baseline injury rate, the incremental effect of an additional hot day on injuries, and the number of hot days in a given worksite per year.[27] We have each of these pieces of information by quintile of the US residential income distribution. For parsimony, we define hot days as those with high temperatures of 90°F or above, and use the average number of days above 90°F at a work site.

By this method, we estimate that workers in the bottom quintile of the income distribution experience approximately 5 times as many additional injuries per year due to heat than those in the top quintile.[28] This suggests that heat-related workplace safety risks is distributed in a way that likely exacerbates headline wage inequality. It also implies that climate change may further widen total compensation inequality. By a similar calculation, men appear to be at least 3 times more affected by heat-related workplace safety risks compared to women, and that workers in their 20's and 30's are approximately 2 times more affected than those in their 50's and 60's.

6 Adaptation

We have shown that hotter temperature increases workplace safety risk net of potential endogenous labor input responses and firm and worker safety investments. The

[27]Heterogeneity in environmental damages is often modeled as a function of exposure – the amount of an environmental hazard individuals are exposed to – and a vector of characteristics that affect "vulnerability", which can be thought of as factors that may make a given exposure more costlier for some individuals to experience than others (Hsiang et al., 2018). Empirical estimates of heterogeneity in realized damages from hotter temperature today may, with important assumptions regarding adaptation, be used as an input to damage functions that estimate both the overall costs and distributional consequences of policies that aim to mitigate the carbon externality.

[28]The calculation is as follows: 5.2 injuries per 100 workers × 53.8 days above 90°F per year × 0.074 percent increase in injuries per day above 90°F = 20.7/365 additional injuries per 100 workers per year; compared to 2.23 injuries per 100 workers × 33.8 days above 90°F per year × 0.054 percent increase in daily injuries per day above 90°F =4.07/365 additional injuries per 100 workers per year.

implications of our findings for climate damages will depend in large part on whether firms and workers can adapt to changes in climate over the longer term.

6.1 Change in Temperature-Injury Relationship Over Time

6.1.1 Event Study

To the extent that changes in technology or cooling costs make temperature control at work more cost-effective, we might expect the temperature-sensitivity of injuries documented in section 4 to be falling over time. In addition, health and safety policies may mandate specific heat-related adaptation investments or protocols, motivated either by efficiency (e.g. information imperfections) or equity motivations. In the U.S., there are no Federal mandates with respect to temperature-related health and safety risks on the job. However, in 2005, California became the first and only state to implement a mandatory heat illness prevention standard which, among other things, required water, shade structures, and rest breaks (5 minutes per hour) for outdoor workplaces on days with temperatures above 95°F.[29] This motivates a specification that assesses heterogeneity in the causal impact of temperature on injuries across time periods.

We start with a version of equation 3 that includes an indicator variable for post-2005:

$$F(Inj_{icdmy}) = \Sigma_{k=1}^{K}\theta^k\Big[Temp_{icdmy} \times Post_{dmy}\Big] + \Sigma_{k=1}^{K}\beta^k Temp_{icdmy} + \Sigma_{p=1}^{P}\delta^p Precip_{icdmy} + Post_{dmy} \times \eta_{im} + \gamma_{cmy} + \epsilon_{icdmy} \quad (4)$$

As in equation 3, $F(Inj_{idmy})$ 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 γ_{cmy} denotes county × month × year fixed effects. In contrast to equation 3, 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 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 and calendar month.

Figure 14 plots the temperature coefficients (θ_1 - θ_K, $\beta_1 - \beta_K$) 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 10 presents each of the coefficients, their respective p-values, and the results from tests of significance in the differences between them

[29] Additional details regarding the policy are provided in Appendix C.

(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. A test for joint significance suggests that the temperature profile of injuries is reduced significantly in the post period.

To approximate the magnitude of the decline, we estimate the difference in implied annual injury burden due to heat in the period prior to and after 2005, using the same method as in section 4.4. We find that hotter temperature caused approximately 6100 injuries per year in the period 2001-2005, versus approximately 4250 injuries per year in the period 2006-2018, suggesting a significant decline of approximately 30 percent. At the same time, these estimates also illustrate the persistent impact of temperature on workplace safety, despite targeted policies.

6.1.2 Robustness

One interpretation may be that the combination of information provision and/or mandated safety investment led to a reduction in the heat-injury relationship. However, alternative interpretations are possible: for instance, that this represents a secular change in cooling technologies, or that 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 such that the reduction in the proportion of injuries reported is lower for those injuries that tend to occur on hotter days. While we cannot rule out these possibilities, several additional analyses suggest that the heat-injury relationship changed significantly and in a non-transitory way around 2005.

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 15 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 16 and 17 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 15, 16 and 17 suggest that there is a significant non-transitory reduction in the heat-sensitivity of injuries post-policy.

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. 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 7 of Appendix D, 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 8 of Appendix D, 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.

6.2 Limits to Adaptation

6.2.1 Heterogeneity in Change Over Time by Average Climate

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 3 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 18, 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. 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 in the presence of market imperfections such as information asymmetries (Rea, 1981).

7 Conclusion

Environmental conditions such as pollution or extreme temperature can impose large costs on workers and firms which may not be captured in headline wage statistics. Understanding the effects of temperature may be of particular welfare and policy relevance given the expected increases in temperature extremes due to climate change. Impacts of climate change on workplaces may be especially important given the broad base of prime-aged individuals whose occupations involve exposure to the elements, particularly for middle and low-skilled workers.

Our results indicate that workplace heat exposure constitutes an important workplace disamenity, particularly for lower income workers and prime-age men, and even for those working in ostensibly protected indoor environments. From a welfare standpoint, temperature's effects on workplace injuries are especially important for at least two reasons. First, workplace injuries not only have large direct health care costs, but lead to persistent wage impacts that affect injured workers' entire subsequent earnings trajectories. Broten et al. (2019) find that workers injured on the job face a subsequent earnings penalty of 8% on average, and 30% for permanent disability. Available estimates suggest that the average social cost of a workplace injury reported to worker's compensation is $35,000 in 2021 dollars (Leigh, 2011). This implies that the welfare impacts associated with heat-related workplace injuries may be on the order of $525 million to $875 million per year in California alone.

Second, the relationship between climatic variables and workplace safety carries important implications for policies aimed at correcting environmental externalities. To the extent that these injuries 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 and morbidity impacts of hotter temperature used to calculate the social cost of carbon (SCC) (Deschênes and Greenstone, 2011; Carleton et al., 2018). One immediate policy implication of these findings is that SCC estimates that do not incorporate temperature's effects on workplace safety may understate the magnitude of the carbon externality.

Moreover, our findings suggest that accounting for non-wage amenities such as workplace climate risk may widen total compensation inequality. The implied regressivity of heat-related welfare impacts within countries suggests that more aggregated estimates (e.g. (Nordhaus, 2017)) may mask important damage heterogeneity: particularly along lines of educational attainment, gender, and age. At the same time, our results also underscore the importance of adaptation. To the extent that firms and workers, particularly those most exposed, can effectively adjust work environments to account for added climate risk, the realized impacts may be smaller than our estimates suggest. On the other hand, if more exposed workers find it relatively costly to adapt, climate change may further exacerbate trends in labor market inequality.

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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.

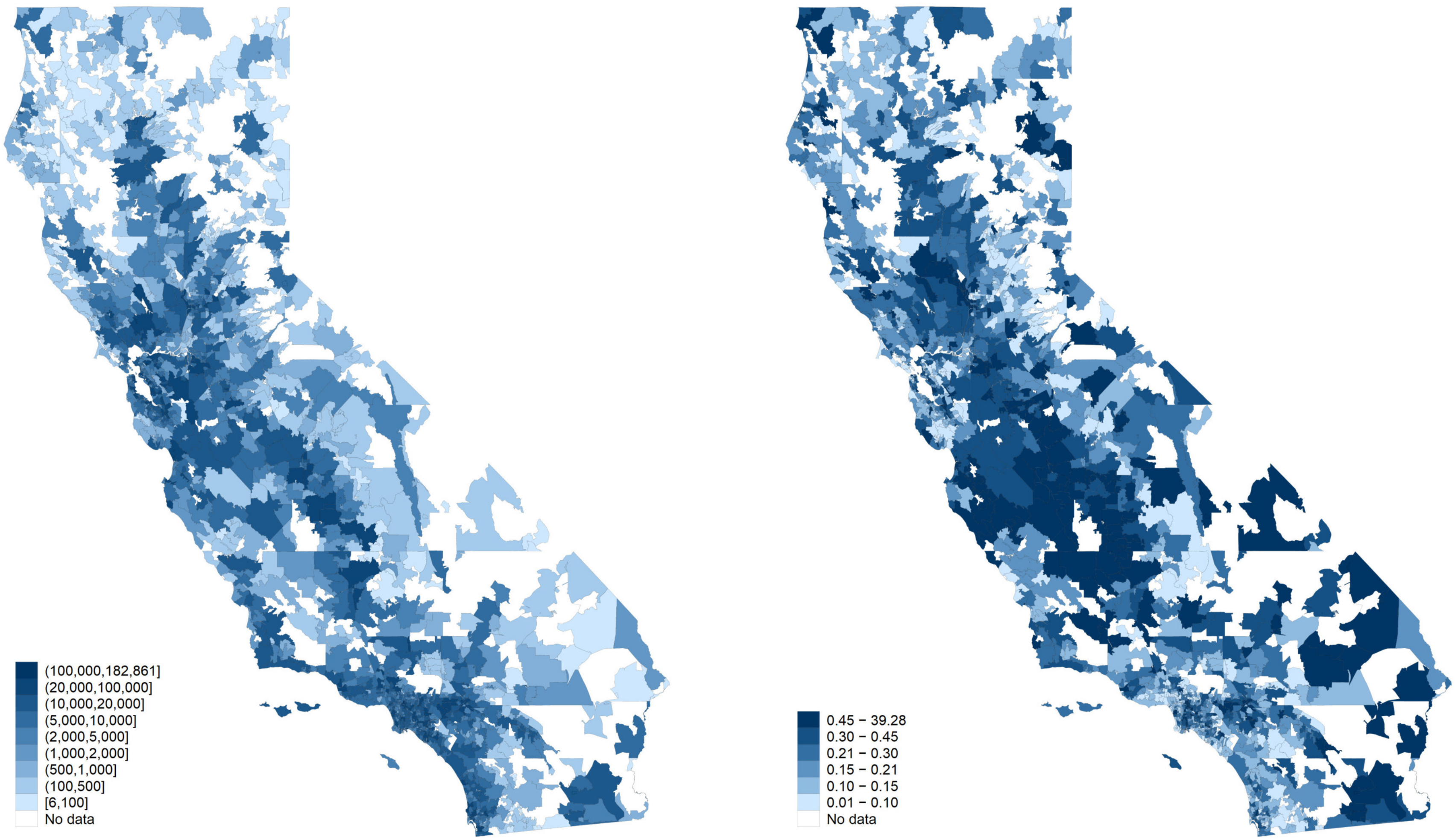
Panel A: Injuries

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: Temperature

Variable	Mean	Median	S.D.	25th	75th	Observations
% Days 60-65F (Omitted Bin)	0.123	0.000	0.302	0.000	0.000	11,596,536
% Days 80-85F	0.096	0.000	0.266	0.000	0.000	11,596,536
% Days 85-90F	0.078	0.000	0.241	0.000	0.000	11,596,536
% Days 90-95F	0.064	0.000	0.220	0.000	0.000	11,596,536
% Days 95-100F	0.043	0.000	0.184	0.000	0.000	11,596,536
% Days 100-105F	0.020	0.000	0.127	0.000	0.000	11,596,536
% Days Above 105F	0.008	0.000	0.083	0.000	0.000	11,596,536
Days/Year 60-65F (Omitted Bin)	45.093	40.000	19.918	32.000	52.676	11,596,536
Days/Year 80-85F	34.961	33.536	14.957	25.889	44.000	11,596,536
Days/Year 85-90F	28.464	29.385	14.314	18.500	38.389	11,596,536
Days/Year 90-95F	23.244	24.000	15.886	8.065	36.882	11,596,536
Days/Year 95-100F	15.618	11.500	14.776	2.000	26.600	11,596,536
Days/Year 100-105F	7.278	2.828	10.335	0.000	10.818	11,596,536
Days/Year Above 105F	2.950	0.000	10.167	0.000	2.000	11,596,536

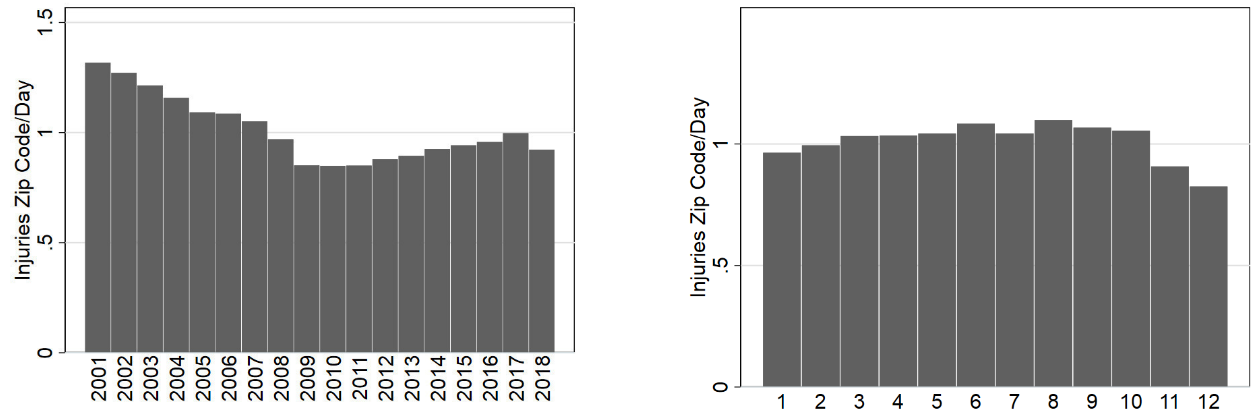
Figure 1: Workplace Injuries by Zip Code (2001-2018)



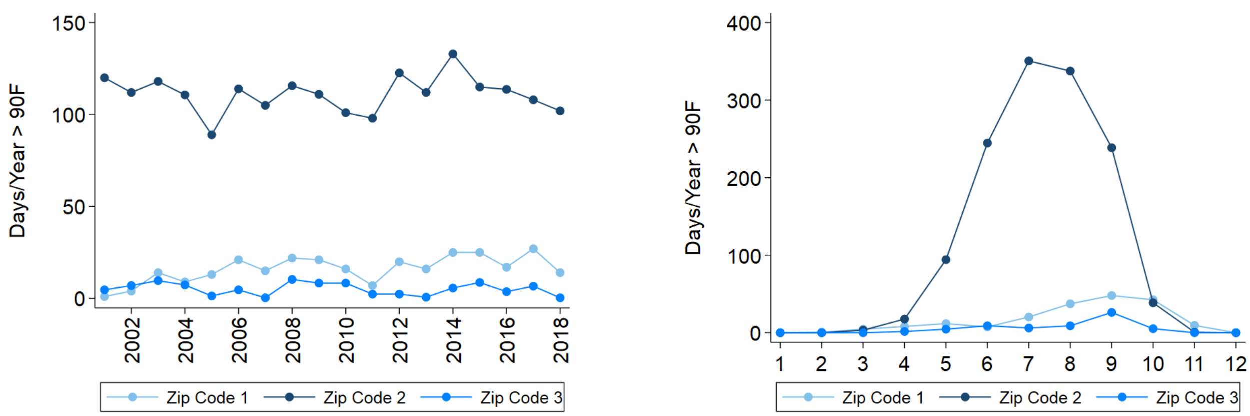
Notes: Figure 1 depicts the number of injury claims in the California Worker's Compensation system over the study period (2001-2018) by zip code, taking location information for the reported work-site of injury. The *left* panel presents raw counts per zip code; the panel on the *right* provides the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

Figure 2: Temporal Variation in Workplace Injuries and Temperature

Panel A: Injuries

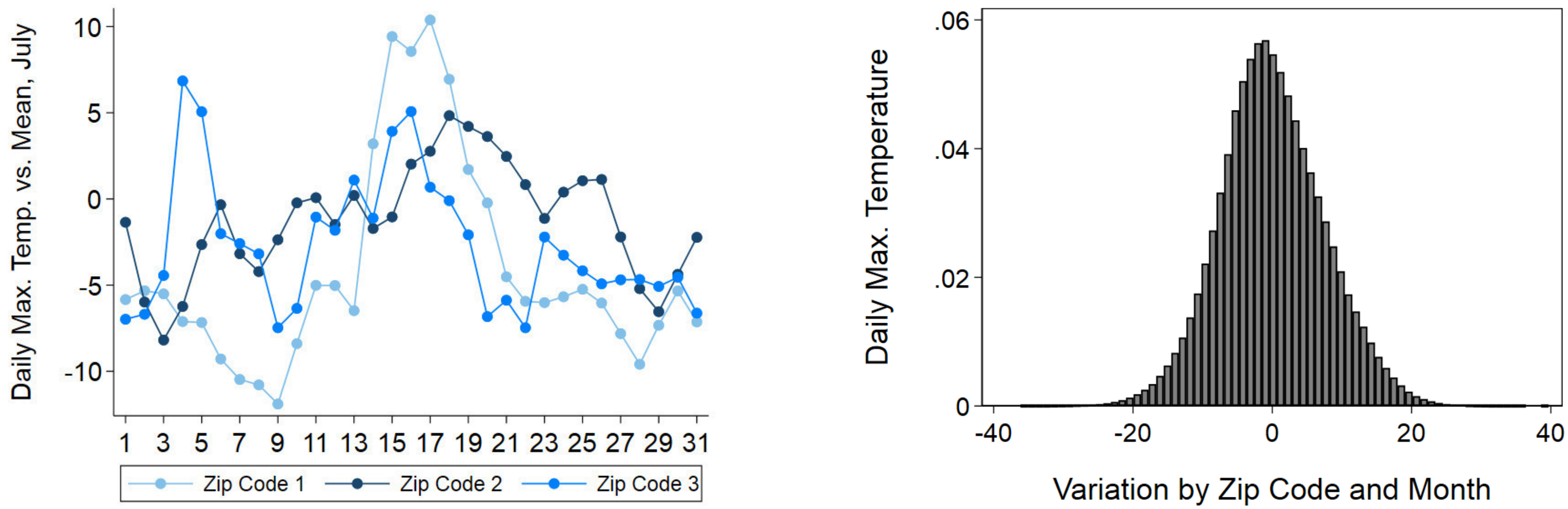


Panel B: Temperature



Notes: Figure 2 presents temporal variation in injuries and temperatures over the years in our sample (*left*), as well as seasonality across calendar months (*right*). The histograms in *Panel A* show counts of injuries occurring in California-based work sites during the period 2001-2018. *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 Temperature



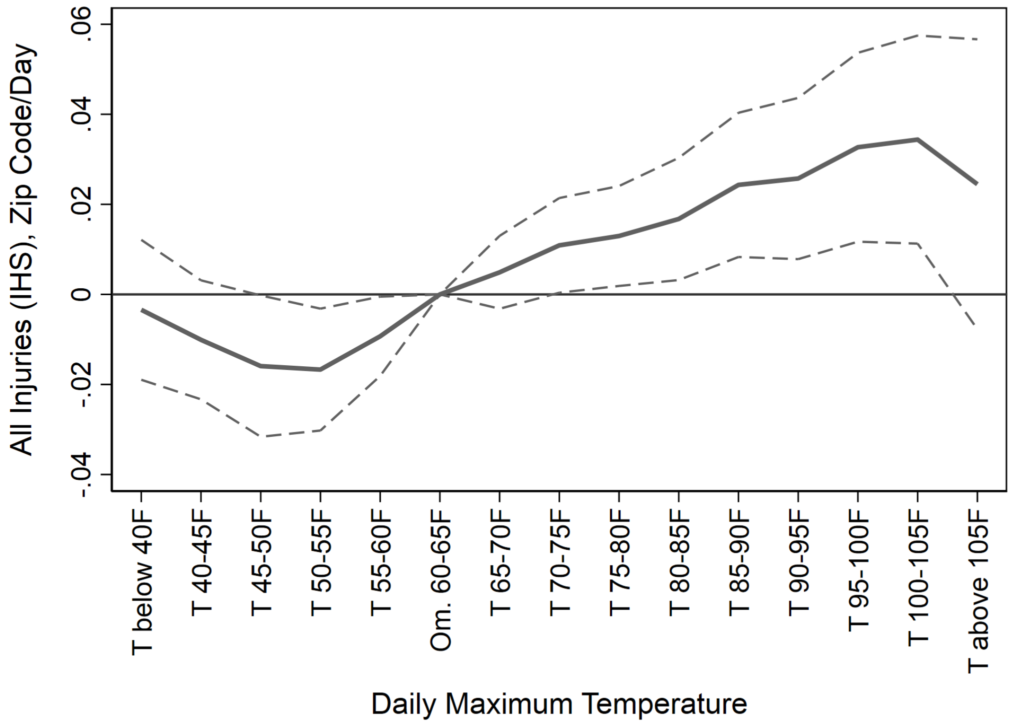
Notes: The *left* panel illustrates the identifying variation in daily maximum temperatures for three representative zip codes across days of the month in July, plotting deviations from zip-code-specific monthly means for zip codes in Los Angeles (*Zip Code 1*), Bakersfield (*Zip Code 2*), and San Francisco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



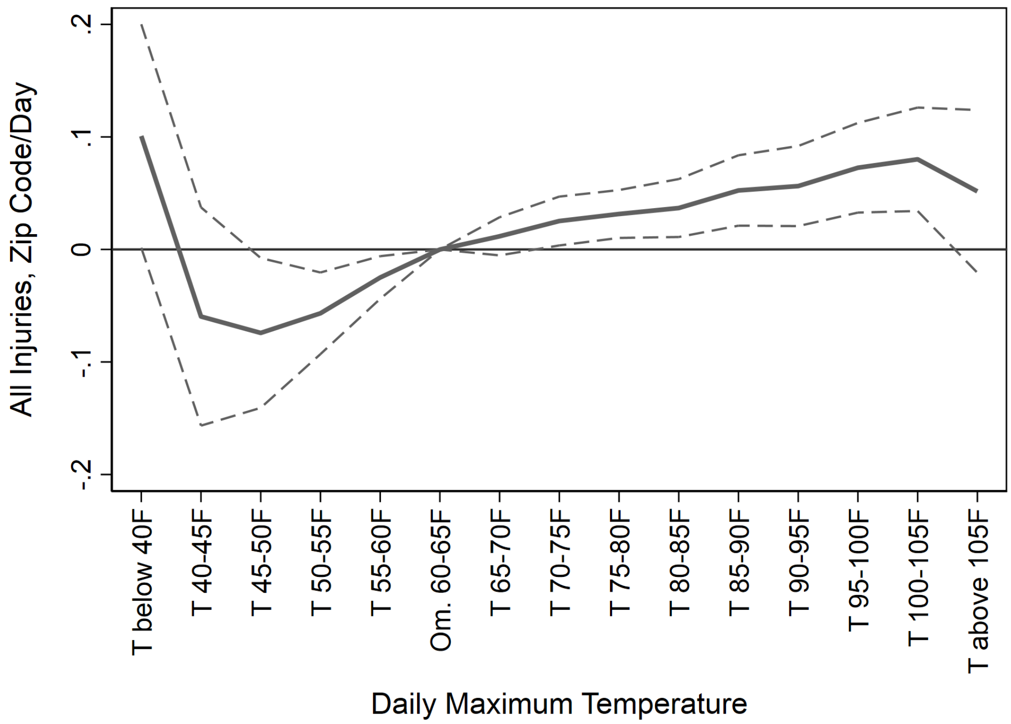
Notes: Figure 4 plots the full set of temperature coefficients obtained from regressions specified in equation 3 (point estimates from column 5 of Table 2). All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. 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 3 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).

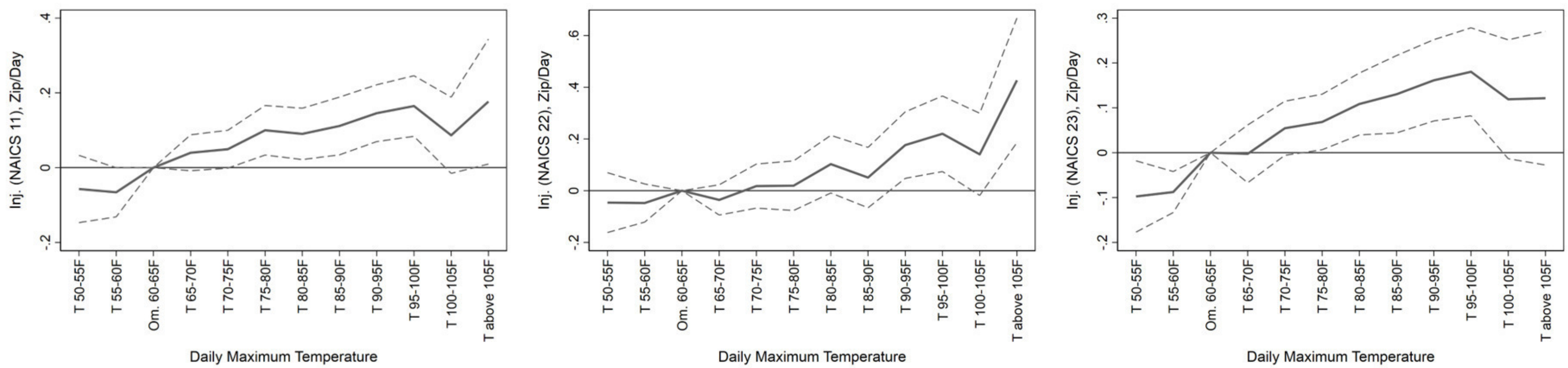
Figure 5: Temperature and Injuries – Primary Specification (Poisson)



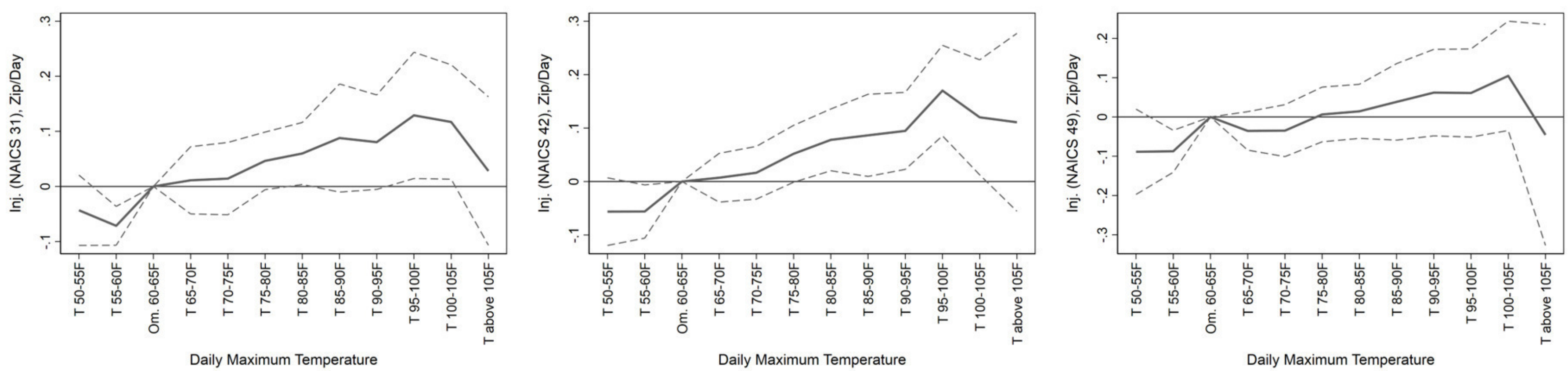
Notes: Figure 5 plots the full set of temperature coefficients obtained from regressions specified in equation 3 (point estimates from column 5 of Table 3). All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. 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. 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.

Figure 6: Temperature and Injuries by Industry: Indoor vs Outdoor Industries

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.

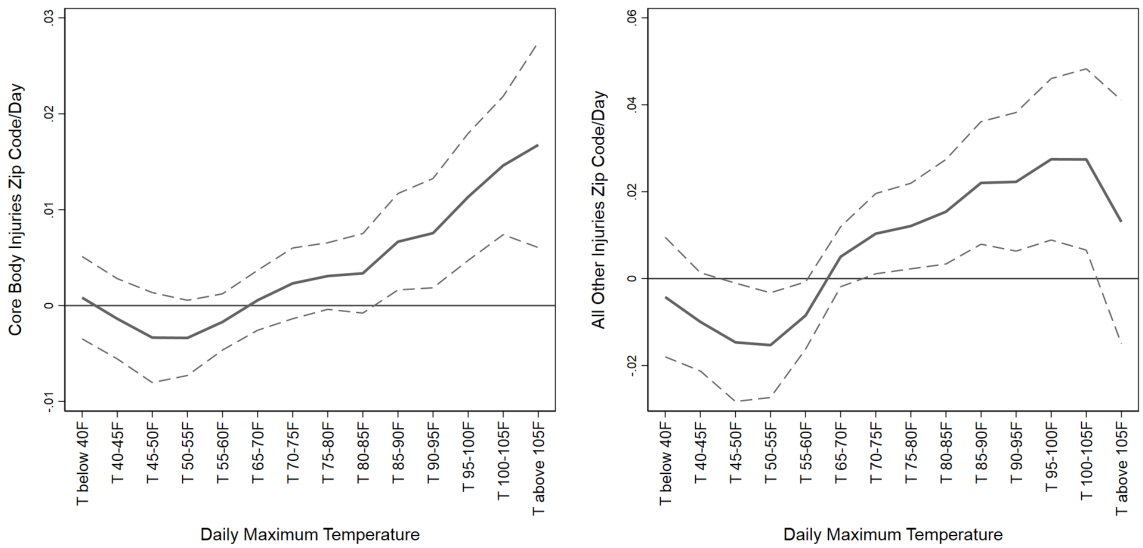
Table 4: Temperature and Injuries by Type: Heat-Illness vs All Other Injuries

	(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

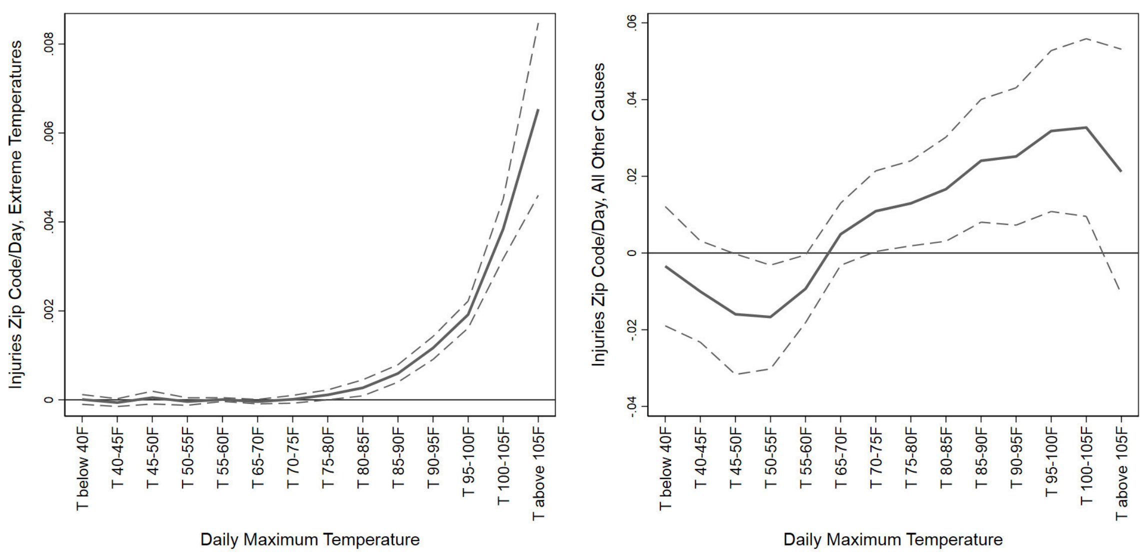
Notes: Table 4 shows the sensitivity of injury claims to temperature for different categories of injuries. All coefficients are obtained from regressions of inverse hyperbolic sine transformed injury counts per zip code and day as the dependent variable. They reflect residual variation in injuries after 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: Temperature and Injuries by Type: Heat-Illness vs All Other Injuries

Panel A: Official Classification

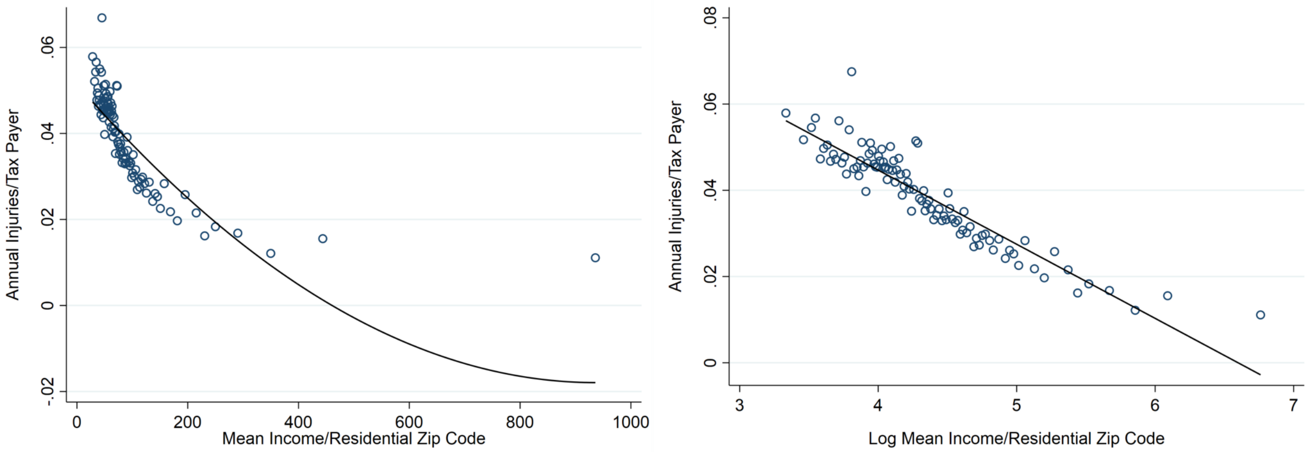


Panel B: Affected Body Parts

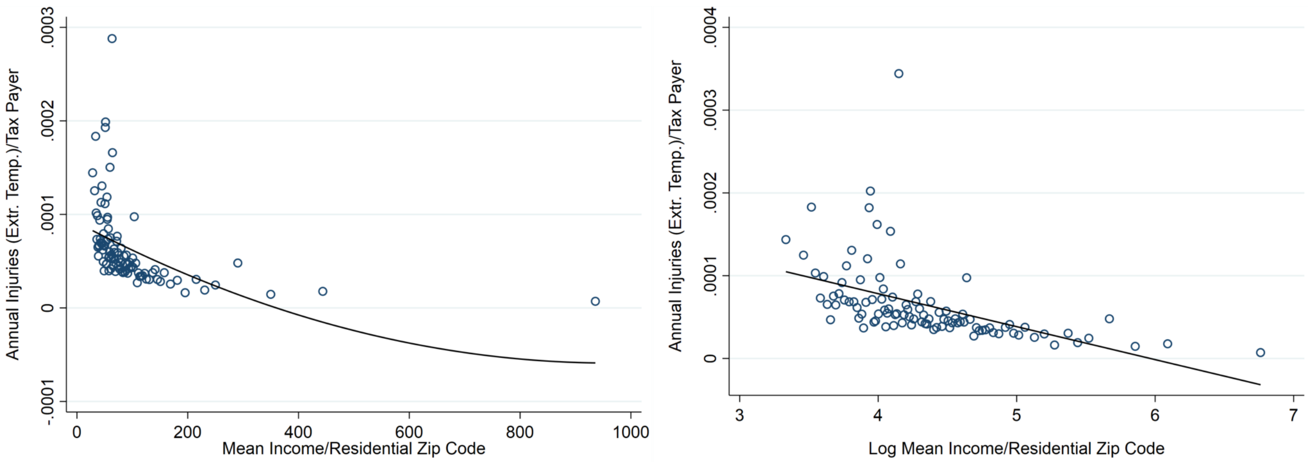


Notes: Figure 7 depicts the full set of temperature coefficients from the regressions presented in table 4. *Panel A* plots coefficients obtained from regressions of the counts of heat-related injuries according to the DWC injury classification as the dependent variable *(left)* and the counts of all 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 $\times$ month and county $\times$ year $\times$ 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: Inequality in Workplace Safety Risk



(a) All Injuries



(b) Injuries Related to Extreme Temperatures

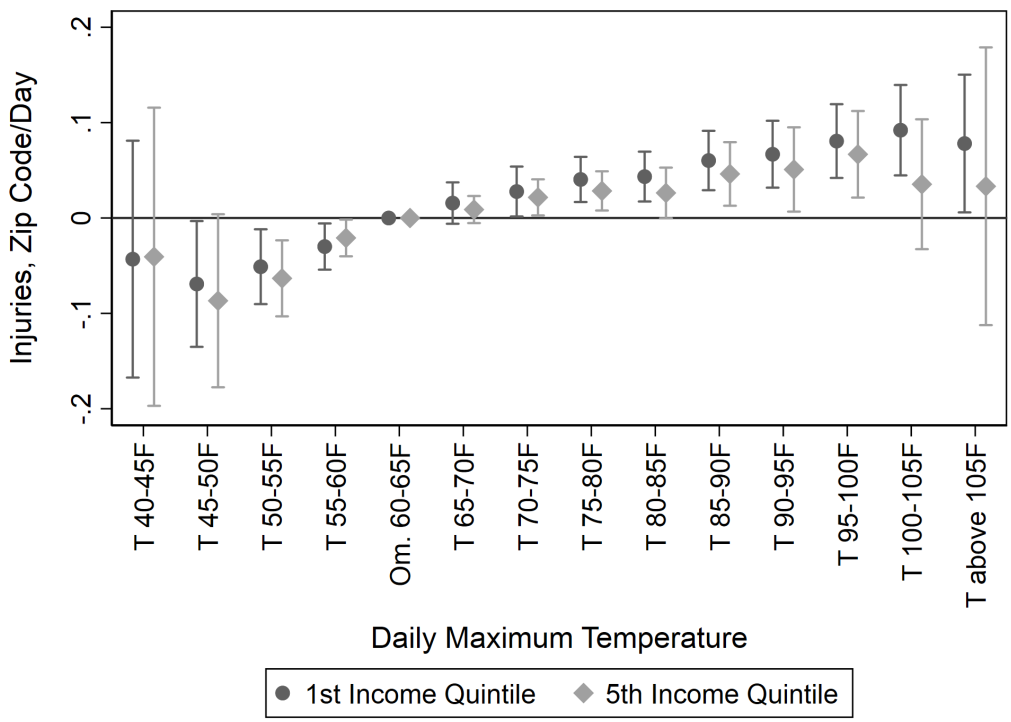
Notes: Figure 8 presents binned scatterplots of average injury rates (injuries per taxpayer) and mean residential income by zip code for the 11.1 million workers compensation claims in our data (2001-2018), by percentile of the residential income distribution in California in the year 2018. Injuries are linked to zip code-level average incomes using claims-level information on the worker's zip code of residence and IRS Individual Income Tax Statistics aggregates by zip code. Injury rates are calculated using information from the IRS on the number of tax filers per zip code.

Table 5: Inequality in Temperature-Related Workplace Safety Risks

	(1) Income Q1	(2) Income Q2	(3) Income Q3	(4) Income Q4	(5) Income Q5
Income Range per Quintile	0-48k	48-61k	61-80k	80-114k	>114k
Mean Injuries per Year and Residential Zip Code	10,779.27	9,198.94	8,201.93	7,161.66	4,623.45
Mean Injuries per 100 Taxpayers	5.02	4.66	4.16	3.26	2.23
Median Taxpayers per Residential Zip Code	10,820.00	8,925.00	10,130.00	13,005.00	11,460.00
Average Temperature Residental Zip Code	75.23	73.11	72.89	72.97	71.48
Average Number of Days > 90F Residential Zip Code	70.01	59.15	52.73	41.40	26.22
Average Temperature at Work Sites	73.51	72.56	72.41	72.39	71.58
Average Number of Days > 90F at Work Sites	53.82	49.73	46.48	41.66	33.84

Notes: Table 5 presents measures of baseline workplace safety risk (injuries per year, injuries per 100 taxpayers), average residential temperature exposure, and average workplace temperature exposure, for the 11.1 million workers compensation claims in our data (2001-2018) by quintile of the residential income distribution in California (2018). Injuries are linked to zip code-level average incomes using claims-level information on the worker's zip code of residence and IRS Individual Income Tax Statistics aggregates by zip code. Injury rates are calculated using information from the IRS on the number of tax filers per zip code. Residential and work site temperatures are calculated using claims-level information on the zip code of worker's residence and the site of injury.

Figure 9: Temperature and Injuries by Income Quintile



Notes: Figure 9 plots the temperature-injury relationship for the top and bottom quintiles of the income distribution in California (2018). Each of the coefficients and their respective 95 percent confidence intervals are obtained from separate Poisson regressions of injuries on daily temperatures as per equation 3, by residential income quintile. For a given zip-code day, we measure the number of injuries in a given residential income quintile that occur at a work site in that zip code. Here, we depict coefficients from regressions that include only injuries in the top and bottom income quintiles. The coefficients represent the change in injury risk relative to a day with maximum temperature in the 60 to 65 degree F range. They reflect residual variation in injuries after regressing on zip code $\times$ month and county $\times$ year $\times$ month fixed effects, as well as controls for precipitation. Heteroskedasticity robust standard errors are clustered two-way by county and year-month.

Table 6: Temperature and Injuries by Income

	(1) Income Q1	(2) Income Q2	(3) Income Q3	(4) Income Q4	(5) Income Q5
T>90F	0.0735***	0.0679***	0.0593***	0.0503**	0.0541***
	(0.0183)	(0.0194)	(0.0185)	(0.0201)	(0.0210)
N	10,092,901.00	10,884,465.00	10,674,396.00	9,745,025.00	8,312,092.00
Mean Injuries per Zip Code-Day	0.26	0.22	0.20	0.17	0.11
Income Range	0-48k	48-61k	61-80k	80-114k	>114k
Z-Test: Quintile 5 vs 1 (p-Value)					(0.24)
Zipcode × Month FE	Yes	Yes	Yes	Yes	Yes
County × Month × Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes

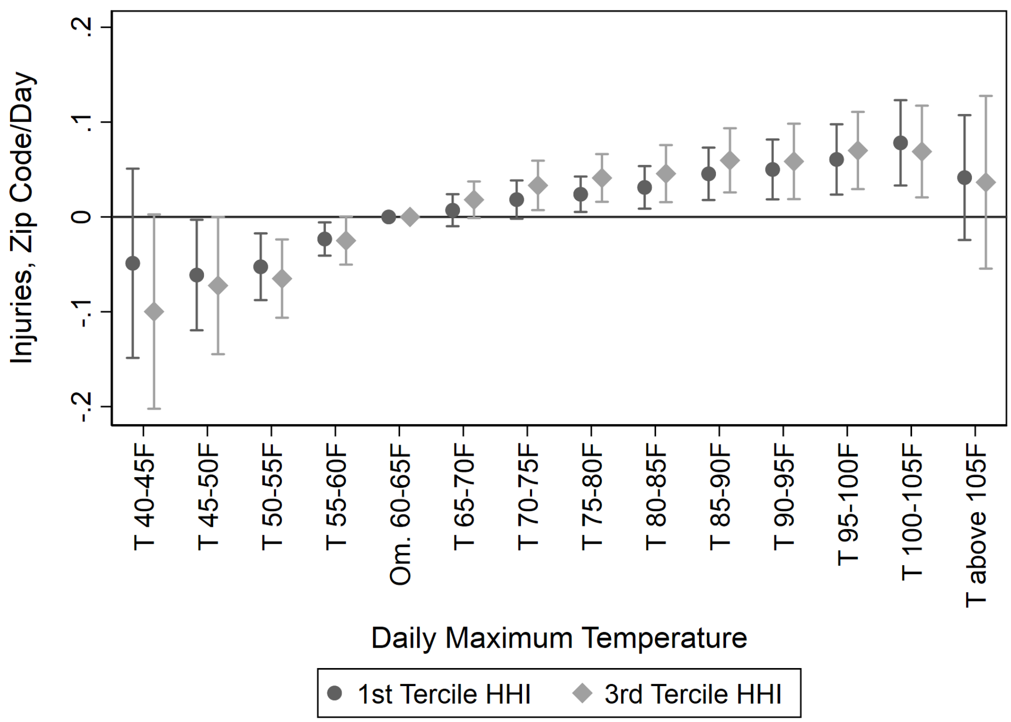
Notes: Table 6 presents results from running separate Poisson regressions of injuries on daily temperatures as per equation 3, by residential income quintile. For a given zip-code day, we measure the number of injuries in a given residential income quintile that occur at a work site in that zip code. The coefficients represent the change in injury risk relative to a day with maximum temperature in the 60 to 65 degree F range. 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 11 temperature bins, ranging from 40°F and below to temperatures greater than 90°F in 5° increments. Temperature bins below 90°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 clustered by county and year-month are noted in parentheses (* p<.10 **p<.05 ***p<.01).

Table 7: Temperature and Injuries by Labor Market Concentration (HHI)

	(1) HHI Tercile 1	(2) HHI Tercile 2	(3) HHI Tercile 3
T>90F	0.0556***	0.0624***	0.0626***
	(0.0164)	(0.0201)	(0.0196)
N	10,907,307.00	10,870,817.00	10,351,309.00
Injuries per Zip Code-Day	0.38	0.19	0.11
Z-Test: Tercile 3 vs 1 (p-Value)			(0.39)
Zipcode $\times$ Month FE	Yes	Yes	Yes
County $\times$ Month $\times$ Year FE	Yes	Yes	Yes
Temperature Bins	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes

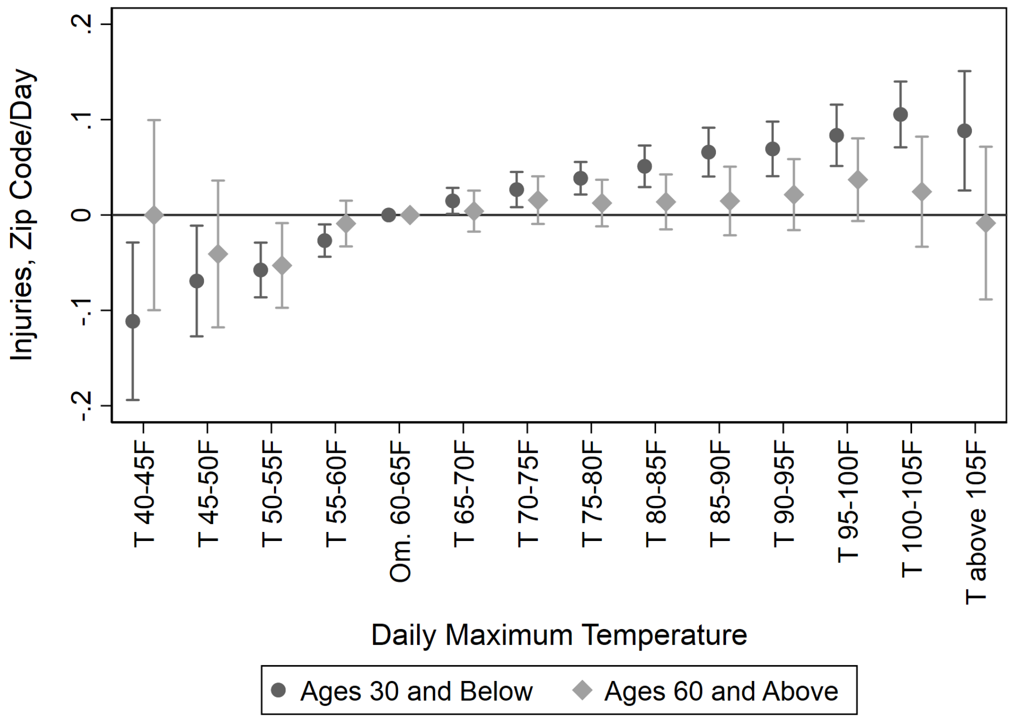
Notes: Table 7 shows the sensitivity of injury claims to temperature by local labor market concentration, using information on occupation-CZ-level Herfindahl-Hirschman Indices (HHI) from Azar et al. (2020). The coefficients are obtained from separate Poisson regressions of injuries on daily temperatures as per equation 3 by tercile of the U.S. HHI distribution in 2016. Daily maximum temperatures are assigned to a vector of 11 temperature bins, ranging from 40°F and below to temperatures greater than 90°F in 5° increments. Temperature bins below 90°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 clustered by county and year-month are noted in parentheses (* p<.10 **p<.05 ***p<.01).

Figure 10: Temperature and Injuries by Labor Market Concentration (HHI)



Notes: Figure 10 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). The light grey bars indicate injuries in occupation-CZs with HHI's in the top tercile; the dark grey bars indicate in the bottom tercile. The coefficients are obtained from separate Poisson regressions of injuries on daily temperatures as per equation 3 by tercile of the U.S. HHI distribution in 2016. 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. 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 11: Temperature and Injuries by Age Group



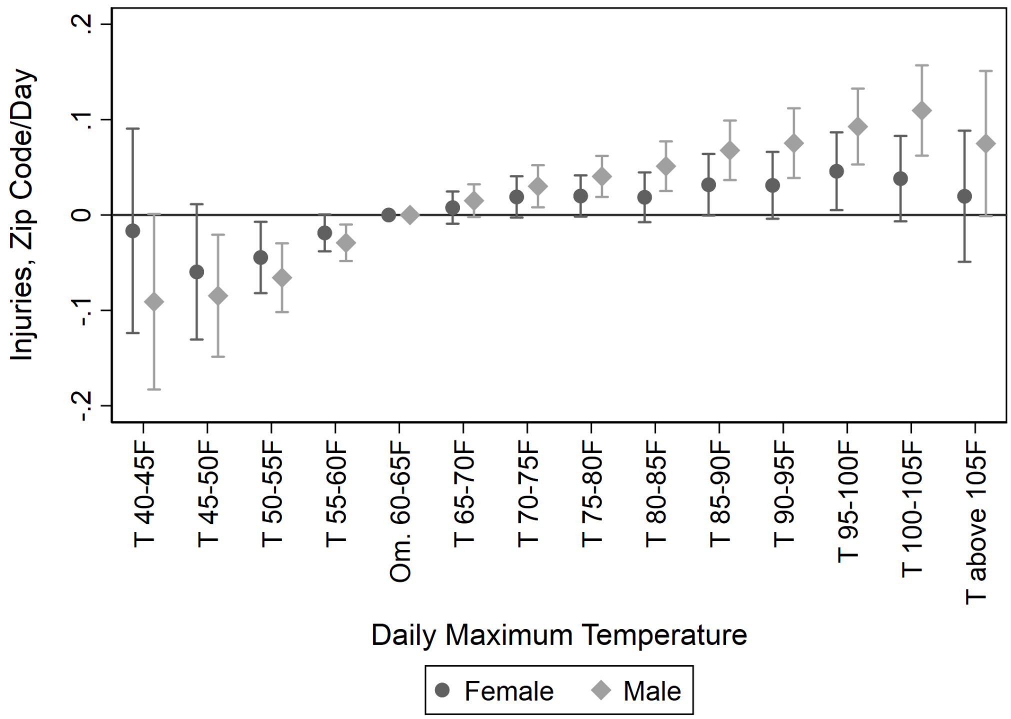
Notes: Figure 11 plots the temperature-injury relationship for individuals in different age groups, comparing coefficients for workers 30 and below at the time of injury versus workers 60 and above. The coefficients are obtained from separate Poisson regressions of injuries on daily temperatures as per equation 3, across five different age categories: below 30, 30-39, 40-49, 50-59, and 60 and above. The coefficients represent the change in injury risk relative to a day with maximum temperature in the 60 to 65 degree F range. 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 90°F in 5° increments. Temperature bins below 90°F are suppressed in this table, but included as controls in all estimations. Heteroskedasticity robust standard errors clustered by county and year-month are noted in parentheses (* p<.10 **p<.05 ***p<.01).

Table 8: Temperature and Injuries by Age Group

	(1) Age Group 1	(2) Age Group 2	(3) Age Group 3	(4) Age Group 4	(5) Age Group 5
T>90F	0.0773***	0.0714***	0.0648***	0.0484**	0.0257
	(0.0145)	(0.0190)	(0.0206)	(0.0222)	(0.0198)
N	10,981,505.00	10,973,195.00	11,018,762.00	10,921,494.00	10,189,362.00
Mean Injuries per Zip Code-Day	0.26	0.24	0.24	0.20	0.08
Age Range	<30	30-39	40-49	50-59	>=60
Z-Test: Group 5 vs 1 (p-Value)					(0.02)**
Zipcode × Month FE	Yes	Yes	Yes	Yes	Yes
County × Month × Year FE	Yes	Yes	Yes	Yes	Yes
Temperature Bins	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes

Notes: Table 8 shows the sensitivity of injury claims to temperature by age groups. The age range in each of the groups is indicated by column. The coefficients are obtained from separate Poisson regressions of injuries on daily temperatures as per equation 3, across five different age categories: below 30, 30-39, 40-49, 50-59, and 60 and above. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 90°F in 5° increments. Temperature bins below 90°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 clustered by county and year-month are noted in parentheses (* p<.10 **p<.05 ***p<.01).

Figure 12: Temperature and Injuries by Gender



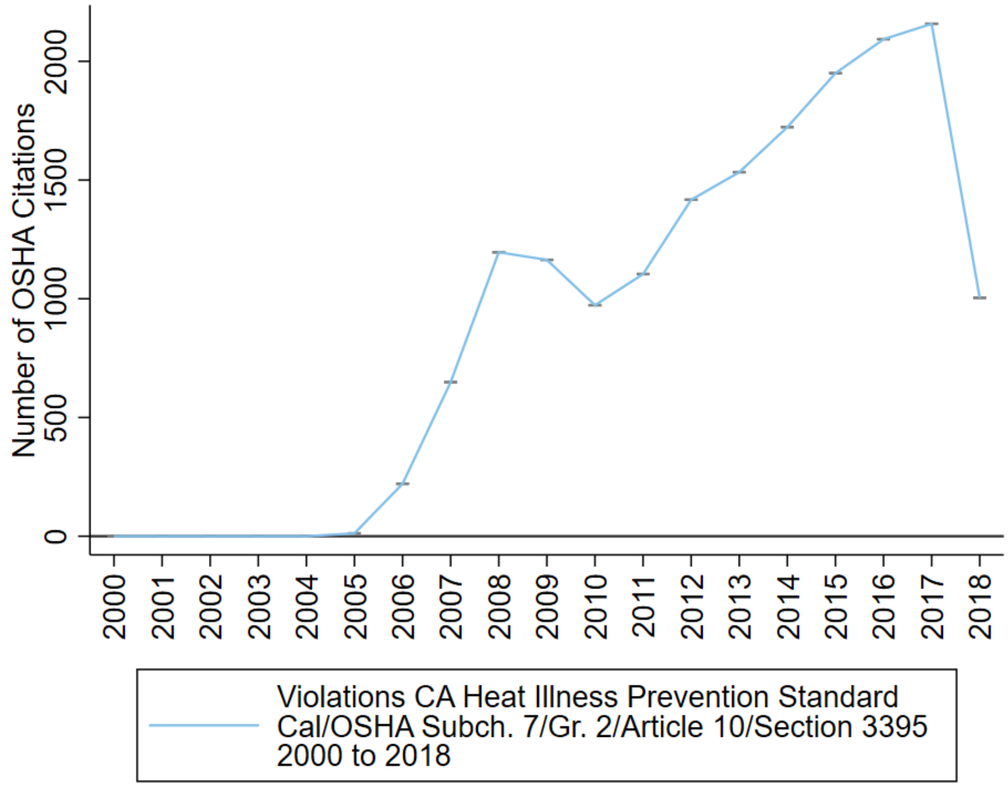
Notes: Figure 12 plots the temperature-injury relationship for male and female workers separately. The coefficients are obtained from separate Poisson regressions of injuries on daily temperatures as per equation 3 by gender. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 90°F in 5° increments. Temperature bins below 90°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 clustered by county and year-month are noted in parentheses (* p<.10 **p<.05 ***p<.01).

Table 9: Temperature and Injuries by Gender

	(1) Female Worker	(2) Male Worker
T>90F	0.0359*	0.0837***
	(0.0186)	(0.0188)
N	11,000,847.00	11,441,381.00
Mean Injuries by Zip Code-Day	0.42	0.58
Z-Test: Male vs Female (p-Value)		(0.04)**
Zipcode × Month FE	Yes	Yes
County × Month × Year FE	Yes	Yes
Temperature Bins	Yes	Yes
Precipitation	Yes	Yes

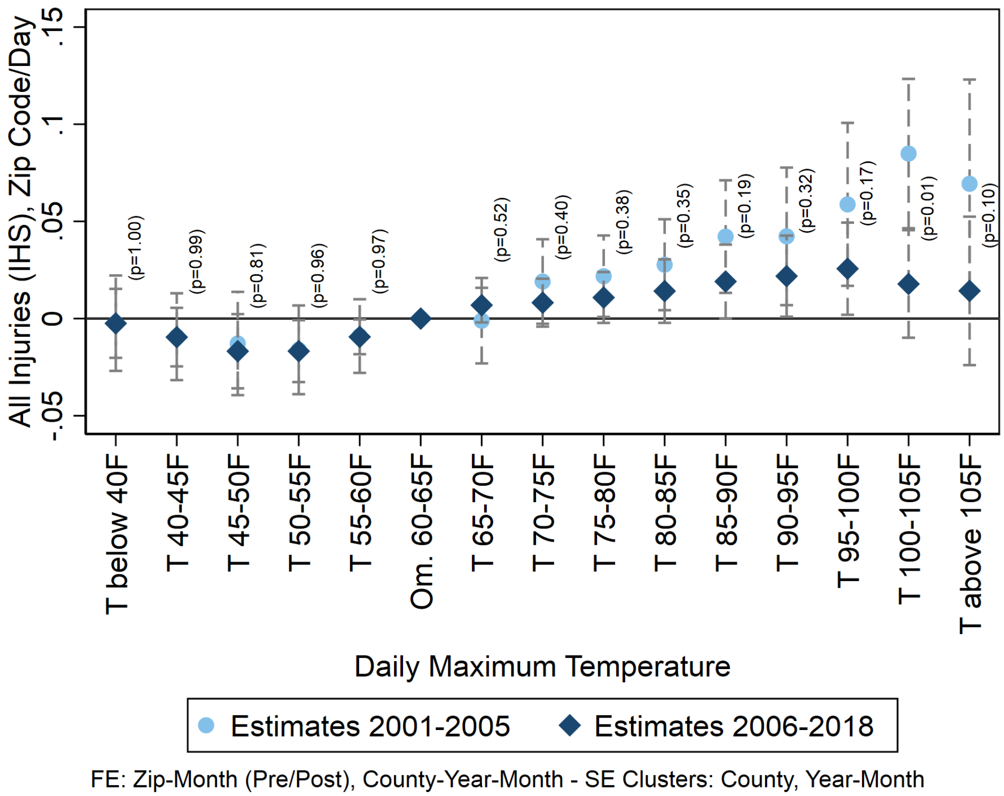
Notes: Table 9 shows the sensitivity of injury claims to temperature by gender. The coefficients are obtained from separate Poisson regressions of injuries on daily temperatures as per equation 3 by gender. Daily maximum temperatures are assigned to a vector of 15 temperature bins, ranging from 40°F and below to temperatures greater than 90°F in 5° increments. Temperature bins below 90°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 clustered by county and year-month are noted in parentheses (* p<.10 **p<.05 ***p<.01).

Figure 13: Cal-OSHA Citations for Workplace Heat Standard Over Time



Notes: Figure 13 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 14: Temperatures and Injuries Over Time: Pre- vs Post-Policy



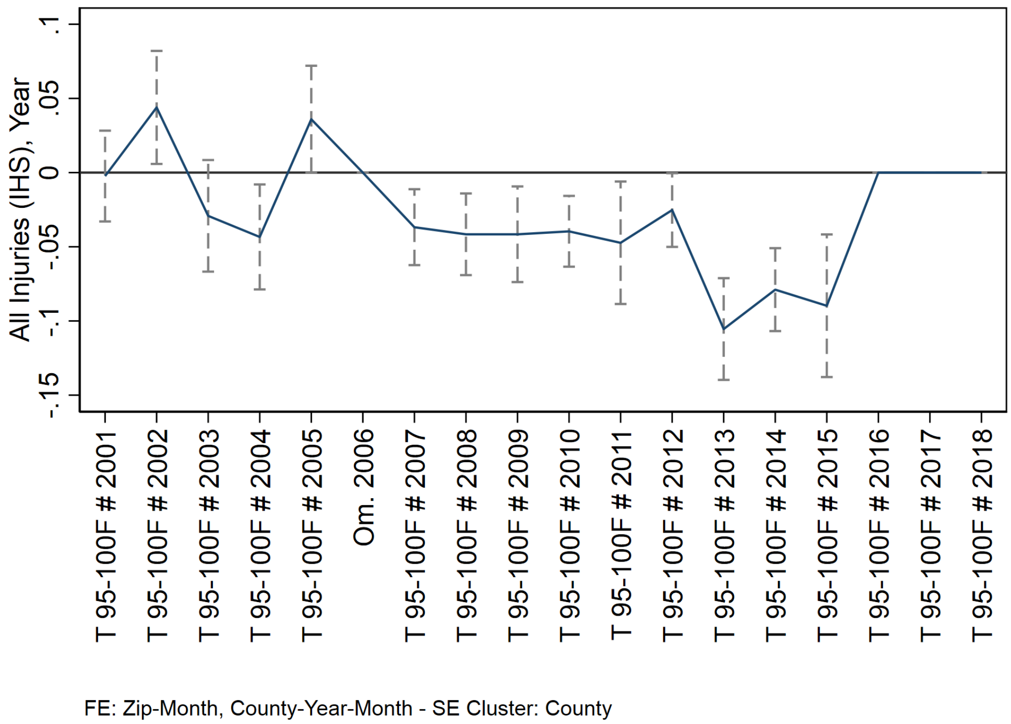
Notes: Figure 14 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 3) 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 10: Temperatures and Injuries Over Time: Pre- vs Post-Policy

	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)

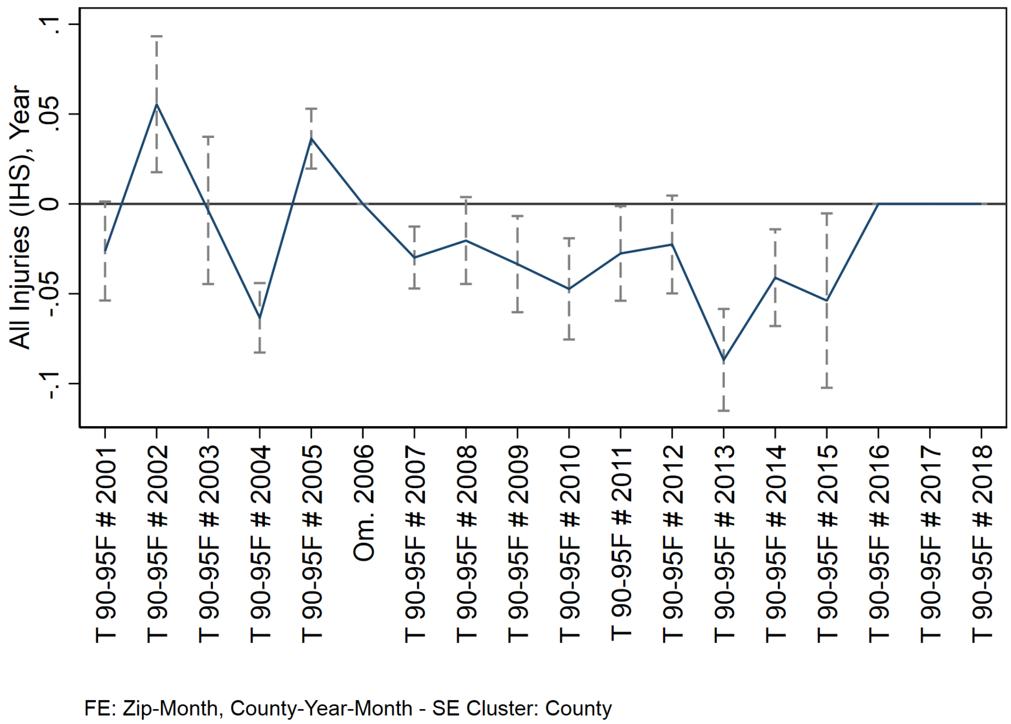
Notes: Table 10 provides point estimates and standard errors from estimating the effect of temperature on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). Coefficients *(b)* and p-values *(p)* are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 3) 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 15: Change in Heat-Sensitivity of Injury Over Time



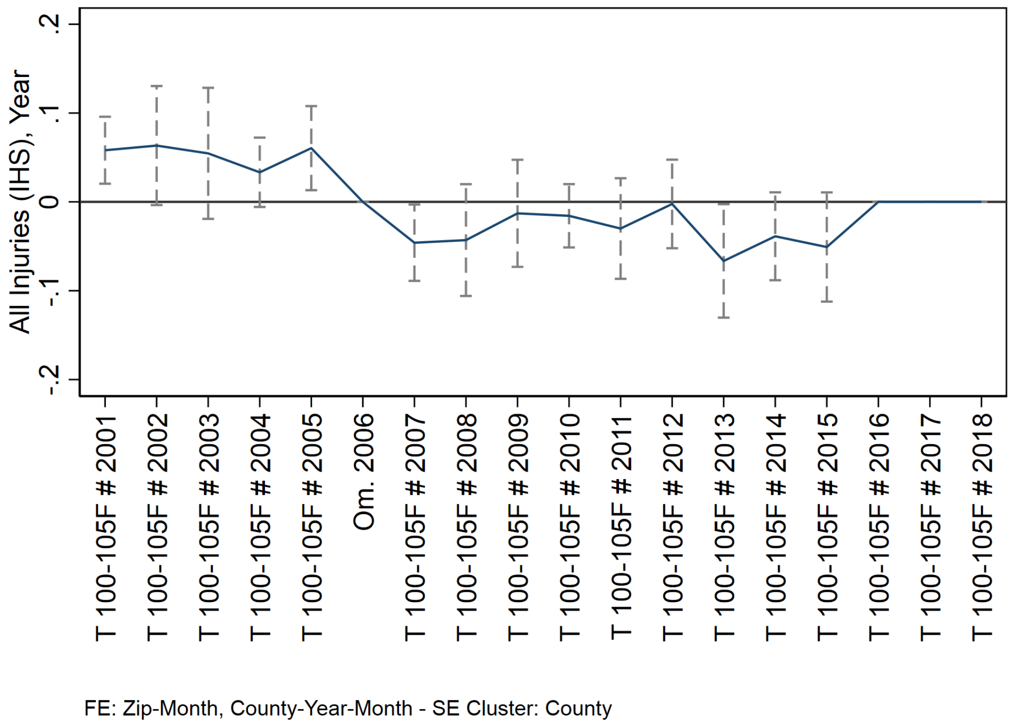
Notes: Figure 15 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 3) 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 16: Change in Heat-Sensitivity of Injury Over Time



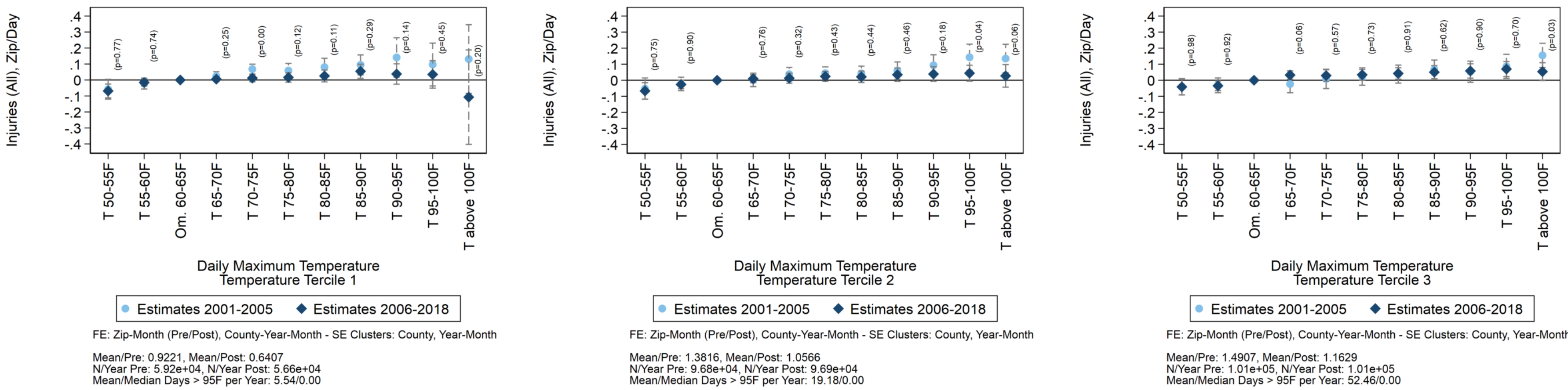
Notes: Figure 16 shows the effect of temperatures on workplace injuries before and after the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395). The plotted coefficients are obtained from a regression of inverse hyperbolic sine transformed injury counts per zip code and day (as specified in 3) 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 17: Change in Heat-Sensitivity of Injury Over Time



Notes: Figure 17 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 3) 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 18: Change in Heat-Sensitivity of Injury Over Time – By Climate Tercile



Notes: Figure 18 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 3) 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.

FOR ONLINE PUBLICATION: APPENDIX TO TEMPERATURE, WORKPLACE SAFETY, AND LABOR MARKET INEQUALITY

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1 Appendix A: Theory and Data Notes

Model of Equalizing Differences in Workplace Safety

Here, we build upon the seminal equalizing differences model of **?** 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.[1] 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.[2]

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 $C = w(R)$.[3] 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 decisions, assuming that workers have the option to switch firms if they aren't being paid the market-clearing compensating differential.[4]

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:

[1] 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.

[2] 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.

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

[4] 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 **??**.

$$c_s = -w_R R_S L \tag{1}$$

$$pf_L(L) = w(R(T,S)) \tag{2}$$

$$w_R = -\frac{\frac{\partial U}{\partial R}}{U_C} \tag{3}$$

Together, these conditions define firms' optimal labor inputs and level of safety investment given workers' preferences, product and input prices, and production parameters. Equation 1 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.[5] Equation 2 shows that perfectly competitive firms will pay workers their marginal revenue product. Equation 3 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).[6] 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:

$$\frac{dL^*}{dT} = \frac{C_S R_{ST}}{W_R R_S^2} \tag{4}$$

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 $\frac{dL^*}{dT} < 0$.

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

$$\frac{dR^*}{dT} = \frac{pf_{LL}\frac{dL^*}{dT}}{W_R} \tag{5}$$

Since p 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

[5] 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.

[6] 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 **?**, 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.

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:

$$\frac{dS^*}{dT} = \frac{\frac{pf_{LL}\frac{dL^*}{dT}}{W_R} - \frac{\partial R}{\partial T}}{\frac{\partial R}{\partial S}} \tag{6}$$

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 ($\frac{dS^*}{dT} > 0$) and/or reducing labor demand ($\frac{dL^*}{dT} < 0$), at least when a set of reasonable conditions are met.

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).[7] 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 **?**), and that the effort levels of surveyors is also temperature-dependent (**?**). In this case, our estimates would likely under-state 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.

[7] 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.

2 Appendix B: Empirical Strategy

Accounting for Potential Labor Input Responses

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:[8]

$$Injuries = Risk \times WorkerHours = R(T) \times L(T) \tag{7}$$

Any observed temperature-injury relationship can therefore be decomposed into a combination of $\frac{dR}{dT}$ and $\frac{dL}{dT}$:[9]

$$\frac{dINJ}{dT} = \frac{dR}{dT}L(T) + \frac{dL}{dT}R(T) \tag{8}$$

Prior evidence suggests that environmental externalities including air pollution (**?**) and hot temperature (**?**) may reduce same-day labor 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 $\frac{dL}{dT} > 0$.

Employment

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

$$ln(Emp_{ijqy}) = \Sigma_{k=1}^{K}\beta^k Temp_{iqy} + \delta Precip_{iqy} + \eta_q + \gamma_{ij} + \theta_{jy} + \epsilon_{ijqy} \tag{9}$$

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

Hours Worked

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.[10]

[8] 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 **?**, who studies deep-sea fisherman by voyage.

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

[10] 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.

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

$$IHS(Hrs)_{iswy} = \Sigma_{k=1}^{K} \beta^k Temp_{iswy} + Precip_{iswy} + \eta_{im} + \gamma_{sy} + \epsilon_{iswy} \tag{10}$$

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. γ_{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.

Additional Results

We 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.[11] 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 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.

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

3 Appendix C: Details of California Workplace Heat Safety Mandate

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.[12]

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:[13]

"*Employers must train all employees, both supervisory and non-supervisory, on the risk 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 1 shows the frequency of the subset of Cal-OSHA inspections that resulted in a violation of the HIP standard between 2006 and 2017. Figure **??** 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.[14] Inspection data from OSHA suggests that there have been over 18,000 recorded violations of the standard since 2006.

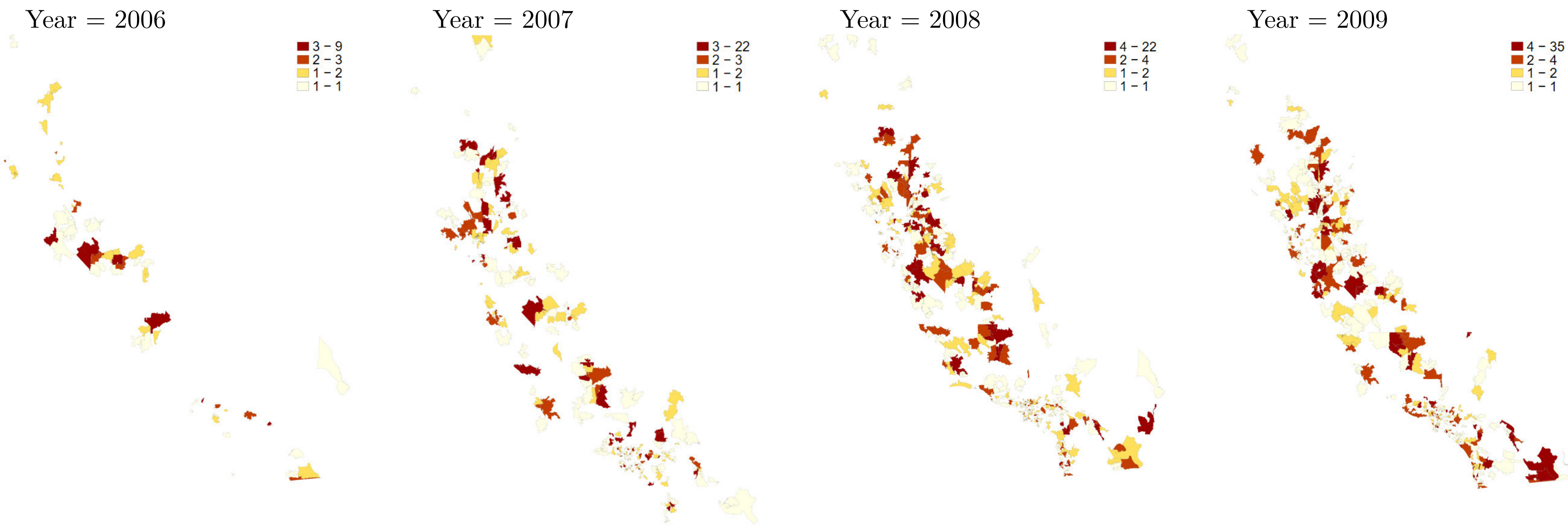
[12]In California, an emergency measure can be filed in "a situation that calls for immediate action to avoid serious harm to the public peace, health, safety, or general welfare." As soon as it is filed, it is effective for 180 days and can be readopted for two 90-day periods. HIP was implemented as 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.

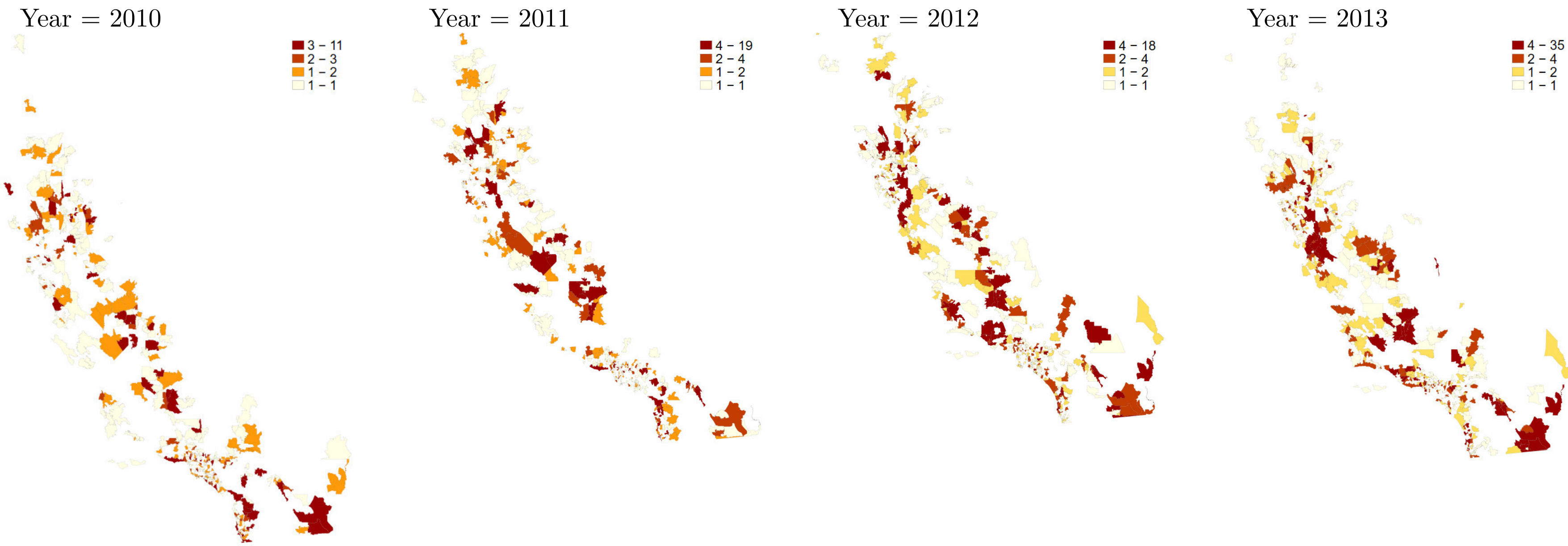
[13]Full text available at: https://www.dir.ca.gov/dosh/heatillnessqa.html. For information on specific informational interventions, see: https://www.dir.ca.gov/dOSH/HeatIllnessCampaign/Heat-Illness-Campaign.Evaluation-Report.Summer-2012.pdf

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

Figure 1: Enforcement of Workplace Safety Mandate: Cal-OSHA Citations

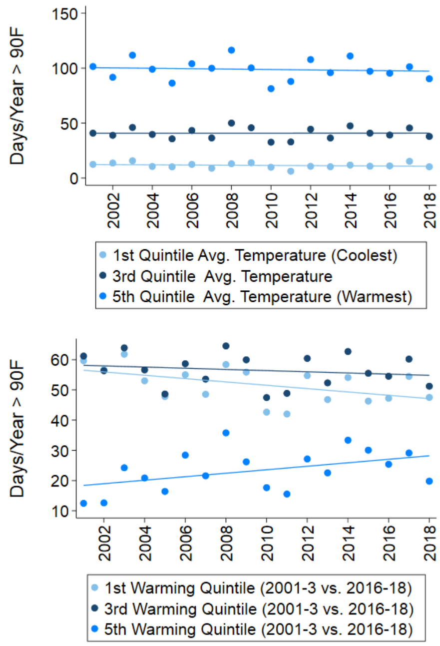
Notes: Figure 1 maps a total of approx. 18,000 violations of the heat illness prevention standards (HIP, Cal-OSHA subchapter 7, group 2, article 10, section 3395) revealed through OSHA inspections of approx. 12,000 establishments in California from 2006 to 2018 (with increasing enforcement frequencies 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.




Year = 2010
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

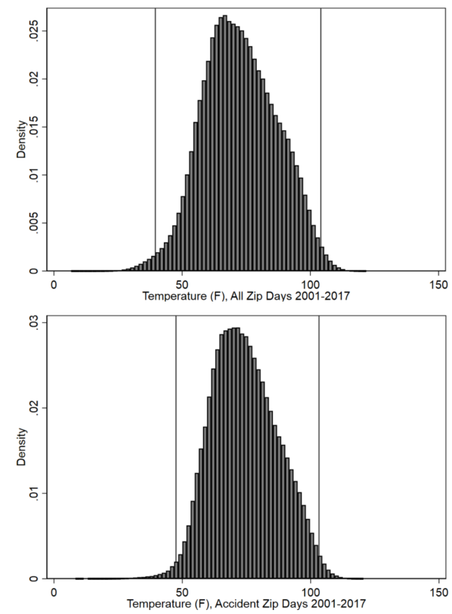
4 Appendix D: Additional Tables, Figures, and Robustness Tests

Figure 2: Injuries and Temperatures Over Time



Notes: Figure 2 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 3: Distribution of Temperatures in California



Notes: Figure 3 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 1: Distribution of Injuries

Notes: Table 1 provides information on the number of injury claims in California by body part (panel A) and injury description (panel B) over the period 2001 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 4: 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

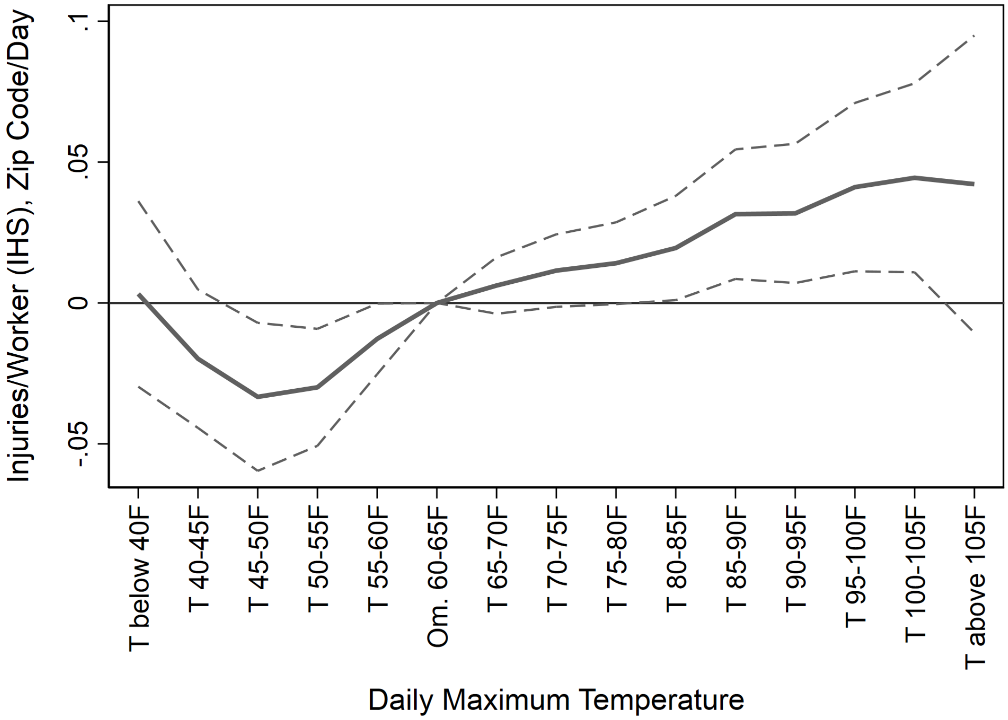
Notes: Table 4 shows the effect of temperature on injury claims for California-based work sites over the period 2001 to 2018. All coefficients are obtained from regressions of injury counts per zip code and day on indicator variables representing each of 15 temperature bins, as well as controls for precipitation and the fixed effects noted above. The results of the main specification corresponding to equation **??** 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 5: 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 5 shows the effect of temperature on injury claims for California-based work sites (2001 to 2018). It differs from Table **??** 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 **??** 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 4: Temperature and Injuries – Injuries per Worker



Notes: Figure 4 plots the coefficients obtained from regressions specified in equation **??**, with point estimates shown in Table **??**, 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 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. 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 6: Temperatures and Injuries - Alternative Fixed Effects

	(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

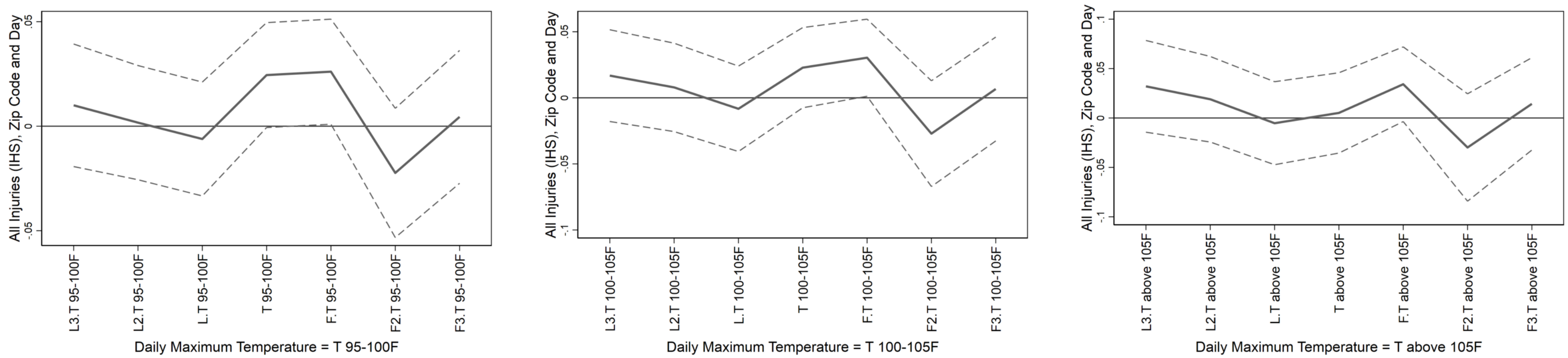
Notes: Table 6 shows the effect of temperatures on injury counts in California from 2001 to 2018, and shows alternative fixed effect specifications not included in Table **??**. The dependent variables in each regression is the IHS transformation of injuries by zip code-day. Daily maximum temperatures 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 7: 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 5: Temperatures and Injuries - Lags and Leads



Notes: Figure 5 plots coefficients from a dynamic distributed lags variant of equation **??**, 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 6: Temperatures and Injuries - Rolling Window Estimates

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 6 show the effect of temperature on injury counts in California (2001-2018), and differs from the results shown in Table **??** 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 8: 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 9: 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.

Table 10: 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 11: 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.

Table 12: Extreme Temperature and Log Wages per worker - Non-Exposed, by Industry

	(1) Who	(2) Ret	(3) Fin	(4) Edu	(5) Hea	(6) Acc
Days above 90 (°F)	-0.024***	-0.032***	-0.026***	-0.018	-0.017**	-0.029***
	(0.008)	(0.004)	(0.006)	(0.016)	(0.007)	(0.005)
Days in 80s (°F)	-0.007	-0.025***	-0.028***	-0.023*	-0.016***	-0.031***
	(0.007)	(0.004)	(0.005)	(0.014)	(0.006)	(0.005)
Days below 30 (°F)	0.008	0.003	-0.006	0.007	-0.005	-0.005
	(0.011)	(0.006)	(0.009)	(0.023)	(0.010)	(0.007)
Snowfall	0.036***	0.039***	0.013	-0.014	0.012	0.033***
	(0.013)	(0.006)	(0.009)	(0.024)	(0.011)	(0.008)
Average monthly precip	-8.189***	-9.020***	-6.148***	-7.890	-5.502**	-4.834***
	(2.712)	(1.405)	(1.967)	(5.144)	(2.378)	(1.673)
N	62,629	84,745	68,220	29,368	47,954	57,485
County FE's	Yes	Yes	Yes	Yes	Yes	Yes
Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
Regional trends	Yes	Yes	Yes	Yes	Yes	Yes

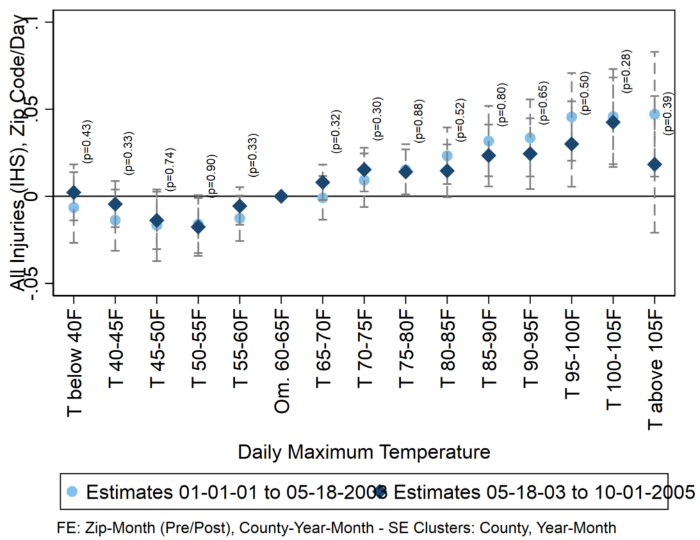
Notes: Heteroskedasticity robust standard errors are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column and panel come from a regression of 100 times log wages per worker in a given county-industry-year on the variables shown, limiting the analysis to the industries listed. Temperature is measured with the daily maximum temperature from nearest weather station. All regressions include controls for days in 30's, 40's, 50's and 60's, with days in the 70's as the omitted category.

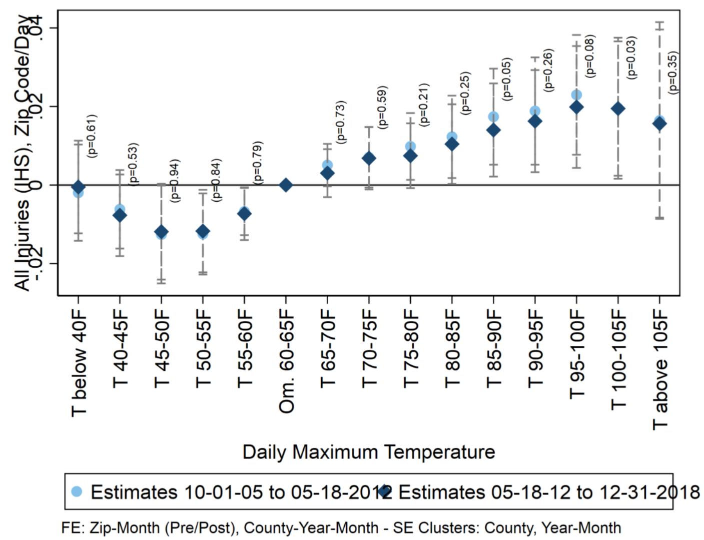
Table 13: Extreme Temperature and Log Wages per worker - Exposed, by Industry

	(1) Agr	(2) Min	(3) Uti	(4) Con	(5) Man	(6) Tra
Days above 90 (°F)	-0.018	-0.006	0.006	0.003	-0.006	-0.009
	(0.011)	(0.017)	(0.011)	(0.007)	(0.006)	(0.009)
Days in 80s (°F)	0.000	0.007	0.004	0.002	-0.004	-0.007
	(0.010)	(0.015)	(0.010)	(0.006)	(0.006)	(0.008)
Days below 30 (°F)	0.029*	0.016	-0.009	-0.002	0.007	-0.000
	(0.017)	(0.028)	(0.018)	(0.010)	(0.009)	(0.013)
Snowfall	0.009	0.034	0.041**	0.004	0.016	0.006
	(0.019)	(0.028)	(0.019)	(0.011)	(0.010)	(0.014)
Average monthly precip	-11.699***	-4.100	7.440**	-9.753***	-3.793*	-3.046
	(3.833)	(5.703)	(3.695)	(2.346)	(2.049)	(2.958)
N	36,049	23,854	26,130	73,087	74,301	46,984
County FE's	Yes	Yes	Yes	Yes	Yes	Yes
Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
Regional trends	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Heteroskedasticity robust standard errors are in parentheses (* p<.10 ** p<.05 *** p<.01). Coefficients in each column and panel come from a regression of 100 times log wages per worker in a given county-industry-year on the variables shown, limiting the analysis to the industries listed. Temperature is measured with the daily maximum temperature from nearest weather station. All regressions include controls for days in 30's, 40's, 50's and 60's, with days in the 70's as the omitted category.

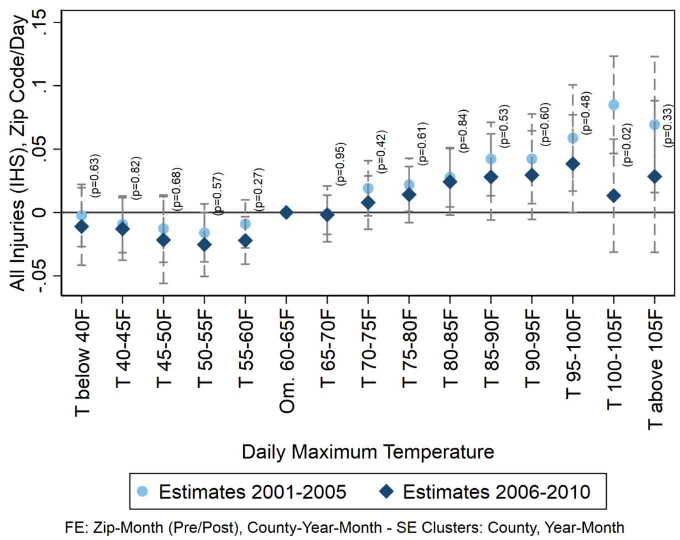
Figure 7: Temperatures and Injuries Before and After the Introduction of the Heat Illness Prevention Standard – Robustness Tests

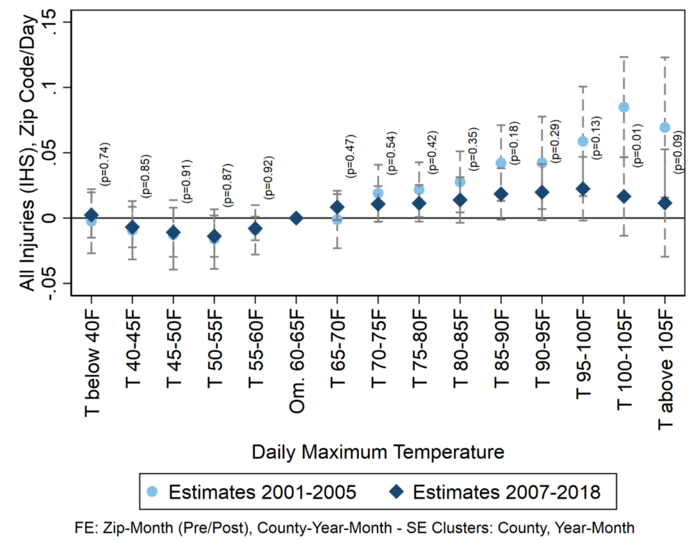




Notes: Figure 7 shows placebo tests of the effect of temperatures on workplace injuries using two different placebo treatments. ON the left we split the period prior to the introduction of the Heat Illness Prevention Standard (HIPS, Cal/OSHA subchapter 7, group 2, article 10, section 3395) into a placebo 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 **??** 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 **??**) 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 8: Temperatures and Injuries Before and After the Introduction of the Heat Illness Prevention Standard – Robustness Tests





Notes: Figure **??** 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 **??**) 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.