Local Labor Market Conditions and Adaptation to Climate Change: The Role of Workers' Outside Options

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Abstract

This study examines the impact of labor market conditions on adaptation to extreme temperatures. Leveraging administrative data on 6 million injury claims and granular information on workers' outside options, we find that improvements in outside option wages significantly mitigate heat-related workplace injuries, with a one standard deviation increase reducing injury sensitivity by 33% to 47%. In contrast, adaptation appears minimal when measured through average climate exposure despite significant climate variation in our setting, suggesting that localized labor market dynamics play an important role in shaping workplace responses to environmental shocks and the incidence of adaptation costs between workers and employers.

Keywords: Climate Change, Adaptation, Labor Markets, Workplace Safety.
JEL Codes: G15, Q54, G30, F64

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1 Introduction

Climate change may have important implications for labor markets. Hazards such as extreme temperature and wildfire smoke are projected to increase in frequency and severity, and have been shown to affect morbidity, labor productivity, and workers' subjective well being across a range of industries and geographies.[1] The magnitude of potential adverse impacts are likely to be economically first order: nearly 1 billion individuals work in agriculture alone, on top of the hundreds of millions working in construction, mining, and transportation, sectors where most jobs are frequently exposed to the elements (World Bank, 2023). The welfare implications of such climate impacts will depend in part on the effectiveness of adaptation measures taken, as well as the costs and how they are distributed.

When workplace climate adaptation encompasses potentially competing demands of workers and their employers, how are such decisions made? Who bears the costs, and to what extent might the realized adaptation depend on local labor market conditions? For instance, when hotter temperatures make construction work more physically demanding and potentially hazardous to health, what determines whether firms implement adaptive but possibly costly work practices such as more frequent breaks, altered work shifts, or installing cooling devices and additional safety equipment? Such questions are of heightened significance in light of debates surrounding the role of public policy in regulating non-wage aspects of labor markets (Levine et al., 2012; Mas and Pallais, 2017; Maestas et al., 2023), as well as more recent debates regarding the extent to which firms voluntarily invest in adaptation and the role of government in mandating adaptation-related investments (Hino and Burke, 2021; Baylis and Boomhower, 2022; Park et al., 2024a). They are also significant in light of evidence that firms may not fully internalize the social costs of workplace health and safety measures (Page and Sheppard, 2018; Dobkin et al., 2018).

In this paper, we leverage rich administrative data and highly granular measures of local job alternatives - referred to here as outside options - to study how workplace climate adaptation is influenced by labor market conditions. Using confidential microdata from the United States' largest worker's compensation system, we explore how changes in workers' expected outside option wages, which in our setting reflect empirically observed job transitions across occupations and local wages in relevant destination occupations, influence their vulnerability to hazardous working conditions arising from extreme temperature. Our setting and the granularity of the data used allow us to measure changes in adaptation arising from highly localized changes in labor market conditions at the level of detailed occupation and

[1] For instance, see Hsiang (2010); Graff Zivin and Neidell (2014); Baylis (2018); Nath (2020); Park et al. (2020); Somanathan et al. (2021); Dillender (2021) and Downey et al. (2023).

metro area. We match nearly 6 million individual injury claims to high-frequency variation in temperature, jointly with quasi-experimental variation in local outside occupation options for approximately 17,030 local occupational labor markets (SOC6 x Metropolitan Statistical Area [MSA]) over time. The former source of identifying variation is well-established in the weather-economy literature, which leverages high-frequency – in our case, daily – temperature variation and detailed information on the date and location of each workplace injury.[2] The latter draws from novel measures of outside occupation wages for over 655 SOC-6 digit occupations constructed by Schubert, Stansbury, and Taska (2024, henceforth SST) using over 16 million U.S. resumes, which we match to claims-level information on industry and occupation of the injured workers and their employers.

We begin by showing that operationally disruptive temperature shocks are commonplace even in a highly developed economy setting across a wide range of industries, and that worker safety declines substantially during such shocks. Utilizing day-to-day variation in temperature within a given MSA over time, we estimate that a day between 90 and 95°F increases same-day injury risk by around 7 percent. The relationship between temperature and injuries appears to be approximately linear over the temperature ranges in our sample, and the magnitude of the effects we find are consistent with prior work, including notably Dillender (2021) and Park et al. (2024a). We show using local occupational employment and time use data that these effects are unlikely to be driven by endogenous temperature-driven changes in labor inputs or the number of workers on the job.

Workers who experience better (worse) outside options may be more (less) likely to bargain for costly workplace adaptations, particularly those that have an amenity value component to them. Conversely, employers who perceive their workers to be more (less) likely to leave for better paying jobs may be more (less) likely to provide such amenities by implementing safer work practices. In line with this, we find that workers who experience a plausibly exogenous improvement in their outside option wages experience a significant reduction in their susceptibility to heat-related workplace injuries.[3]

Our measure of outside options comprises a weighted average index of wages in each of up to a maximum of 786 destination occupations within a local commuting area (MSA)[4],

[2]For reviews of this literature, see Dell et al. (2014), Heal and Park (2016), and Auffhammer (2018).

[3]To help interpret our empirical results, we present a simple model of job search and bargaining that builds on Schubert et al. (2024), wherein workers and firms bargain over wages such that the wage depends on the expected quality of workers' best outside options, where workers' total compensation can be thought of as the combination of wages and workplace amenities, including safe and thermally comfortable working conditions.

[4]Metropolitan Statistical Areas (MSA) have at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties.

weighted by the empirically observed likelihood of job transition between each occupation pairing in a sample of over 16 million U.S. resumes. As such, it arguably represents labor market dynamics in a specific subset of jobs that are both desirable and feasible for a given worker given skill and task similarities.[5] Our identification strategy for outside options leverages highly localized variation in expected local outside options, netting out labor market shocks common to other workers in the same occupation (SOC6-by-year fixed effects) and those common to all other workers in the same metropolitan area (MSA-by-year fixed effects).

For the median worker, improving outside option wages by 1 standard deviation reduces the causal effect of heat on injuries by approximately 33 percent. Moving from the 10th to the 90th percentile of the outside option wage distribution reduces the temperature-sensitivity of workplace injuries by around 61 percent, or from approximately 9.8 percent to 3.9 percent.[6] This is consistent with workplace adaptation to temperature shocks including a significant consumptive amenity value to workers, in addition to any possible productivity benefits.[7] Using similar variation in outside option wages, we do not find evidence for such improvements in non-wage amenities coming at the cost of reduced wages. In fact, we observe higher local occupational wages when outside options improve, consistent with SST.

To bolster confidence in our interpretations, we show that our estimates of the effect of outside option wages on workplace adaptation are effectively unchanged when leveraging a shift-share IV approach. One challenge faced by previous studies of labor market responses to climate shocks has been in disentangling demand- and supply-side effects. For instance, a relationship between hotter temperature and hours worked (Graff Zivin and Neidell, 2014; Rode et al., 2023) may be driven by reductions in labor supply due to unpleasant working conditions, or by correlated reductions in labor demand arising from firms' responses to reduced labor productivity or changes in product demand (e.g. less retail foot traffic). Our IV strategy uses variation in the national leave-one-out mean wages for all potentially relevant outside option occupations (net of fixed effects for each occupation-year and metro-year), to instrument for changes in outside options faced for a worker in a given local occupational labor market that are plausibly orthogonal to correlated changes in the worker's own

[5]For instance, in the outside option wages indices for construction day laborers or landscaping helpers, local wages for warehouse operatives and dockworkers would likely have much higher weights than those for pilots and dentists.

[6]Note that this could be driven by a combination of exit or voice. We do not take a stand. Also, we are not measuring productivity or subjective well being. With reasonable assumptions about preferences, wages, and labor market competition, we can infer from our finding that a reduction (increase) in temperature-injury sensitivity is reflective of improved (diminished) worker welfare.

[7]It is also consistent with informational imperfections whereby adaptation has productivity benefits that are less salient to management than they are to workers in the context of coordination frictions.

productivity or own-occupation labor demand.

The effect of outside options on the temperature-injury relationship remains negative, significant, and similar in magnitude when estimated off of such an IV. Our preferred IV estimate suggests that a one standard deviation increase in outside options reduces the temperature-injury relationship by 47 percent. The fact that both approaches yield similar results is instructive, and suggests that improved local labor market conditions lead to greater levels of adaptation to workplace climate risk. The fact that the results hold in our IV specification indicates that rising wages in local jobs that are likely to be realistic and desirable outside options lead to an improved ability to bargain for less environmentally risky working conditions for a given job. While we cannot observe the specific adaptations that occur, our findings are consistent with such mechanisms as inter-temporal reallocation of work to avoid the worst times of day; investment in safety equipment as required by law in some industries; and changes in workers' willingness to take on riskier work activities, among other possible explanations.

Our estimates suggest substantial scope for adaptation to workplace climate hazards within local labor markets. In contrast, when we employ standard existing approaches to empirically identifying adaptation to climate shocks, including estimating heterogeneity in short-run causal effects across average climates or local average incomes, we do not find significant evidence of adaptation. This is despite the fact that there is considerable cross-sectional variation in average climate across the geographies in our sample. Workers in places that experience over 74 days per year above 90°F (top quartile) and those that experience fewer than 11 days per year above 90°F (bottom quartile) do not appear to exhibit significantly different levels of adaptation to the adverse safety impacts associated with working in hotter temperatures, as measured by the temperature-sensitivity of workplace injuries. This suggests that, at least in the context of labor markets, adaptation may depend on highly localized factors – including workers' individual outside options – which often exhibit substantial variation across workers and over time within granular geographic cells (e.g. MSA's). One implication is that projecting future climate damages using cross-geography heterogeneity in damage functions may lead to misleading conclusions, at least in the context of labor impacts.

The primary contribution of this study is to the literature on adaptation to climate change. A growing body of scholarship attempts to empirically estimate the scope for and determinants of adaptation to changing climatic conditions, leveraging variation in short-run causal estimates of temperature and precipitation shocks.[8] Notable related papers include Carleton et al. (2022), Rode et al. (2021), Dillender (2021) and Rode et al. (2023), who study

[8]See Auffhammer (2018) for an excellent review.

mortality, energy use, and labor supply responses respectively. While Carleton et al. (2022) and Rode et al. (2021) find that the effects of temperature on mortality and energy use vary considerably with average climate and average income, such relationships are decidedly less pronounced for labor supply (Rode et al., 2023), which is interpreted as evidence of limited scope for adaptation. For a subset of workers in the mining sector, this relationship appears to even be reversed, with places with hotter average climates experiencing *steeper* heat-injury relationships (Dillender, 2021), consistent with such places being *less* adapted. Our findings suggest that there may in fact be significant scope for adaptation to the effects of climate shocks on labor market outcomes, but that a portion of such variation arises from highly localized labor market conditions, including within-geography and within-occupation variation in outside option wages, and determinants of worker bargaining power more broadly.

Our paper builds on a nascent literature that combines joint quasi-experimental variation in climatic shocks and adaptation behaviors, including Baylis and Boomhower (2022), who study the effect of mandated building codes' effects on the relationship between wildfire and housing destruction, and Mullins and White (2019), who examine the role of community health centers in mitigating heat-related mortality among the elderly. Both exploit plausibly exogenous variation in the adaptation determinant of interest. Our contribution is to show that local variation in workers' bargaining position – including variation plausibly exogenous to other determinants of firms' production decisions (e.g. shocks to production technology) – can significantly influence realized climate adaptation.[9] As with these studies, our findings suggest that there may be a discrepancy between the technical feasibility of adaptation options and their realized adoption. In particular, our study points to a potentially important role of labor market policies in facilitating workplace climate adaptation, as well as the fact that climate change may have distinct distributional consequences for labor versus holders of capital.

Previous work finds that when workers' outside occupation options improve, wages in their current occupation tend to rise (Schubert et al., 2024), and that overall rates of workplace accidents and injuries also improve (Park et al., 2024b). Our findings build on this work, and suggest that such changes in wages may not fully capture the realized change in total compensation, which may include non-wage amenities such as safer and more pleasant work environments. In this sense our work is also relevant to the literature that explores

[9] Our work is relevant also to studies, including Graff Zivin and Neidell (2014), Adhvaryu et al. (2014) and Chang et al. (2016), that examine the influence of environmental factors such as hotter temperature and air pollution on labor market outcomes. We provide what is to our knowledge the first analysis of how workers' and firms' responses to environmental shocks depend on workers' bargaining position. In particular, we build on an intuition set forth in Neidell et al. (2021), who suggests that workers' time-use decisions may depend on macroeconomic business cycle fluctuations.

non-wage aspects of compensation and their contribution to worker welfare (Mas and Pallais, 2017; Maestas et al., 2023).

2 Background and Conceptual Framework

2.1 Workplace Adaptation

We define workplace adaptation as investments or changes in work practices that result in a reduced sensitivity of economic outcomes to environmental shocks. While our empirical focus is on workplace health and safety and its relationship with hotter temperature, our interest is broader in that we seek to shed light on the process by which adaptation in the workplace may be influenced by complex dynamics between workers and their employers, including changes in workers' outside options. As an analogous setting, one might think of the varying willingness and ability of workers in different industries and occupations to bargain for workplace protections or flexible work arrangements in the context of the Covid-19 pandemic, or the actions taken by workers and employers in response to wildfires and their attendant smoke plumes.

We note that, from the perspective of the firm, labor costs typically comprise both wage and non-wage elements. Similarly, the workers' total compensation includes but is not limited to money wages, and may encompass such non-wage amenities as safe working conditions, schedule flexibility, and opportunities for further human capital accumulation. As such, workplace adaptation may comprise both productive and/or consumptive elements that are costly to provide for the firm.

Our primary hypothesis is that such adaptations are driven in part by highly local labor market conditions, including workers' individual outside options, which among other things may influence their relative bargaining power and/or the risks they are willing to take while on the job.

How might outside options matter? To build intuition, consider an environment with profit maximizing firms and utility maximizing workers. Given multiple adaptation options with heterogeneous costs, it is possible for the mix of adaptation technologies preferred by workers to diverge from that deemed optimal by employers. For instance, consider the extreme case where temperature control has no productivity benefit (i.e., neither labor nor capital productivity are influenced by temperature), and is simply a consumptive amenity for workers, either in the form of thermal comfort and/or improved health and safety on the job.[10] In such a case, the optimal level of workplace adaptation for the firm is non-zero only

[10]To be precise, improved safety could affect labor productivity to the extent that it affects firms' worker's

to the extent that such on-the-job amenities affect wages (e.g. via compensating differentials in the labor market). This would imply that workplace adaptation is directly related to the wage bargaining process, the result of which is dependent on workers' expected outside options.[11] In the opposite extreme, where firms fully internalize the benefits of workplace adaptation in the form of increased productivity, worker's outside options do not factor in the decision process. For instance, if heat exclusively reduces capital productivity with no direct effects on worker's comfort and health, the decision to invest in more heat-resilient equipment is independent of workers' outside options.

Anything in between these two stylized extremes would suggest that local labor market factors, including worker's potentially changing outside option values, may influence realized workplace adaptation. In other words, to the extent that there is a lack of perfect overlap in the optimal vector of adaptation investments preferred by either party, one can imagine that the level and composition of workplace adaptations may ultimately be influenced by local labor market conditions. This is the hypothesis we examine.

2.2 Temperature and Working Conditions

We study this in the setting of temperature's affect on working conditions. This is a setting in which existing evidence suggests that workplace adaptation may have both productive and consumptive dimensions.

For instance, hotter temperature (and to a limited extent colder temperatures) can adversely affect labor productivity in manufacturing (Dechezleprêtre et al., 2018; Somanathan et al., 2021), consistent with experimental (Mackworth, 1946) and quasi-experimental (Park, 2022) work suggesting that physical and cognitive task performance declines with temperature extremes.[12] Thermal stress at work may also constitute a disamenity for some workers, as evidenced by changes in labor supply on hotter days for workers in a subset of highly exposed industries (Graff Zivin and Neidell, 2014; Rode et al., 2023).[13]

compensation insurance premiums. For the purposes of this example, suppose these costs can be passed on entirely to workers.

[11] This could be in a bargaining model, where the outside option value constitutes the floor for the value of the worker's total compensation, or in a monopsony model, where the availability of outside options is related to the elasticity of the labor supply to any individual firm.

[12] However, evidence of productivity impacts appears to be highly heterogeneous across countries and sectors, with evidence of more muted effects on manufacturing productivity in most developed countries (Nath, 2020) and of some sectors experiencing flipped signs (Addoum et al., 2023). For instance, Nath (2020) finds that, whereas a day above 40°C reduces annual output in developing countries by 0.4 percent, which is the equivalent of losing nearly a full day of output, in middle income countries, the impacts are roughly half as large, and in rich countries the average effect is negligible save for a subset of least adapted firms.

[13] Qualitative evidence suggests that workers in many industries consider heat to be a poten-

Perhaps a more direct indication that workplace adaptation to temperature extremes may have important consumption value to workers comes from Dillender (2021), who finds using data from Texas that workplace injuries and illnesses increase significantly on hotter days, including many serious injuries that lead to death or permanent disability. This is consistent with an extensive but largely correlational public health literature which notes that extreme temperatures can pose direct health hazards to workers in the form of increased fatigue and dehydration (Ramsey et al., 1983; Ramsey, 1995; Adam-Poupart et al., 2014; Kjellstrom et al., 2016). It is also consistent with the idea that, when working in baseline hazardous work environments (e.g. at heights, or operating heavy machinery), incremental diminutions to cognitive capacity may lead to increased errors, which may have potentially severe health repercussions.

Unlike changes in labor supply, which may also result in increased leisure time and potentially higher marginal value of consumption, changes in injuries most likely represent a reduction in worker utility.[14] We therefore focus our empirical analysis on the effect of temperature on workplace accidents and injuries.

2.3 Outside Occupation Options and Workplace Adaptation

Below, we outline a simple model of job search with wage bargaining, modifying that presented in SST to incorporate non-wage aspects of total compensation and focusing on the effects of changing outside occupation options on realized adaptation investments as experienced by workers.[15] The model suggests that higher wages or more opportunities in other feasible jobs increase total compensation. If adaptation to climate hazards on the job comprises a discretionary investment that includes some amenity value to workers, we would expect the realized amount to depend on workers' outside options, either due to greater

tial health hazard and a detriment to working conditions. For instance, a telephone line technician notes that while "we're always trying to keep customers' telephone service alive, it's exhausting work and can cause heat illness. Heat exhaustion can hit you when you're climbing a telephone pole or crawling under a house or through an attic (Constible et al., 2020)." Teachers in many U.S. public schools have petitioned for air conditioning in classrooms, while drivers of buses and delivery trucks have reported lack of air conditioning in their vehicles in labor disputes. For instance, see: https://www.cleveland19.com/2024/08/31/cleveland-heights-teachers-union-files-grievance-over-extreme-heat-buildings/ and https://www.nbcnews.com/news/us-news/ups-driver-passed-crashed-vehicle-texas-due-heat-related-symptoms-unio-rcna167448

[14] An exception may be if workers are engaging in worker's compensation insurance fraud by faking or misrepresenting the severity of injuries. While such behaviors cannot be ruled out, available evidence indicates that, for the majority of workplace accidents, worker's compensation benefits typically cover only a fraction of the total costs to workers in terms of lost wages, hospital bills, and other non-pecuniary costs (Page and Sheppard, 2018).

[15] As in SST, our measure of outside options is the outside *occupation* option in a given local labor market. Unlike SST, we do not explicitly model potential changes in within-occupation outside options using employer concentration, largely due to data limitations.

voice or exit or both.

Job search

Each job seeker applies to all feasible local employers $j \in N$ in a given period, where a fraction of workers are exogenously displaced and search for a new job each period. Each employer offers a job that pays total compensation $\tau_j = \text{wages} + \text{amenities}$ with some probability. When a worker receives her offers, she accepts the offer with the highest total compensation. If no offers within the feasible set of employers are received, then the jobseeker enters unemployment, with a payoff of u. The search is repeated in the next period. We assume for simplicity that amenities are valued homogenously across workers within a given labor market, and that a successful job applicant to firm j is offered a compensation package equivalent to those paid to existing workers at firm j.

Wage bargaining

Each employed worker engages in a Nash bargain with the employer i. The outcome is a compensation package τ_i, which is equal to the value of the worker's outside option if she leaves, oo_i, plus a share β, which reflects worker bargaining power, of the match-specific surplus ($\text{MPL}_i - oo_i$), where MPL denotes the marginal revenue product of labor.

$$\tau_i = \beta \cdot (\text{MPL}_i - oo_i) + oo_i = \beta \cdot \text{MPL}_i + (1 - \beta) \cdot oo_i \tag{1}$$

The outside option is defined as:

$$oo_i = \sum_{j=1}^{N} \alpha_j \tau_j + \prod_{j=1}^{N} (1 - \alpha_j) \cdot u \tag{2}$$

where α_j denotes the probability of successful transition into job j, and the expression $\prod_{j=1}^{N}(1 - \alpha_j)$ captures the probability of receiving no other job offers. u denotes the value of unemployment, which comprises unemployment benefits plus the value of leisure and any other amenities associated with non-employment.

As such, oo_i can be thought of as both the expected total compensation offered by other firms in the same local occupational labor market for the current occupation, and the expected total compensation offered by successful job matches with employers in other feasible occupations. In our empirical analysis, we focus on *outside occupation options* - specifically, local occupations outside of one's current occupation that have qualities that make it a feasible and desirable option.[16]

[16] In SST, oo_i is defined empirically to also include the former component, as a focus of their paper is in studying the role of employer concentration. For simplicity, and given data limitations, we focus on variation in the latter component - outside occupation options in a given local labor market - meaning that we do not consider the role of employer concentration within a given local occupational labor market, nor do we consider job options outside the worker's city.

A worker's compensation is thus a function of the expected compensation offered by her current firm, and the expected compensation offered in all other occupations to which she can realistically transition ($p \in N^{occs}$), weighted by the probability that the best job offer the worker receives will be in each occupation p. SST show using highly granular data from online job postings that using empirically observed occupation-to-occupation transitions to estimate transition probabilities provides a good approximation of realistic outside options. For instance, by observing the full set of occupations to which roofers tend to transition when leaving that occupation (and their relative transition probabilities), in conjunction with local wage information for each destination occupation, the expected outside option wage value for roofers in each local labor market can be empirically estimated. We leverage similar data and approaches to approximate outside options for the 17,000-plus local occupational labor markets in our data.

Our primary hypothesis is that exogenous variation in a worker's outside options can influence the extent to which her job is adapted to environmental conditions, which can be thought of as a component of total compensation. Our empirical objective is to isolate variation in oo_i that is orthogonal to changes in productivity ($\beta \cdot MPL_i$) and to relate this to observable dimensions of workplace adaptation.

3 Data and Summary Statistics

3.1 Workers' Compensation Microdata

We use confidential records of workplace injuries in California from the Division of Workers' Compensation (DWC) over the period 2000 to 2020. A significant advantage of the workers' compensation data compared to other measures of injuries is its relative comprehensiveness, though it is possible that some more minor injuries go unreported. California legally obliges employers to maintain workers' 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 raw data include over 15 million injuries.

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). We generate industry (NAICS) and occupation (SOC) codes for a subset of the injury claims using a tool provided by the National Institute of Occupational Safety and Health (NIOSH)[17]. This tool allows us to assign probabilistic matches of occupation codes to NAICS code-

[17]The NIOSH Industry and Occupation Computerized Coding System tool is publicly accessible.

occupation description pairings in the raw data[18]. For instance, an observation with NAICS code "11" ("Agriculture, Forestry, Fishing and Hunting") and occupation description "Day Laborer" would be assigned to SOC code 45-2092, "Farmworkers and Laborers". We only retain observations with a SOC code match probability of at least 90%. The NIOSH tool output includes the 2018 vintage SOC codes (SOC2018), which we convert to the 2010 vintage (SOC2010) to match with the outside occupations index data from Schubert, Stansbury, and Taska (2024). We do so using a crosswalk from the Bureau of Labor Statistics (BLS)[19]. The resulting dataset includes 655 SOC2010 occupations[20].

3.2 Local Labor Market Conditions: Outside Occupation Options

Our primary measure of worker outside options is the average wage value of their job opportunities outside of their current occupation, as formulated in SST. For each of 686 detailed occupations across the United States, SST measure the probability that a worker transitions to a different occupation, which captures the feasibility and desirability of alternate destination occupations. Adjusting for the local relative employment share, which accounts for local availability of jobs in each destination occupation, they construct an outside occupation options index (OOI), which is an MSA-occupation-year measure of the quality of a worker's job opportunities outside their current occupation. It is defined as follows:

$$\text{OOI}_{o,z,y} = \sum_{p \neq o}^{N_{occs}} \pi_{o \to p} \cdot \frac{s_{p,z,y}}{s_{p,y}} \cdot w_{p,z,y}, \tag{3}$$

where $w_{p,z,y}$ is the wage for occupation p in MSA z and year y, and $\frac{s_{p,z,y}}{s_{p,y}}$ is the local employment share of occupation p relative to the national average, adjusting for the local availability of jobs in p. $\pi_{o \to p}$ measures the probability that a worker moves to occupation p given that they leave their job in occupation o, which SST measure using worker transitions observed in resume data from Burning Glass Technologies. Specifically,

$$\pi_{o \to p} = \text{leaveshare}_o \cdot P(o \to p | \text{leave } o), \tag{4}$$

[18]Before passing these descriptions through the parsing tool, we remove observations with clearly erroneous NAICS codes. We also consolidate occupation descriptions by removing non-alphabetic characters (e.g. "Cook2" and "Cook)" both become "Cook").

[19]We keep only the 673 SOC2018 codes that are assigned to a single SOC2010, dropping 31 SOC2018 codes that are matched to multiple SOC2010 codes. We also drop 6 SOC2018 codes that start with 00 (e.g., 00-9830: military, rank not specified), as these do not have matches in the crosswalk. Altogether, we retain 92.5% of SOC2018-MSA-day observations with at least one injury.

[20]In our dataset, we only include occupations with at least one injury in our study period.

where leaveshare$_o$ measures the probability that a worker leaving a job in occupation o finds a new job in a different occupation, and $P(o \to p|\text{leave o})$ is the probability that a worker leaving occupation o works in occupation p.

Such a measure captures the fact that being a dockworker is more likely to be a relevant outside option for construction workers than for office secretaries, and so changes in employment prospects among dockworkers will influence construction workers' behavior more than office secretaries' behavior, including the potential willingness to refuse physically hazardous tasks (at risk of termination) and to bargain for working conditions that are better adapted to unpleasant environmental conditions. Importantly, this measure captures dimensions of the relevant labor market not captured by standard occupational definitions or even aggregating up the standard SOC hierarchy.[21]

We use an amended version of the OOI, which we denote OOW for outside occupation options wages. In brief, the OOW replaces the $\pi_{o \to p}$ term in the OOI with $P(o \to p|\text{leave o})$, excluding the leaveshare$_o$ term. For further details regarding how we construct outside option wages for the local occupational labor markets in our sample, see Appendix A.1.

We create the OOW using data for the 17,030 local occupational labor markets (occupation-MSA's) in California. Our final analysis dataset includes the roughly 6 million accident and injury claims that can be matched to an occupation code and are in zip codes within MSA boundaries (as opposed to, for example, in micropolitan statistical areas) in California over the period 2000 to 2020.

3.3 Local Weather Data

We use weather data from the PRISM Climate Group. These data consist of daily maximum temperatures and precipitation at a 4km by 4km resolution for the continental United States. We obtain the PRISM data for the period 2000 to 2020 and match them with workplace injuries based on the MSA 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 grid point-day to a vector of 15 temperature bins, using 5°F increments ranging from below 40°F to above 105°F, a range that captures the distribution of observed temperatures in California. We then collapse grid points to the MSA-day level. In our model, we control for potential effects of rainfall on workplace safety. We assign precipitation records to a vector of four rainfall bins, namely: days with no precipitation, days with less than half an inch of precipitation, days with half an inch to one inch, and days with more than one inch

[21] As noted in SST, for the median occupation, 87% of moves to a different 6-digit occupation are also to a different 2-digit occupation. Even excluding transitions into and out of management, which is its own 2-digit category, 67% cross 2-digit boundaries.

of precipitation.

3.4 Summary Statistics

We collapse injuries to the MSA-SOC2010-day level and combine them with MSA-day level weather data and MSA-SOC2010-year level OOW data. The analysis dataset includes 5,973,282 injuries across 126,872,850 MSA-SOC2010-day observations with non-missing OOW data.

Table 1 shows summary statistics for the core variables. The average number of injuries per MSA-SOC2010-day is 0.0471, and 97.5% of observations have zero injuries, consistent with the highly geographically and temporally granular level at which we measure injuries. The median worker has a weighted outside option index of $15.30, with a standard deviation of $12.93. The median MSA in California experiences 1.4 days per year above 105°F, 8 days between 100 and 105°F, and 19.5 days between 95 and 100°F.

Figure 1 shows how average levels of injuries, temperature, and outside options quality vary across MSAs. Panel B shows the number of yearly days with a maximum temperature of 90°F or above. It highlights the climatic diversity of California: some MSAs in the Bay Area have as few as 11-25 days per year above 90°F, compared to over 150 days in Imperial County. As shown in panel C, the average level of OOW varies significantly across MSAs as well, with the wealthier coastal areas such as the San Jose-Sunnyvale-Santa Clara MSA exhibiting average outside option wage levels of $40 or higher, and more heavily agricultural areas like the Chico MSA exhibiting average OOW values across all occupations of less than $20 over the period 2000-2020.

In addition to such cross-geography variation in average outside option wages, however, there is considerable variation across occupational labor markets within a given MSA, as well as within local occupational labor markets over time. For instance, within the Los Angeles-Long Beach-Anaheim labor market in 2010, occupations at the 5th percentile of the outside option wage distribution had an OOW value of $20.9, whereas those at the 95th percentile had an OOW value of $43.8. Over the study period, outside option wage indexes for Construction Laborers in the Los Angeles-Long Beach-Anaheim varied from a low of $14 to a high of $34, depending on changing local an macroeconomic conditions, including changes in the composition of available local jobs and their respective wages.[22]

[22]For comparison, OOW for Construction Managers in the same area ranged from a low of $18 to a high of $55; for Landscaping and Grounds-keeping workers, from $13 to $30.

4 Estimation and Results

4.1 The Impacts of Temperature on Worker Safety

Our core empirical specifications exploit random variation in temperature realizations within a given MSA over time, in addition to plausibly exogenous variation local labor market outside option wages using both a fixed effects and an instrumental variables (IV) regression framework described below. We first test whether injuries are higher on hotter-than-average days. We then assess the extent to which workers' outside occupation options meaningfully influence the relationship between temperature and workplace injuries, followed by an assessment of the effect of local average climate on this relationship.

The first step is implemented by estimating a regression of the following form:

$$Inj_{o,z,d,m,y} = \sum_{k=1}^{K} \beta^k Temp_{z,d,m,y} + \sum_{p=1}^{P} \delta^p Precip_{z,d,m,y} + \eta_{z,m} + \gamma_{m,y} + \lambda_o + \epsilon_{z,o,d,m,y}, \quad (5)$$

where $Inj_{o,z,d,m,y}$ is the count of injuries for a given occupation o in MSA z on day d of month m of year y.

The key right-hand side variable is $Temp_{z,d,m,y}$, which denotes a vector of K daily maximum temperature bins, ranging from below 40°F to 105°F and above in 5°F increments, with the 60-65°F bin omitted. Binning allows for temperature to affect injuries with flexible functional form, following Barreca et al. (2016) and Carleton et al. (2022) among others. $Precip_{z,d,m,y}$ denotes a vector of P precipitation bins, assigned based on daily precipitation in inches. Given the number of MSA-SOC-day cells where the outcome variable has a count of zero, we elect to estimate a Poisson regression as our primary specification. We show below that the findings are robust to alternative specifications, including OLS with injury rates per worker as the dependent variable.

We identify the causal effect of temperature on injuries by leveraging daily variation in temperatures within an MSA-month. $\eta_{z,m}$ denotes a MSA-calendar-month fixed effect, which subsumes MSA fixed effects and accounts for all time-invariant determinants of workplace safety by MSA (e.g., local industry and demographic composition) as well as MSA-specific seasonality in injury risk (e.g., regional differences in construction or agricultural harvest seasons) that might otherwise give rise to spurious correlations between temperature and injuries. $\gamma_{m,y}$ denotes month by year fixed effects, which account for any state-wide economic shocks and macroeconomic trends. λ_o denotes occupation fixed effects, which helps to improve precision by controlling occupation-specific characteristics that may influence average

injury rates.

The coefficients of interest, β^k, capture the effect of a day in temperature bin k relative to a day in the omitted category of 60-65°F, net of these controls. In effect, we are isolating day-to-day variation in temperature within local labor markets, net of location-specific seasonality controls and state-wide time series patterns. Our identification assumption therefore is that day-to-day variation in temperature within a given zip code is plausibly orthogonal to unobserved determinants of workplace safety. We test the robustness of our findings by estimating specifications with different combinations of fixed effects, as well as a specification at the MSA-day level.

Figure 3 and Table 2 column 2 show the coefficients from estimating Equation 5. All coefficients (after being multiplied by 100) can be interpreted as roughly equivalent to the percentage change in the injury count for a day in the corresponding temperature bin relative to the omitted category of 60-65°F. Days with temperatures above 85°F lead to significantly higher risk of injury. All coefficients above 85°F are statistically significant at the 1% level, other than the noisier $\geq$ 105°F bin. A day between 85 and 90°F increases injuries by 7.3%, and a day between 100 and 105°F increases injuries by 8.5%. The effect of colder temperatures (e.g. days below 40°F) is highly noisy owing in part to the relative infrequency of such days in much of California. These findings are robust to a series of robustness checks presented in Table 2, where we control for various alternative combinations of geography, time, and occupation fixed effects.

Day-to-day temperature variation is plausibly exogenous. However, inasmuch as the conceptual object of interest is realized accident and injury risk, potential sources of bias in these coefficients include the possibility that temperature shocks may change the number of workers and/or hours worked in a given MSA. Given the lack of granular daily employment data, there is not a precise way to account for this possibility empirically. We note however that previous work consistently finds that labor supply tends to be reduced (outdoor industries) or unchanged (indoor industries) in periods with more very hot days (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Rode et al., 2023), which would suggest that our estimates using injury counts (as above) if anything understate the change in injury rates. In the Appendix (Tables A7 and A8 and Figure A5), we present variations of the above analysis that use injuries per worker using yearly employment counts by MSA and occupation and show that doing so does not significantly alter the direction or magnitude of these effects.[23] We also present separate analyses in Table A5 using time-use data from the American Time

[23]If anything, these analyses suggest that the coefficients on the hottest temperature bins (between 100 and 105°F , $\geq$ 105°F) may be slightly downward biased due to reduced labor supply in years with more extremely hot days.

Use Survey. In summary, these analyses reveal that in our setting hotter temperature has an insignificant or small negative impact on labor inputs, making it unlikely for our injury results to be driven by endogenous positive changes on either the intensive margin of hours worked or the extensive margin of workers employed.

4.2 Outside Options and Workplace Adaptation

In response to temperature shocks, one can imagine a wide range of possible adaptation responses. Work may proceed as usual but firms may need to pay higher wages to compensate for additional discomfort and health risks. Employers may change output levels by altering the pace of work, or change the production technology to be less outdoor labor-intensive. Workers may unilaterally decide to temporarily reduce their labor supply (e.g. calling in sick), potentially undergoing some risk of termination, or they may decide to negotiate with employers for changes in work practices (e.g. working during different times of day, taking more frequent breaks) to ameliorate some of the adverse effects.

Without taking a stand on the particular mechanism at play, we note that, whenever there is a discrepancy between workers' and employers' preferred response, adaptation may depend on workers' outside options. This could be through a bargaining channel, where workers negotiate adaptation investments as a component of total compensation. Or it could be through the voice channel, where workers with better outside options are less willing to engage in tasks that they deem hazardous or unpleasant, even if it risks termination.

To test whether the quality of workers' outside occupation options moderate the temperature-injury relationship, we interact the temperature bins from above with outside option wages (OOW), and estimate the following regression:

$$Inj_{o,z,d,m,y} = \sum_{j=1}^{J} \beta^j Temp_{z,d,m,y} + \sum_{j=1}^{J} \alpha^j Temp_{z,d,m,y} * log(OOW_{o,z,y}) + \zeta log(OOW_{o,z,y}) + \sum_{p=1}^{Q} \delta^q Precip_{z,d,m,y} + \eta_{z,m} + \gamma_{m,y} + \lambda_{o,y} + \mu_{z,y} + \epsilon_{o,z,d,m,y}, \quad (6)$$

where $\sum_{j=1}^{J} \alpha^j Temp_{z,d,m,y} * log(OOW_{o,z,y})$ represents an interaction between temperature bin j (at the MSA-day level) and the log of the outside occupation options wages (at the occupation-MSA-year level). For computational and expositional purposes, we focus on results that collapse to three temperature bins: below 50°F , between 50°F and 90°F , and 90°F and above. Therefore, the β^j coefficients should be interpreted as relative to a day

between 50 and 90°F. The coefficients of interest, α^j, represent the change in the effect of a day in temperature bin j for a 1 log-point increase in the OOW.

In order to isolate variation in outside options specific to a given local occupational labor market, we add occupation-year $\lambda_{o,y}$ and MSA-year $\mu_{z,y}$ fixed effects. This isolates variation in outside options for a given local occupational labor market netting out common shocks across all workers in a given occupation and shocks common to all workers in a given MSA. This measure therefore captures the degree to which, when outside option wages for roofers in Los Angeles are particularly good in a given year relative to roofers in other cities and relative to workers in other occupations in Los Angeles, Los Angeles roofers' susceptibility to injuries influenced by climate shocks may or may not be attenuated.

Figure 2 shows the residual variation for our two main explanatory variables: daily maximum temperature and outside options wages. Panel A shows the distribution of the residualized number of days above 90°F, after netting out the core fixed effects in Equation 6.[24] Panel B shows the same for the log of OOW. As shown, there is considerable within MSA-month variation in daily maximum temperature, as well as with within MSA-year and occupation-year variation in outside option wages. These are our sources of identifying variation.

Table 3 shows the results of running variations of equation 6. As shown in column 2, the interaction between log OOW and whether a day has temperature above 90°F is negative and significant at -0.041. The un-interacted coefficient on the hot temperature variable (T>90°F) is +0.18, implying that for the median worker, a day above 90°F leads to an approximately 7 percent increase in injuries, and that a one standard deviation increase in expected outside option wages reduces this coefficient by approximately 33 percent.[25] A move from the 10th to the 90th percentile of OOW reduces the effect of a day above 90°F on injuries from 9.8 percent to 3.9 percent.

This pattern persists when using lagged and 3 year moving average measures of outside option wages, as shown in columns 3 and 4, which account for the possibility that the effect of changing labor market conditions on workplace adaptation may not manifest immediately, as well as the fact that our underlying wage variables may be measured with error in a given year.[26]

[24]Panel C gives an example of this within-month variation for three MSAs (Los Angeles, San Francisco, and Riverside) in July of 2010.

[25]Specifically, this corresponds to an 0.56 increase in the log(OOW) from the median of 2.72 to 3.28.

[26]The OOW uses wages from the BLS Occupational Employment and Wage Statistics. These wages are only representative at the MSA-occupation-year level on a three year average basis. To address this potential issue, we calculate the three year average of OOW. For example, for 2015 OOW, we take the average of the OOW for 2013-2015 of the OOW, which we denote OOW_3. We also calculate a lagged measure of the 3 year average of OOW, called $OOW_{3,1l}$. We present results from estimating Equation 6 using these alternative

These estimates are consistent with the idea that highly localized changes in labor market conditions can exert a statistically significant and economically meaningful influence on the extent of climate adaptation in the workplace. In particular, they suggest that workers' individual outside options may be an important determinant of their ability to be protected from harsh environmental conditions on the job, including their adverse effects on overall workplace injury rates not limited to heat illnesses.

4.2.1 Outside Options as Primary Mechanism: IV Estimation

In this section, we engage in additional analyses that help pin down changing outside options as a potential mechanism, noting the potentially distinct welfare and policy implications. The evidence presented above provides a strong case that changing labor market conditions broadly can influence climate adaptation, and that improved outside options at highly localized levels can meaningfully influence the uptake of resiliency-enhancing technologies and processes. However, even with such granular measures of local OOW's, and the fixed effects noted above, it is possible for factors other than workers' changing outside options to be driving this relationship. Common technology or product market shocks may for instance drive local labor demand in both a worker's own occupation and other similar occupations, which may lead employers to ramp up production and increase compensation across the board, including along the dimension of workplace amenities.[27]

While such a relationship would reflect real changes in adaptation realized by workers, it may be of limited value in determining what kinds of policies may be most helpful in facilitating workplace adaptation. For instance, the social planner could choose to directly improve firms' or workers' financial positions via transfers, or they could engage in other more indirect interventions such as reducing frictions associated with job search.

In order to assess the extent to which the relationship documented above is driven by changes in outside options, we use a Bartik shift-share instrument that isolates exogenous shocks to an occupation's local outside option wages that are uncorrelated with local within-occupation working conditions. In this setting, a valid instrument will need to isolate variation in wages (total compensation) in a worker's expected set of outside options that does not affect and are not affected by local wages (total compensation) in their own occupation.

Our instrument is operationalized by replacing two of the three OOW terms. First, it instruments for local wages ($w_{p,z,y}$) with the national mean wage in occupation p and year y, excluding MSA z ($w_{p,\not{z},y}$). It also instruments for the local relative occupation share with the

OOW measures in Table 4 Columns 3 (OOW_3) and 4 ($OOW_{3,1l}$). The coefficients are slightly smaller than the core estimates, but in both cases their ratio is similar.

[27] For example, Charles et al. (2019) find that commodity price shocks influence firms' investments in safety, consistent with the labor demand channels.

value from 1999, the first year of available data ($\frac{s^{1999}_{p,m}}{s^{1999}_{p}}$). The transition probabilities remain the same and reflect national origin-destination occupation pairing-specific averages. The equation describing the instrument for the OOW is as follows:

$$\text{OOW}^{inst}_{o,z,y} = \sum_{p \neq o}^{N_{occs}} P(o \to p | \text{leave } o) \cdot \frac{s^{1999}_{p,z}}{s^{1999}_{p}} \cdot w_{p,\not{z},y}. \tag{7}$$

For the instrument to be valid, the national leave-one-out mean wages for all outside option occupations p must be positively correlated with local wages in p, but not affect wages in o other than through its outside occupation options, conditional on the fixed effects. Note that the instrument excludes local wages as well as local changes in relative employment. Identifying variation within an occupation across metro areas comes via each metro area's initial employment composition; identifying variation within an occupation-metro area over time comes via national shocks to wages of the relevant outside option occupations.

Because our reduced form equation is non-linear and includes high dimensional fixed effects, we estimate these regressions using a control function method (Wooldridge, 2015). For the $log(OOW)$ and each of its interactions with our temperature bins, we estimate the following first stage equation:

$$Y = \sum_{j=1}^{J} \beta^j Temp_{z,d,m,y} + \sum_{j=1}^{J} \alpha^j Temp_{z,d,m,y} * log(OOW^{inst}_{o,z,y}) + \zeta log(OOW^{inst}_{o,z,y}) + \sum_{p=1}^{Q} \delta^q Precip_{z,d,m,y} + \eta_{z,m} + \gamma_{m,y} + \lambda_{o,y} + \mu_{z,y} + \epsilon, \tag{8}$$

where Y is the given outcome. For each of these endogenous variables, we generate residual values (denoted u_o, u_{o50}, u_{o90}). We then estimate equation 6 with the addition of these residual values:

$$Inj_{z,o,d,m,y} = \sum_{j=1}^{J} \beta^j Temp_{z,d,m,y} + \sum_{j=1}^{J} \alpha^j Temp_{z,d,m,y} * log(OOW_{z,o,y}) + \zeta log(OOW_{z,o,y}) + \sum_{p=1}^{Q} \delta^q Precip_{z,d,m,y} + \omega_o u_o + \omega_{o50} u_{o50} + \omega_{o90} u_{o90} + \eta_{z,m} + \gamma_{y,m} + \lambda_{o,y} + \mu_{z,y} + \epsilon_{z,o,d,m,y}, \tag{9}$$

where u_o, u_{o50}, and u_{o90} are the residuals generated in equation 8 for $log(OOW)$, its interaction with the below 50°F temperature bin, and its interaction with the below 90°F

temperature bin, respectively. By including these residual control functions in equation 9, we control for the portions of the *OOW* that are orthogonal to the instruments and therefore possibly correlated with local within-occupation working conditions (Wooldridge, 2015).

Because this procedure does not correctly estimate standard errors, we calculate them using a bootstrap method. We resample the observations at the MSA-occupation-year level[28] with replacement 100 times. For each resample, we reestimate the coefficients, and the standard error for the coefficient is equal to the standard deviation of the coefficients across samples.

4.2.2 IV Results and Robustness

Table 4 Column 1 presents results from estimating Equation 9, where we instrument for OOW. The non-interaction coefficient on a day of at least 90°F is 0.22, and the coefficient for the interaction between the log of OOW and Max T $\geq$ 90°F is -0.056. This implies that, for the median worker, a 1 standard deviation increase in the OOW decreases the impact of a 90°F day on injuries by 47 percent, from 6.7 percent to 3.6 percent, consistent with the notion that improved outside options lead to improved bargaining for workplace adaptations. The point estimate of this interaction term is larger than that in the OLS estimation (33 percent). We present the full list of coefficients from our estimates in Table A2. We calculate bootstrap standard errors clustered at the MSA-occupation-year level, and present the distribution of the coefficients across bootstrap samples in Figure A3. As with the OLS results, this finding is robust to using variants of the OOW measure tha t account for potential lagged effects and measurement error in the underlying wage data.

Improved protections against workplace accidents and injuries due to hotter temperature may not be welfare improving for workers if it comes at the cost of reduced wages. While we cannot test whether an increase in outside occupations quality lead to a larger decrease in wages due to extreme heat because of data limitations, we can assess whether higher wages in one's outside occupation options leads to an increase in one's one wage. As shown in Table 5, which presents the results of an instrumental variables regression of the log of hourly wages at the MSA-occupation-year level on the log of their outside occupation options wages, instrumenting for the log(OOW) as described above, a 1 percentage point increase in the log(OOW) leads to a 0.09 percent higher wage. This is consistent with prior work, including SST, and suggests that the (non-wage) workplace adaptation benefits documented above likely were not offset by a reduction in wages.

[28]This is the level of the variation in the OOW treatment, and this sampling procedure results in our estimating the standard errors that are clustered at the MSA-occupation-year level.

4.3 Comparing Measures of Adaptation - Average Climate

Recent work empirically estimates potential adaptation to climate change by looking at how short-run coefficients like those estimated in section 4.1 vary by local average climate. The intuition is that, even though the researcher is unable to observe specific determinants of adaptation in the data, such heterogeneity would describe the net effect of all adaptation decisions deemed optimal conditional on a given climate.[29] Such approaches have yielded conflicting findings, particularly in the context of labor responses.

Here, we explore how the estimates of adaptation given by changing outside options compares to those generated using these standard cross-sectional approaches. We estimate an analogous regression to that specified in equation 5, but at the zip-code by day level given the lack of meaningful climate variation across occupations within a zip code. To reflect this reshaping of the data, we replace the MSA-month fixed effect with a zip-month fixed effect, and remove the occupation fixed effect given its redundancy. For each zip code, we calculate the average number of summer days it experiences with a maximum temperature above 90°F. We define climate zones by quartiles of this number of days. By this definition, zip codes in climate zone 1 experience an average of 4.4 such days (ranging from 0 to 10.6 days), climate zone 2 experiences 22.1 (ranging from 10.7 to 38.9); those in climate zone 3 experience 56.6 (ranging from 39.1 to 74.0); and those in climate zone 4 experience 99.3 (ranging from 74.1 to 179.1). We estimate this regression separately for each of these climate zones, first with the full set of 5°F temperature bins from <40°F to ≥ 105°F, then with a more parsimonious set of three bins.

Figure 4 plots the estimated coefficients for climate zones 1 and 4. Panel A shows the full set of temperature bins. The estimated coefficients for both climate zones display a similar pattern, with an increase in the number of injuries during warmer days. The point estimate for a day between 90 and 95°F is slightly larger in the coldest climate zone 1 (0.1) than in the hottest climate zone 4 (0.06), though they are not statistically significantly different.[30] For the 95 to 100°F bin, the difference in coefficients between the hottest and coolest quartiles of California zip codes is also statistically insignificant. For days above 105°F, only climate

[29] For example, Auffhammer (2017) shows that the responsiveness of residential energy consumption to hot and cold temperature varies systematically with average exposure to hot and cold days. Similarly, Carleton et al. (2022) show that all-cause mortality responses to extreme temperature vary by average climate, such that a given heat (cold) event leads to more muted mortality responses in places that experience more such heat (cold) events on average. In seminal work, Dillender (2021) shows that, in the context of safety among mining workers, the opposite appears to be true, whereby the marginal impact of a hotter day on injuries is actually larger in historically hotter areas of the United States.

[30] For reference, this 40% difference in the point estimates compares to the statistically significant 60% difference between the 90th and 10th percentiles of the OOW distribution.

zone 4 has coefficient that is statistically significant at conventional levels.[31] Therefore, we cannot conclude that the effect of days above 95°F are statistically significantly different across climate zones.

In Panel B, we show the coefficient estimates for the more parsimonious bin specification used in our analysis of outside options, <50°F and ≥90°F (with 50-90°F as the omitted category) for ease of comparison. Similar to the specification with the full set of temperature bins, we do not find that warmer climates experience significantly shallower effects of days above 90°F on injuries.[32] While it is difficult to directly compare these implied adaptation estimates, they indicate that a substantial portion of adaptation decisions relevant to workers may depend on highly local labor market conditions, which vary across time and across workers within a given local climate.

There are several potential explanations for these results, which appear to be in conflict with findings in non-labor contexts such as household energy use or mortality. One possibility is that, unlike residential energy use and personal health, which represent contexts in which individuals more clearly internalize both the costs and benefits of adaptation decisions, labor may involve competing tradeoffs between workers and employers. These tradeoffs may mean that local labor market conditions play an important role in adaptation decisions, masking the typical average climate-weather adaptation gradient found outside of the labor market. A related possibility, suggested by Dillender (2021), is that adapting to extreme heat is actually more costly to firms and workers in warmer climates. If the most cost-effective way to adapt to days with ambient temperature extremes is to reduce time spent working on such days, and production entails fixed costs, then the marginal cost of this adaptation response is likely rising in the average number of disruptively hot days per year/season. This dynamic would offset the fact that more frequent hot weather better justifies the fixed costs associated with adaptation (e.g., installing air condition).

5 Conclusion

Ongoing climate change is projected to lead to significant increases in the frequency of hotter temperature events, with some places expected to experience over 100 additional days per year with temperatures in the 90s Fahrenheit (32°C) or above by mid-century (Reidmiller et al., 2018). The realized economic consequences of such added heat will depend largely on the extent and effectiveness of adaptation decisions made by a range of actors,

[31] In cooler areas, this coefficient is extremely imprecise, due in part to how rare such days are: climate zone 1 only experiences 0.03 days above 105°F per year during the summer.

[32] The full set of coefficients for all four climate zones for each of these specifications are presented in Tables A3 and A4 in the Appendix.

including workers and their employers. And yet, economists know relatively little about the determinants of adaptation in workplace settings, particularly for the many hundreds of millions of workers whose jobs expose them to the elements. Particularly relevant for welfare and policy is the possibility that workplace adaptation may in some cases involve both productive and consumptive amenities, leading to potential conflicts between what is optimal from the perspective of firms versus that of their employees, particularly in settings where firms do not internalize the full social costs of workplace health and safety.

This paper takes advantage of highly granular, empirically validated, and plausibly exogenous variation in local outside occupation option wages to identify the role of local labor market conditions in influencing workplace climate adaptation. The results from both fixed effects and IV analyses, both of which exploit within-zip code-month variation in temperature and within-MSA-occupation variation in outside option wages, suggest that workers with higher outside option wages are significantly less vulnerable to temperature-related workplace injuries. A day with high temperatures of 90°F or above increases accidents and injuries by around 7 percent. A one standard deviation increase in workers' expected local outside occupation options – the national transition probability- and local-employment-weighted average wage in all occupations which represent a realistic outside option for a worker in a given origin occupation – leads to a 33 to 47 percent reduction in this effect. In contrast, we observe limited variation in the same-day temperature-injury relationship across climates with different summer temperature distributions, despite significant variation in our setting on par with that across the U.S.[33]

The fact that changes in workers' outside options independent of employers' own economic conditions influences the realized temperature-injury relationship highlights the potential divergence between the optimal adaptation preferences of employers and workers. This has important implications for understanding the distributional implications of climate change, particularly regarding the incidence born by labor and capital respectively, as well as for the design of policies aimed at facilitating climate adaptation.

Our findings are consistent with suggestive evidence from Somanathan et al. (2021), who find that high temperatures in preceding days and weeks lead to increases in worker absenteeism, but only for workers with paid leave. Our results might also help to explain why the relationship between temperature and labor inputs documented in other studies such as (Rode et al., 2023) does not appear to exhibit the same pattern of adaptation found in other contexts such as mortality or energy use, and is found to be negligible even in some

[33]The difference between the 5th and 95th percentiles of the average summer climate distribution in our data, as measured by the average number of days per zip code per year with high temperatures above 90°F is 113 (0 versus 113) days. The analogous difference across all U.S. counties is 104 (0 versus 104) days.

settings, such as industrial manufacturing in China (Zhang et al., 2018), where the health and productivity impacts of extreme temperatures have been documented to be high (Cai et al., 2018). Our results suggest that such patterns may be consistent with many workers in these settings having limited outside options.

Overall, the results are consistent with the view that workers' bargaining power matters in determining the extent and distributional incidence of climate adaptation. These findings are particularly significant in light of emerging evidence that, in many settings, labor markets can be imperfectly competitive, whether due to employer concentration (Azar et al., 2020) or monopsonistic frictions in the labor market such as employer-sponsored visa programs (Naidu et al., 2016), occupational licensing requirements (Johnson and Kleiner, 2020), or non-compete agreements (Johnson et al., 2023). Future research might examine the extent to which policies that reduce these and other labor market frictions confer benefits to workers in the form of increased resilience to environmental shocks such as climate change.

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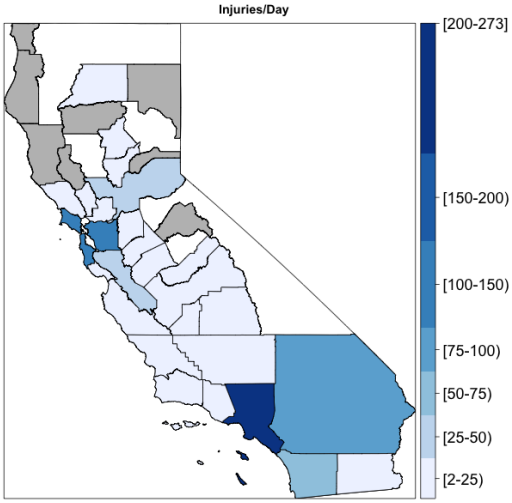
6 Tables and Figures

Table 1: Summary Statistics

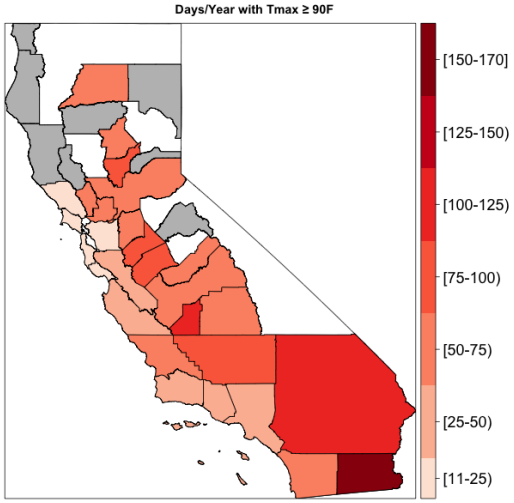
	Mean	Median	SD	25th	75th	Observations
Injuries (MSA-day)	32	10	64	4	26	199,446
Injuries (MSA-SOC-day)	0.0471	0	0.510	0	0	126,872,850
Outside Options Wages, Levels	18.57	15.30	12.93	10.69	21.89	126,872,850
Log(Outside Options Wages)	2.75	2.73	0.56	2.37	3.09	126,872,850
Outside Options Wages Inst., Levels	16.35	14.33	9.16	10.56	19.25	126,872,850
Log(Outside Options Wages Inst.)	2.67	2.66	0.49	2.36	2.96	126,872,850
Days/Year 60-65°F	43.55	42.32	11.27	36.17	49.76	126,872,850
Days/Year 65-70°F	40.84	38.35	10.56	32.96	48.96	126,872,850
Days/Year 70-75°F	37.52	35.88	10.04	29.80	45.91	126,872,850
Days/Year 75-80°F	34.62	34.19	7.46	29.18	39.63	126,872,850
Days/Year 80-85°F	31.75	31.07	6.22	27.14	35.98	126,872,850
Days/Year 85-90°F	29.36	29.47	7.38	24.40	34.23	126,872,850
Days/Year 90-95°F	27.18	26.91	9.66	21.32	33.50	126,872,850
Days/Year 95-100°F	20.23	19.48	10.13	13.26	27.00	126,872,850
Days/Year 100-105°F	10.08	8.03	9.18	4.00	12.16	126,872,850
Days/Year $\geq$ 105°F	4.67	1.35	11.65	0.33	2.98	126,872,850

This table shows the distribution of injuries, outside occupation options wages, and temperature in our sample. The injury data are from the California Division of Workers' Compensation, the outside option wages data are from Schubert et al. (2024), and the weather data are from the PRISM Climate Group.

A) Injuries per Day



B) Yearly Days with Max T $\geq$ 90°F



C) Mean OOW

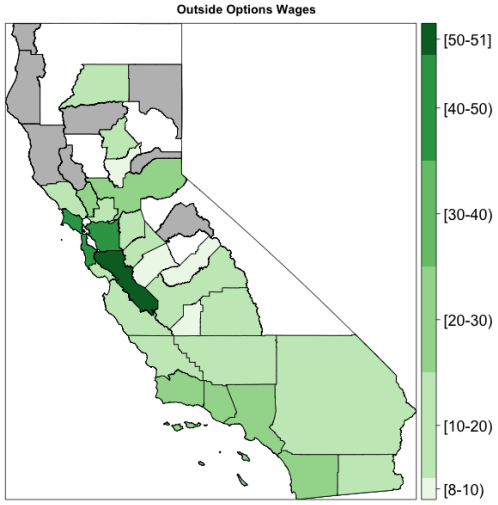
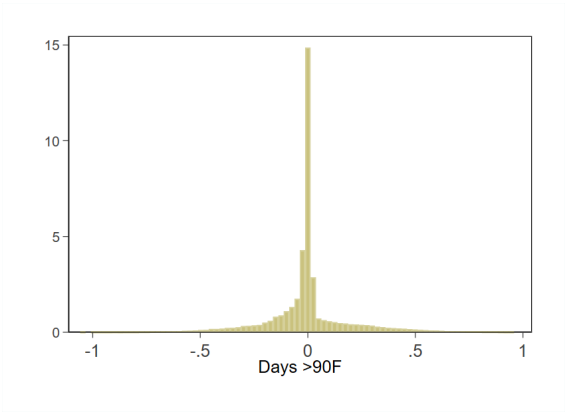


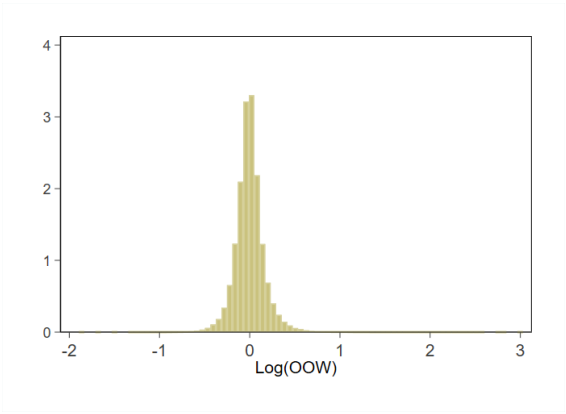
Figure 1: Statistics by MSA

This figure shows summary statistics at the metropolitan statistical area (MSA) level. Panel A shows the average number of injuries per day. Panel B shows the average number of days per year with a maximum temperature above 90°F. Panel C shows the average outside occupation options wages (OOW). The data cover 26 metropolitan statistical areas in California from 2000-2020. Micropolitan statistical areas (not included in our analysis) are shaded in gray, and other parts of California are shaded in white.

A) Max T $\geq$ 90°F



B) Log(OOW)



C) Residual Variation in Temperature

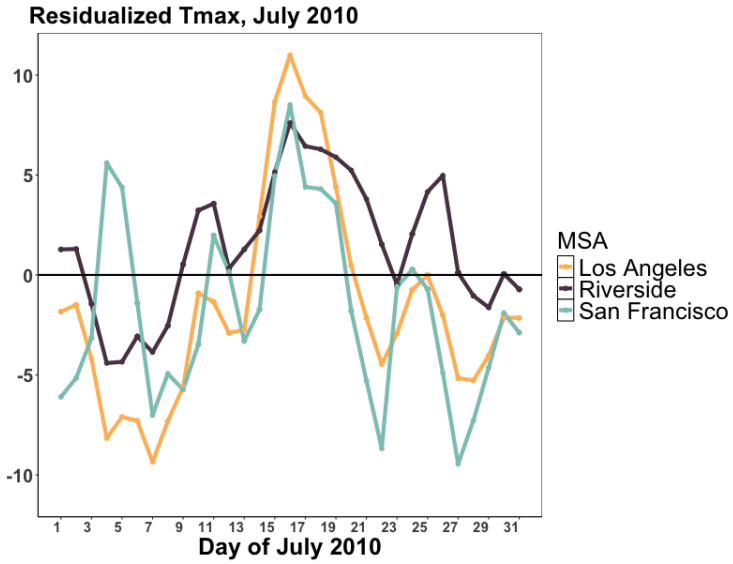


Figure 2: Residual Variation

This figure shows the residual variation in the explanatory variables after controlling for the core set of fixed effects in the interaction regressions: MSA-month, year-month, MSA-year, and occupation-year. Panel A is a histogram of residualized days above 90°F. Panel B is a histogram of residualized log(OOW). Panel C shows the residual maximum temperature across the month of July 2010 for three different MSAs: Los Angeles-Long Beach-Anaheim (31080), San Francisco-Oakland-Fremont (41860) and Riverside-San Bernardino-Ontario (40140). The data cover 26 metropolitan statistical areas in California from 2000-2020.

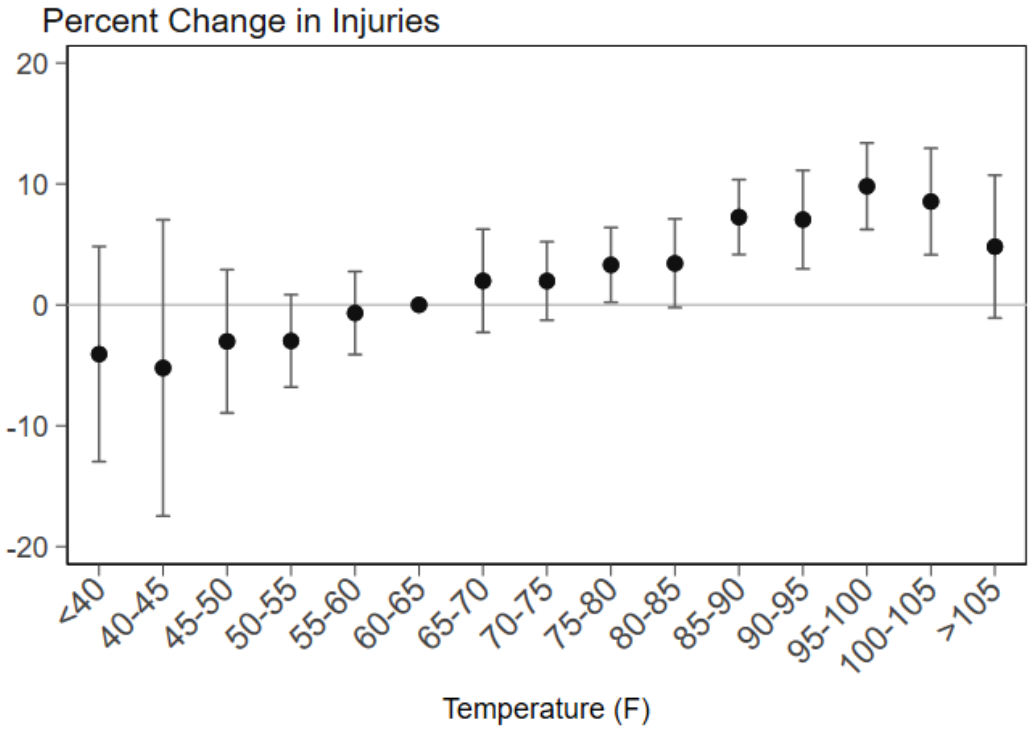


Figure 3: Temperature and Injuries - Primary Specification

This figure plots the full set of temperature coefficients obtained from regressions specified in Equation 5 (point estimates from column 2 of Table 2). All coefficients are obtained from Poisson regressions of injury counts per MSA, occupation, and day as the dependent variable. They reflect residual variation in injuries after regressing on MSA-month, year-month, and occupation fixed effects, as well as controls for precipitation. Daily maximum temperatures are assigned to a vector of 15 temperature bins from below 40°F to 105°F and greater in 5°F increments. The coefficients should be interpreted as (roughly) the percentage increase in injuries for an additional day in that temperature range relative to a day in the omitted category (daily maximum temperatures between 60 and 65 °F). Heteroskedasticity robust standard errors are clustered by MSA-year, and error bars denote 95 percent confidence intervals. The regression includes 126,872,850 data-points across 26 metropolitan statistical areas in California from 2000-2020.

Table 2: Temperature and Injuries

	(1)	(2)	(3)	(4)
Max T (°F)	MSA-Day	MSA-Soc-Day	MSA-Soc-Day	MSA-Soc-Day
≥105	0.0428	0.0481	0.0036	0.0490
	(0.0551)	(0.0301)	(0.0268)	(0.0299)
100-105	0.0817**	0.0854***	0.0775***	0.0897***
	(0.0328)	(0.0225)	(0.0230)	(0.0224)
95-100	0.0987***	0.0981***	0.101***	0.0914***
	(0.0302)	(0.0183)	(0.0186)	(0.0176)
90-95	0.0688**	0.0705***	0.0588***	0.0709***
	(0.0278)	(0.0208)	(0.0210)	(0.0206)
85-90	0.0745***	0.0726***	0.0491***	0.0699***
	(0.0229)	(0.0158)	(0.0161)	(0.0157)
80-85	0.0335	0.0344*	0.0246	0.0282
	(0.0237)	(0.0187)	(0.0188)	(0.0189)
75-80	0.0335*	0.0331**	0.0236	0.0237
	(0.0194)	(0.0158)	(0.0161)	(0.0150)
70-75	0.0199	0.0198	0.0137	0.0202
	(0.0218)	(0.0166)	(0.0167)	(0.0166)
65-70	0.0201	0.0199	0.0123	0.0109
	(0.0193)	(0.0218)	(0.0223)	(0.0210)
55-60	-0.0091	-0.0068	-0.0227	-0.0163
	(0.0241)	(0.0175)	(0.0201)	(0.0178)
50-55	-0.0318	-0.0298	-0.0517**	-0.0441**
	(0.0253)	(0.0195)	(0.0200)	(0.0202)
45-50	-0.0350	-0.0302	-0.0229	-0.0385
	(0.0495)	(0.0302)	(0.0357)	(0.0298)
40-45	-0.0588	-0.0522	-0.0083	-0.0480
	(0.0749)	(0.0625)	(0.0624)	(0.0616)
<40	-0.0459	-0.0407	-0.1169***	-0.0472
	(0.0611)	(0.0454)	(0.0441)	(0.0459)
Observations	199,446	126,872,850	126,872,850	111,612,582
	MSA-Day	MSA-Soc-Day	MSA-Soc-Day	MSA-Soc-Day
MSA-Month FEs	X	X		X
Year-Month FEs	X	X		X
Soc Code FEs		X	X	
MSA FEs			X	
Month FEs			X	
Year FEs			X	
MSA-Year FEs				X
Soc-Year FEs				X
Precipitation	X	X	X	X
Clustering	MSA, Year-Month	MSA-Year	MSA-Year	MSA-Year

This table shows the effect of temperatures on injury claims for California-based work sites over the period 2000 to 2020. The coefficients in all columns are obtained from Poisson regressions of injury counts on the listed temperature and precipitation variables, as well as the listed fixed effects. Column 1 is at the MSA-day level, and includes MSA-month and year-month fixed effects. Column 2 (our preferred specification, as plotted in Figure 3) is at the MSA-occupation-day level and adds occupation fixed effects. Column 3 includes MSA, month, year, and occupation fixed effects. Column 4 includes MSA-month, year-month,

Table 3: Temperature, Injuries, and Outside Occupation Options: OLS

	(1)	(2)	(3)	(4)
	No Interaction	Contemporaneous OOW	3 year average of OOW	3 year average, 1 year lag of OOW
Max T $\geq$ 90°F	0.0557***	0.1830***	0.1594***	0.1280***
	(0.0079)	(0.0233)	(0.0254)	(0.0259)
Log(OOW)*Max T $\geq$ 90°F		-0.0414***	-0.0359***	-0.0284***
		(0.0078)	(0.0085)	(0.0087)
Observations	126,872,850	111,612,584	101,656,256	96,582,032
MSA-Month FEs	X	X	X	X
Year-Month FEs	X	X	X	X
Soc FEs	X			
MSA-Year FEs		X	X	X
Soc-Year FEs		X	X	X
Clustering	MSA-Year	MSA-Soc-Year	MSA-Soc-Year	MSA-Soc-Year

This table shows the effect of temperatures and outside occupation options on injury claims for California-based work sites over the period 2000 to 2020. The coefficients in all columns are obtained from Poisson regressions of injury counts on the listed temperature, precipitation, and outside options quality variables (columns 2-4), as well as the listed fixed effects. Column 1 does not include the outside options variable or its interaction with temperature bins. It is equivalent to column 2 in Table 2, but it only includes two temperature bins: below 50°F and above 90°F. Coefficients should be interpreted as relative to a day between 50 and 90°F. Columns 2-4 include the log of the outside options wages (log(OOW)), as well as interaction terms between log(OOW) and each of the temperature bins. Column 2 is our core specification and includes MSA-month, year-month, MSA-year, and occupation-year fixed effects. Column 3 replaces our measure of the log(OOW) with a 3 year average of log(OOW). This accounts for the fact that the wages used in our OOW measure are representative at a 3-year averaged level. Column 4 replaces our measure of the log(OOW) with a 3 year average of log(OOW), lagged by 1 year. This accounts for the fact that the effects of stronger outside options may not materialize right away. Heteroskedasticity robust standard errors are clustered by MSA-year in column 1 and MSA-occupation-year in columns 2-4. For the full set of coefficients, see Table A1. *p<0.1 **p<0.05 ***p<0.01

Table 4: Temperature, Injuries, and Outside Occupation Options: IV

	(1) Contemporaneous OOW	(2) 3 year average of OOW	(3) 3 year average, 1 year lag of OOW
Max T $\geq$ 90°F	0.2194***	0.1891***	0.1597***
	(0.0221)	(0.0287)	(0.0289)
Log(OOW)*Max T $\geq$ 90°F	-0.0561***	-0.0479***	-0.0412***
	(0.0075)	(0.0100)	(0.0102)
Observations	111,612,584	101,656,256	96,582,032
MSA-Month FEs	X	X	X
Year-Month FEs	X	X	X
MSA-Year FEs	X	X	X
Soc-Year FEs	X	X	X
Clustering	MSA-Soc-Year	MSA-Soc-Year	MSA-Soc-Year

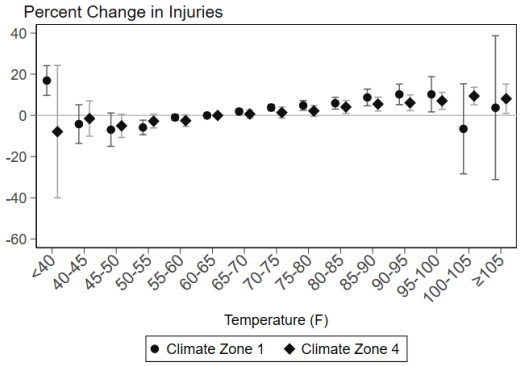
This table shows the effect of temperatures and outside occupation options on injury claims for California-based work sites over the period 2000 to 2020. The coefficients in all columns are obtained from Poisson regressions of injury counts on the listed temperature, precipitation, and outside options quality variables, as well as the listed fixed effects. We control for the endogeneity of the OOW and its interaction with temperature bins by using the control function method described in equation 9. We calculate the standard errors with 100 runs of a bootstrap. For each run, we resample observations at the MSA-occupation-year level, with replacement. Column 1 is our core specification and includes MSA-month, year-month, MSA-year, and occupation-year fixed effects. Column 2 replaces our measure of the log(OOW) with a 3 year average of log(OOW). This accounts for the fact that the wages used in our OOW measure are representative at a 3-year averaged level. Column 3 replaces our measure of the log(OOW) with a 3 year average of log(OOW), lagged by 1 year. This accounts for the fact that the effects of stronger outside options may not materialize right away. Heteroskedasticity robust standard errors are clustered by MSA-occupation-year. For the full set of coefficients, see Table A2. *p<0.1 **p<0.05 ***p<0.01

Table 5: Wages and Outside Occupation Options

	(1)	(2)
	Hourly Wage	Log(Hourly Wage)
Log(OOW)	4.662***	0.0934***
	(0.2120)	(0.0055)
Observations	183,657	183,601
MSA-Year FEs	X	X
Soc-Year FEs	X	X
Clustering	MSA-Soc	MSA-Soc

This table shows the effect of outside occupation options on the hourly wage in California over the period 2000 to 2020. The coefficients in all columns are obtained from 2SLS IV regressions of MSA-occupation-year hourly wage on the log of outside options. We instrument for the log of OOW with the log of the OOW instrument. The dependent variable in Column 1 is the hourly wage in levels, and in column 2 it is the log of the hourly wage. Both specifications include MSA-year and occupation-year fixed effects, and heteroskedasticity robust standard errors are clustered by MSA-Soc. *p<0.1 **p<0.05 ***p<0.01

A) All Temperature Bins



B) Two Temperature Bins

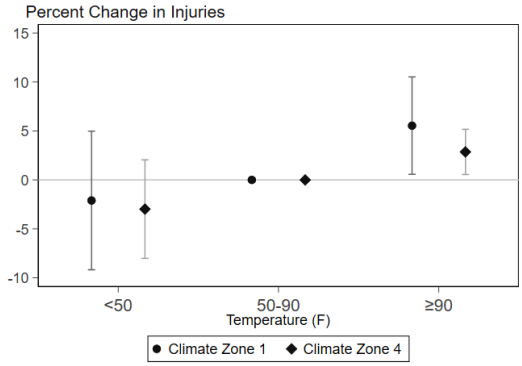


Figure 4: Temperature and Injuries: Climate Zones 1 and 4

Panel A plots the full set of temperature coefficients obtained from regressions specified in Equation 5, separately for climate zones 1 (coolest zip codes) and 4 (warmest zip codes). All coefficients are obtained from Poisson regressions of injury counts per zip-day as the dependent variable. They reflect residual variation in injuries after regressing on zip-month and year-month fixed effects, as well as controls for precipitation. In Panel A, daily maximum temperatures are assigned to a vector of 15 temperature bins from below 40°F to 105°F and greater in 5°F increments. The coefficients should be interpreted as (roughly) the percentage increase in injuries for an additional day in that temperature range relative to a day in the omitted category (daily maximum temperatures between 60 and 65 °F). Panel B is identical to panel A, but with limited temperature bins: <50°F and ≥90°F, with 50-90°F omitted. Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The data cover 1,764 zip codes in California from 2000-2020.

A Appendix

A.1 Construction of Outside Option Wages (OOW)

Our measure of outside option wages (OOW) modifies that presented in SST. It is defined as follows:

$$\text{OOW}_{o,z,y} = \sum_{p \neq o}^{N_{occs}} P(o \to p | \text{leave } o) \cdot \frac{s_{p,z,y}}{s_{p,y}} \cdot w_{p,z,y}. \tag{10}$$

Including the leaveshare_o term would result in combining the effects of two, possibly contradictory, moderators on the temperature-injury relationship: 1) an occupation's time- and location-invariant leave share (which may be higher for lower quality occupations), and 2) the OOW, which varies at the MSA-occupation-year level. We are only interested in capturing the effects of the latter.

To further elucidate this issue, first consider the relationship between OOI, OOW, and leaveshare_o:

$$\begin{aligned}
\text{OOI}_{o,z,y} &= \sum_{p \neq o}^{N_{occs}} \text{leaveshare}_o \cdot P(o \to p | \text{leave } o) \cdot \frac{s_{p,z,y}}{s_{p,y}} \cdot w_{p,z,y} \\
&= \text{leaveshare}_o \sum_{p \neq o}^{N_{occs}} P(o \to p | \text{leave } o) \cdot \frac{s_{p,z,y}}{s_{p,y}} \cdot w_{p,z,y} \\
&= \text{leaveshare}_o \times OOW_{o,z,y}. \qquad (11)
\end{aligned}$$

Next, consider the following equation representing the interaction term between the log of OOI and temperature:

$$\begin{aligned}
log(OOI_{o,z,y}) \times T_{z,d,m,y} &= log(\text{leaveshare}_o \times OOW_{o,z,y}) \times T_{z,d,m,y} \\
&= log(\text{leaveshare}_o) \times T_{z,d,m,y} + log(OOW_{o,z,y}) \times T_{z,d,m,y}, \qquad (12)
\end{aligned}$$

where the first equality comes from the relationship between OOI and OOW in equation 11, and the second equality comes from the logarithm product rule. One might expect that occupations with a higher leave share have a stronger temperature-injury relationship. In contrast, our hypothesis is that a higher OOW would result in a weaker temperature-injury relationship. Including leaveshare_o (i.e., using the OOI instead of the OOW) would combine these two, possibly contradictory, moderating effects, preventing us from capturing the true relationship between increased outside option quality and worker vulnerability to temperature.[34]

[34]Note that, if estimating the relationship between the non-interacted log(OOI) and injuries (or any outcome), occupation-specific fixed effects would remove the $\log(\text{leaveshare}_o)$ term. Therefore, one could use

A.2 Additional Summary Statistics and Results

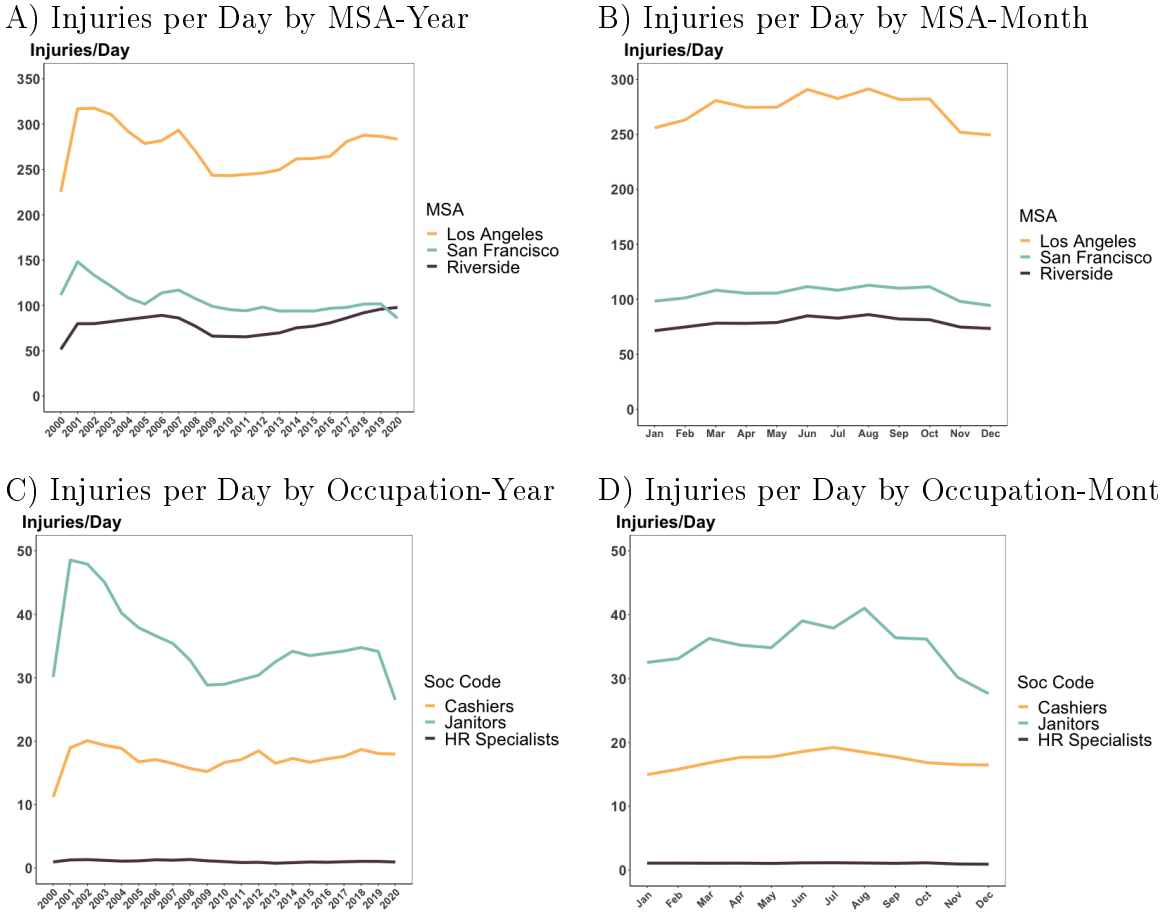
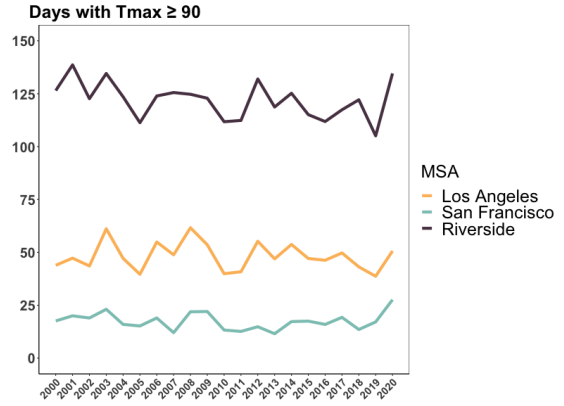


Figure A1: Injuries per Day

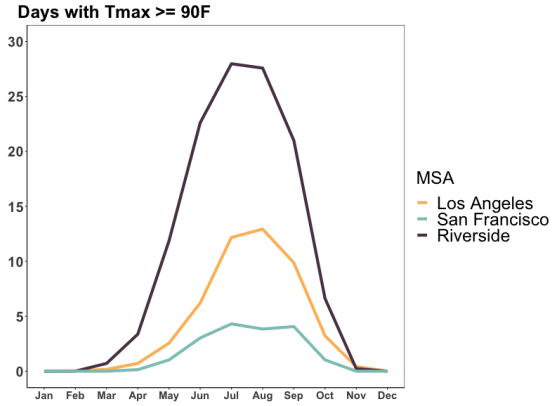
This figure shows the variation in daily injuries over time, space, and occupation. Panel A graphs the average daily injuries by year for three MSAs: Los Angeles-Long Beach-Anaheim (31080), San Francisco-Oakland-Fremont (41860) and Riverside-San Bernardino-Ontario (40140). Panel B graphs the average injuries per month for the same three MSAs. Panel C graphs the total injuries per year for three occupations: Cashiers (41-2011), Janitors (37-2011), and HR Specialists (13-1071). Panel D graphs the average injuries per month for the same three occupations. The data cover injury claims from 26 metropolitan statistical areas in California from 2000-2020.

log(OOW) or log(OOI) interchangeably and produce the same results.

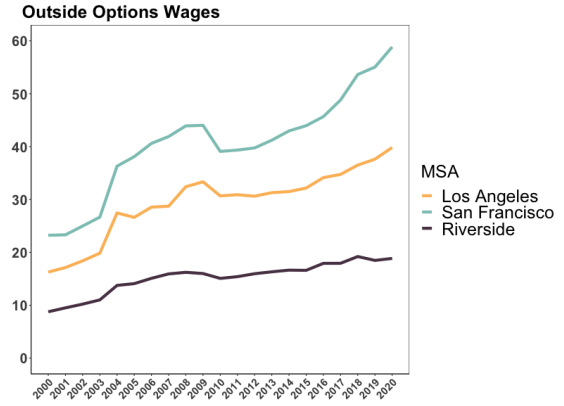
A) Days with Max T $\geq$ 90°F by MSA-Year



B) Days with Max T $\geq$ 90°F by by MSA-Month



C) OOW by MSA-Year



D) OOW by Occupation-Year

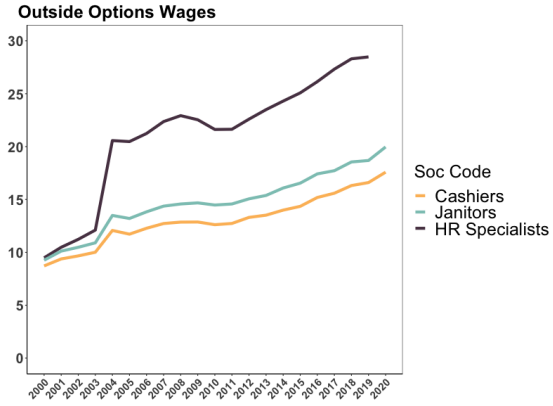


Figure A2: Temperature and Outside Options

This figure shows the variation in days with temperature above 90F over time and space, and variation in outside occupation options wages (OOW) over occupation, time, and space. Panel A shows the yearly number of days with a maximum temperature above 90F for three MSAs: Los Angeles-Long Beach-Anaheim (31080), San Francisco-Oakland-Fremont (41860) and Riverside-San Bernardino-Ontario (40140). Panel B shows the average monthly days with a maximum temperature above 90F for the same three MSAs. Panel C shows the change in the mean of the outside occupation options wages (OOW) for the same three MSAs. Panel D shows the change in the mean of the OOW for three occupations: Cashiers (41-2011), Janitors (37-2011), and HR Specialists (13-1071). The data cover 26 metropolitan statistical areas in California from 2000-2020.

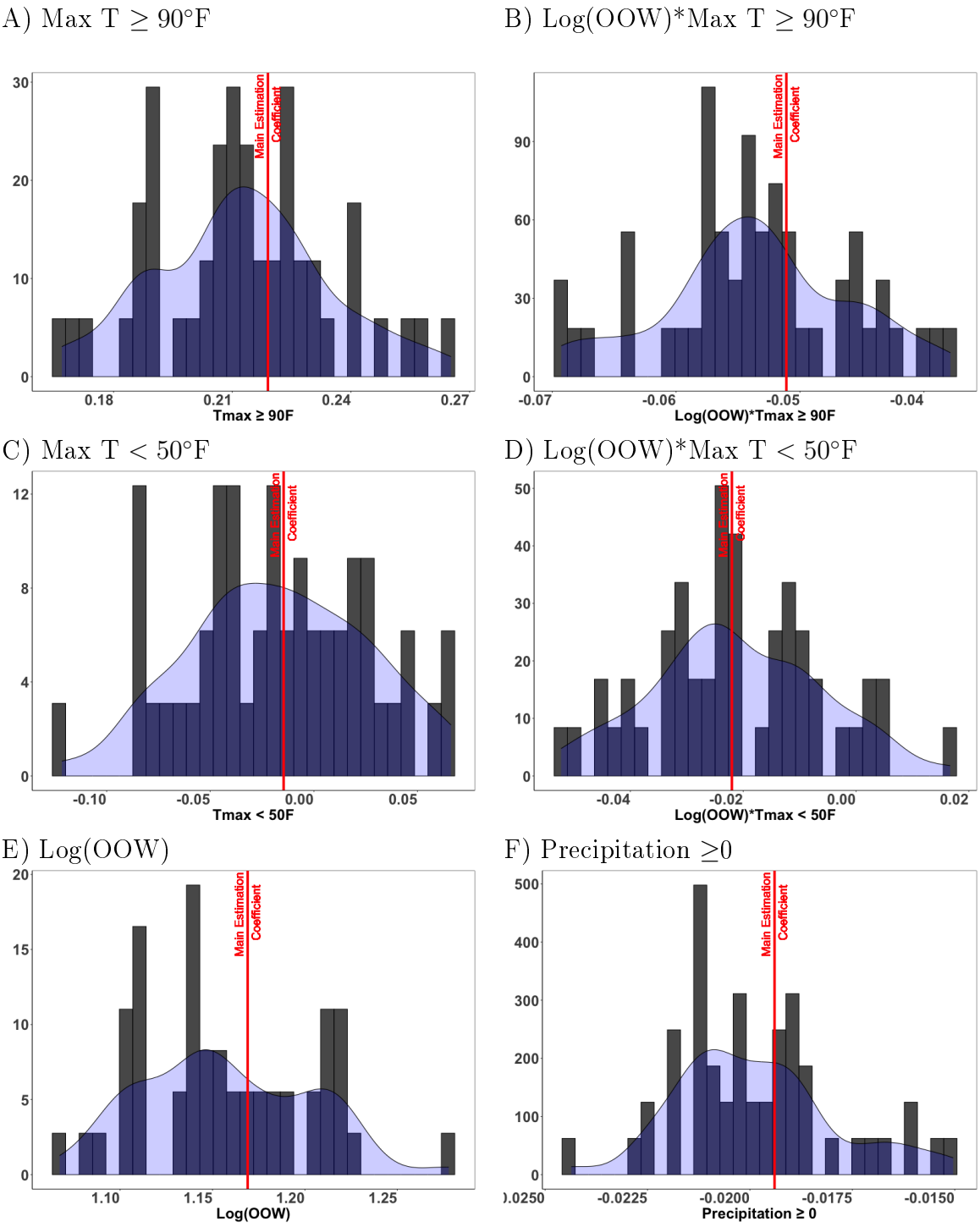


Figure A3: Bootstrapped Coefficients

This figure shows the distribution of coefficients from the 100 bootstrapped estimations of Equation 9. Panel A shows the distribution for the Max T ≥90°F coefficient, Panel B shows it for the coefficient on log(OOW)*Max T ≥90°F, Panel C shows it for the Max T <50°F coefficient, Panel D shows it for the coefficient on log(OOW)*Max T <90°F, Panel E shows it for the coefficient on log(OOW), and Panel F shows it for the precipitation≥0 coefficient. The red line represents the coefficient for the full-sample estimate. Each bootstrap resamples MSA-occupation-year groups with replacement. We take the standard deviation of each coefficient's bootstrap distribution as its standard error.

Table A1: Temperature, Injuries, and Outside Occupation Options: OLS

	(1) No Interaction, MSA-Day	(2) No Interaction, MSA-SOC-Day	(3) Contemporaneous OOW	(4) 3 year average of OOW	(5) 3 year average, 1 year lag of OOW
Max T $\geq$ 90°F	0.0541***	0.0557***	0.1830***	0.1594***	0.1280***
	(0.0179)	(0.0079)	(0.0233)	(0.0254)	(0.0259)
Max T $<$ 50°F	-0.0828**	-0.0632***	-0.0683*	-0.1146***	-0.1256***
	(0.0389)	(0.0145)	(0.0370)	(0.0394)	(0.0410)
Ppt $>$ 0	-0.0061	-0.0200***	-0.0196***	-0.0209***	-0.0194***
	(0.0059)	(0.0060)	(0.0021)	(0.0023)	(0.0023)
Log(OOW)*Max T $\geq$ 90°F			-0.0414***	-0.0359***	-0.0284***
			(0.0078)	(0.0085)	(0.0087)
Log(OOW)*Max T $<$ 50°F			0.0008	0.0131	0.0148
			(0.0122)	(0.0129)	(0.0135)
Log(OOW)			1.162***	1.255***	1.268***
			(0.0363)	(0.0403)	(0.0427)
Observations	199,446	126,872,848	111,612,584	101,656,256	96,582,032
MSA-Month FEs	X	X	X	X	X
Year-Month FEs	X	X	X	X	X
Soc FEs		X			
MSA-Year FEs			X	X	X
Soc-Year FEs			X	X	X
Clustering	MSA, Year-month	MSA-Year	MSA-Soc-Year	MSA-Soc-Year	MSA-Soc-Year

This table shows the effect of temperatures and outside occupation options on injury claims for California-based work sites over the period 2000 to 2020. The coefficients in all columns are obtained from Poisson regressions of injury counts on the listed temperature, precipitation, and outside options quality variables, as well as the listed fixed effects. Columns 1 (MSA-day level) and 2 (MSA-Soc-day level) include no interaction effects. They are equivalent to columns 1 and 2 in Table 2, but they only include two temperature bins: below 50°F and above 90°F. Coefficients should be interpreted as relative to a day between 50 and 90°F. Columns 3-5 include the log of the outside options wages (log(OOW)), as well as interaction terms between log(OOW) and each of the temperature bins. Column 3 is our core specification and includes MSA-month, year-month, MSA-year, and occupation-year fixed effects. Column 4 replaces our measure of the log(OOW) with a 3 year average of log(OOW). This accounts for the fact that the wages used in our OOW measure are representative at a 3-year averaged level. Column 5 replaces our measure of the log(OOW) with a 3 year average of log(OOW), lagged by 1 year. This accounts for the fact that the effects of stronger outside options may not materialize right away. Heteroskedasticity robust standard errors are clustered by MSA and year-month in column 1, by MSA-year in column 2, and by MSA-occupation-year in columns 3-5. *p<0.1 **p<0.05 ***p<0.01

Table A2: Temperature, Injuries, and Outside Occupation Options: IV

	(1)	(2)	(3)
	Contemporaneous OOW	3 year average of OOW	3 year average, 1 year lag of OOW
Max T $\geq$ 90°F	0.2194***	0.1891***	0.1597***
	(0.0221)	(0.0287)	(0.0289)
Max T $<$ 50°F	-0.0146	-0.0403	-0.0436
	(0.0432)	(0.0483)	(0.0436)
Ppt $>$ 0	-0.0194***	-0.0206***	-0.0192***
	(0.0020)	(0.0019)	(0.0023)
Log(OOW)*Max T $\geq$ 90°F	-0.0561***	-0.0479***	-0.0412***
	(0.0075)	(0.0100)	(0.0102)
Log(OOW)*Max T $<$ 50°F	-0.0220	-0.0180	-0.0193
	(0.0152)	(0.0165)	(0.0149)
Log(OOW)	1.169***	1.223***	1.239***
	(0.0456)	(0.0464)	(0.0473)
Residual: Log(OOW)*Max T $\geq$ 90°F	0.1410***	0.1241***	0.1337***
	(0.0351)	(0.0415)	(0.0471)
Residual: Log(OOW)*Max T $<$ 50°F	0.2314***	0.3033***	0.3256***
	(0.0714)	(0.0665)	(0.0668)
Residual: Log(OOW)	-0.0511	0.0713	0.0817
	(0.0779)	(0.0774)	(0.0908)
Observations	111,612,584	101,656,256	96,582,032
MSA-Month FEs	X	X	X
Year-Month FEs	X	X	X
MSA-Year FEs	X	X	X
Soc-Year FEs	X	X	X
Clustering	MSA-Soc-Year	MSA-Soc-Year	MSA-Soc-Year

This table shows the effect of temperatures and outside occupation options on injury claims for California-based work sites over the period 2000 to 2020. The coefficients in all columns are obtained from Poisson regressions of injury counts on the listed temperature, precipitation, and outside options quality variables, as well as the listed fixed effects. We control for the endogeneity of the OOW and its interaction with temperature bins by using the control function method described in equation 9. We calculate the standard errors with 100 runs of a bootstrap. For each run, we resample observations at the MSA-occupation-year level, with replacement. Column 1 is our core specification and includes MSA-month, year-month, MSA-year, and occupation-year fixed effects. Column 2 replaces our measure of the log(OOW) with a 3 year average of log(OOW). This accounts for the fact that the wages used in our OOW measure are representative at a 3-year averaged level. Column 3 replaces our measure of the log(OOW) with a 3 year average of log(OOW), lagged by 1 year. This accounts for the fact that the effects of stronger outside options may not materialize right away. Heteroskedasticity robust standard errors are clustered by MSA-occupation-year. *p<0.1 **p<0.05 ***p<0.01

B Climate Zone Analysis

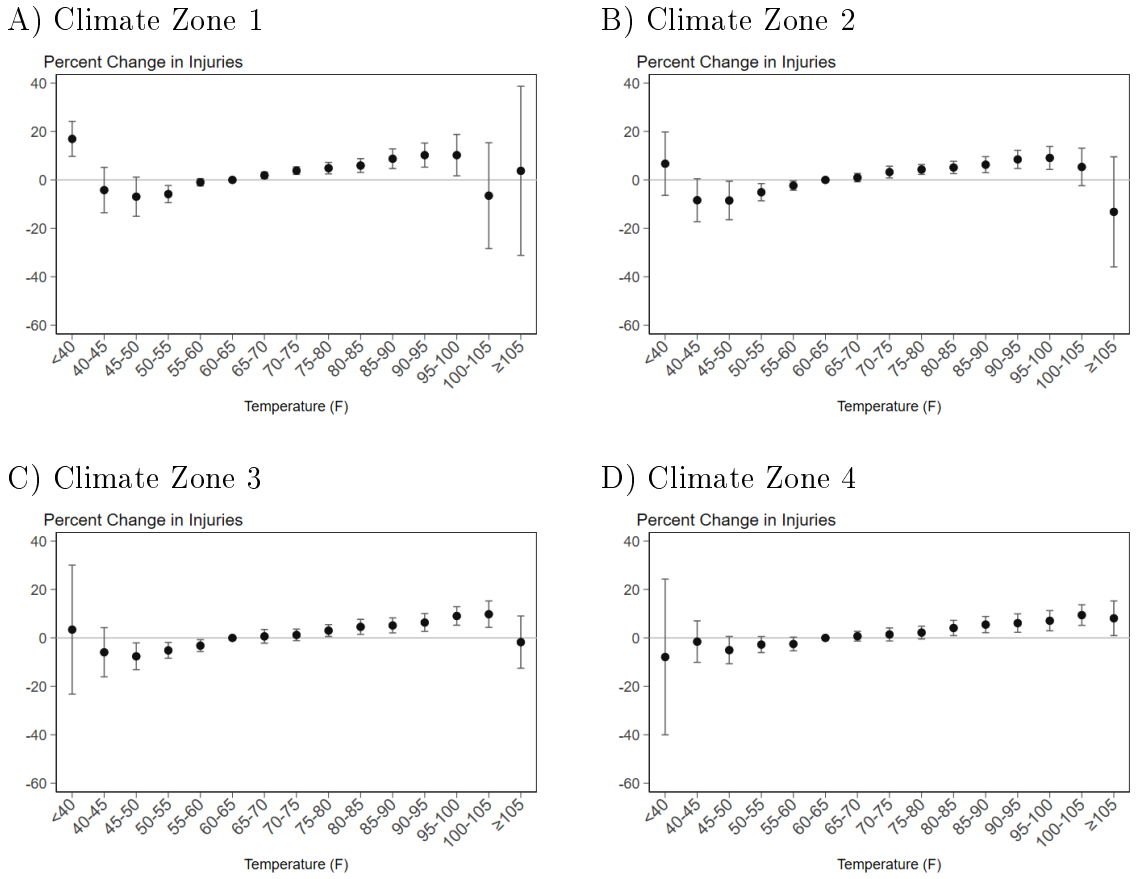


Figure A4: Temperature and Injuries by Climate Zone

This figure plots the full set of temperature coefficients obtained from regressions specified in Equation 5, but at the zip-code by day level. Panel A shows the coefficients for climate zone 1 (coolest), Panel B for climate zone 2, Panel C for climate zone 3, and Panel D for climate zone 4 (warmest). We define climate zones based on their average number of days above 90°F in the summer months (June-September). The coefficients reflect residual variation in injuries after regressing on zip-month, and year-month fixed effects, as well as precipitation controls. Daily maximum temperatures are assigned to a vector of 15 temperature bins from below 40°F to 105°F and greater in 5°F increments. The coefficients should be interpreted as (roughly) the percentage increase in injuries for an additional day in that temperature range relative to a day in the omitted category (daily maximum temperatures between 60 and 65°F). Heteroskedasticity robust standard errors are clustered by county and year-month, and error bars denote 95 percent confidence intervals. The data cover 1,764 zip codes in California from 2000-2020.

Table A3: Temperature and Injuries by Climate Zone

	(1)	(2)	(3)	(4)
Climate Zone	1	2	3	4
Max T (°F)				
≥105	0.0375	-0.1319	-0.0174	0.0812**
	(0.1781)	(0.1159)	(0.0550)	(0.0365)
100-105	-0.0650	0.0535	0.0981***	0.0944***
	(0.1115)	(0.0396)	(0.0279)	(0.0217)
95-100	0.1024**	0.0909***	0.0906***	0.0709***
	(0.0436)	(0.0243)	(0.0195)	(0.0212)
90-95	0.1024***	0.0847***	0.0637***	0.0613***
	(0.0254)	(0.0191)	(0.0188)	(0.0194)
85-90	0.0875***	0.0629***	0.0517***	0.0551***
	(0.0206)	(0.0168)	(0.0159)	(0.0170)
80-85	0.0594***	0.0514***	0.0457***	0.0411**
	(0.0145)	(0.0129)	(0.0158)	(0.0162)
75-80	0.0486***	0.0430***	0.0303**	0.0221
	(0.0120)	(0.0104)	(0.0125)	(0.0135)
70-75	0.0382***	0.0324***	0.0125	0.0143
	(0.0079)	(0.0124)	(0.0122)	(0.0138)
65-70	0.0189***	0.0096	0.0065	0.0069
	(0.0070)	(0.0088)	(0.0144)	(0.0103)
55-60	-0.0097	-0.0235**	-0.0318**	-0.0251*
	(0.0077)	(0.0098)	(0.0125)	(0.0143)
50-55	-0.0584***	-0.0508***	-0.0513***	-0.0276
	(0.0180)	(0.0181)	(0.0167)	(0.0169)
45-50	-0.0692*	-0.0849**	-0.0760***	-0.0505*
	(0.0412)	(0.0406)	(0.0282)	(0.0287)
40-45	-0.0419	-0.0838*	-0.0592	-0.0153
	(0.0478)	(0.0453)	(0.0518)	(0.0437)
<40	0.1695***	0.0671	0.0342	-0.0787
	(0.0369)	(0.0667)	(0.1359)	(0.1641)
Observations	3,375,870	3,347,976	3,364,527	3,369,006
Zip-Month FEs	X	X	X	X
Year-Month FEs	X	X	X	X
Precipitation	X	X	X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effect of temperatures on injury claims for California-based work sites over the period 2000 to 2020. The coefficients in all columns are obtained from Poisson regressions of injury counts on the listed temperature, precipitation controls, as well as the listed fixed effects. Each column corresponds to a different climate zone, defined by the number of days above 90°F during the summer months (June-September). Heteroskedasticity robust standard errors are clustered by county and year-month. *p<0.1 **p<0.05 ***p<0.01

Table A4: Temperature and Injuries by Climate Zone, Two Temperature Bins

	(1)	(2)	(3)	(4)
Climate Zone	1	2	3	4
Max T $\geq$ 90°F	0.0554**	0.0376***	0.0333***	0.0286**
	(0.0254)	(0.0145)	(0.0103)	(0.0118)
Max T $<$ 50°F	-0.0210	-0.0554	-0.0421*	-0.0298
	(0.0361)	(0.0347)	(0.0249)	(0.0257)
Observations	3,375,870	3,347,976	3,364,527	3,369,006
Zip-Month FEs	X	X	X	X
Year-Month FEs	X	X	X	X
Precipitation	X	X	X	X
Clustering	County, Year-Month	County, Year-Month	County, Year-Month	County, Year-Month

This table shows the effect of temperatures on injury claims for California-based work sites over the period 2000 to 2020. The coefficients in all columns are obtained from Poisson regressions of injury counts on the listed temperature, precipitation controls, as well as the listed fixed effects. Each column corresponds to a different climate zone, defined by the number of days above 90°F during the summer months (June-September). Heteroskedasticity robust standard errors are clustered by county and year-month. *p<0.1 **p<0.05 ***p<0.01

C Temperature and Employment

Here, we present evidence that our main temperature-injury count findings cannot be explained by an increase in employment or time worked during hotter weather. This potential concern is due to the productivity-decreasing effects of hot weather, which could lead employers to hire more workers, or workers to work more hours. First, we show, in line with past evidence from Graff Zivin and Neidell (2014), that hot weather does not lead to an increase in time worked in California. Second, using yearly employment at the MSA-occupation level, we show that our findings are robust to setting the dependent variable as the rate of injuries rather than the count.

To study the potential effect of temperature on the intensive margin of labor supply (i.e., hours worked per day), we use data from the American Time Use Survey (ATUS) from 2003 to 2020. We estimate the following regression, similar to that used in Graff Zivin and Neidell (2014), for two samples of workers: 1) the continental United States, and 2) just California.

$$Hours_{w,o,f,d,m,y} = \sum_{k=1}^{K} \beta^k Temp_{f,d,m,y} + \sum_{p=1}^{P} \delta^p Precip_{f,d,m,y} + \Delta\chi + \eta_f + \gamma_{m,y} + \theta_\delta + \epsilon_{f,o,d,m,y}, \quad (13)$$

where $Hours_{w,o,f,d,m,y}$ represents the number of hours worked by worker w in occupation o, county f, on day d of month m and year y. The specification includes county, year-month, and day-of-week fixed effects, as well as a vector of controls χ that includes age, gender, the number of children, earnings, employment status, race, education, marital status, and family income, as well as local sunrise and sunset time controls. In addition, we present an alternative set of fixed effects that more closely mirrors Equation 5 with county-month, year-month, occupation, and day-of-week fixed effects.

As shown in Table A5, we do not find any evidence that workers increase their labor supply on hot days. As in estimates for workers in high risk industries from 2003 to 2018 in Neidell et al. (2021), our coefficients are negative but not statistically significant at conventional levels. In Table A6, we show estimates for regressions that only include two temperature bins: below 50°F and 90°F and above. Again, we find no evidence that workers increase their labor supply on hot days.

Table A5: Temperature and Minutes Worked

	(1)	(2)	(3)	(4)
Max T (°F)	USA		California	
≥105	-13.023	-3.604	-24.242	-29.615
	(11.143)	(22.093)	(19.023)	(37.471)
100-105	-6.210	-16.824	14.259	6.697
	(7.546)	(15.828)	(16.404)	(18.025)
95-100	-0.793	-1.878	-19.020	-29.581*
	(5.606)	(8.252)	(16.879)	(15.968)
90-95	-3.931	-8.752	12.194	32.093*
	(3.814)	(5.459)	(19.673)	(17.495)
85-90	-6.245*	-5.154	-14.150	-15.809
	(3.321)	(4.997)	(12.319)	(15.245)
80-85	-5.450*	-4.579	-0.259	8.159
	(3.274)	(4.411)	(21.833)	(18.208)
75-80	-3.485	-5.368	4.172	2.936
	(2.963)	(4.487)	(8.788)	(10.123)
70-75	-0.774	-0.969	6.506	14.557
	(3.190)	(4.294)	(8.401)	(9.697)
65-70	-5.166	-8.372*	-7.723	-19.922
	(3.220)	(4.665)	(7.324)	(11.384)
55-60	-3.590	-5.169	-11.498	-8.103
	(3.567)	(4.712)	(7.434)	(17.252)
50-55	-1.186	-3.381	-0.973	-8.608
	(3.542)	(5.145)	(20.154)	(38.729)
45-50	-6.791*	-11.064**	-30.245*	-28.523
	(3.605)	(4.992)	(15.114)	(23.588)
40-45	-0.893	-2.418	-71.414	-79.603
	(3.682)	(5.135)	(54.575)	(108.372)
<40	-6.694**	-8.941*	64.811**	101.395*
	(3.205)	(4.642)	(24.282)	(53.220)
Observations	167,429	104,381	20,945	12,487
County FEs	X		X	
Year-Month FEs	X	X	X	X
Day of Week FEs	X	X	X	X
County-Month FEs		X		X
Occupation FEs		X		X
Demographic Controls	X	X	X	X
Precipitation	X	X	X	X
Daylight	X	X	X	X
Clustering	State-Month	State-Month	State-Month	State-Month

This table shows the effect of temperatures on minutes worked for workers over the period 2003 to 2020. The coefficients in all columns are obtained from regressions of minutes worked on the listed temperature, precipitation and daylight controls, and the listed fixed effects. The demographic controls include age, gender, the number of children, earnings, employment status, race, education, marital status, and family income. Standard errors are clustered at the state-month level. Columns 1 and 2 correspond to workers in the full continental United States, and columns 3 and 4 correspond to workers based in California. Heteroskedasticity robust standard errors are clustered by state-month. *p<0.1 **p<0.05 ***p<0.01

Table A6: Temperature and Minutes Worked

	(1)	(2)	(3)	(4)
Max T (°F)	California		USA	
≥ 90	0.428	-2.914	-2.649	-0.241
	(3.404)	(3.404)	(5.152)	(5.905)
< 50	-3.307*	-3.919	-18.769	-15.624
	(2.753)	(2.753)	(12.649)	(21.632)
Observations	12,487	20,945	104,381	167,429
County FEs	X		X	
Year-Month FEs	X	X	X	X
Day of Week FEs	X	X	X	X
Demographic Controls	X	X	X	X
Precipitation	X	X	X	X
Daylight	X	X	X	X
County-Month FEs		X		X
Occupation FEs		X		X
Clustering	State-Month	State-Month	State-Month	State-Month

This table shows the effect of temperatures on minutes worked for workers over the period 2003 to 2020. The coefficients in all columns are obtained from regressions of minutes worked on the listed temperature, precipitation and daylight controls, and the listed fixed effects. The demographic controls include age, gender, the number of children, earnings, employment status, race, education, marital status, and family income. Standard errors are clustered at the state-month level. Columns 1 and 2 correspond to workers in the full continental United States, and columns 3 and 4 correspond to workers based in California. Heteroskedasticity robust standard errors are clustered by state-month. *p<0.1 **p<0.05 ***p<0.01

Next, we show that our results are robust to changing the dependent variable to injuries per 1000 workers. In the absence of more granular employment data (for example, MSA-occupation-day), we calculate injury rates by dividing the daily number of injuries by employment at the MSA-occupation-year level. This approach accounts, to the best of our ability, for any changes in employment that may be correlated with the weather. Figure A5 and Table A7 column 1 show the results from estimating equation 5 with injury rates, per 1000 workers, as the dependent variable. There is an increasing relationship between temperature and injury rates, with a day above 105°F leading to an increase in 0.0099 injuries per 1000 workers relative to a day between 60 and 65°F. In column 2 of Table A7, we show that a day above 90°F leads to an increase of 0.0035 injuries per 1000 workers relative to a day between 50 and 90°F. In Table A8, we show the results of estimating our interaction specification with the dependent variable injury rates. The ratio between the interacted (with log of OOW) and non-interacted coefficients for a day above 90°F is 0.26, very similar to the ratio of 0.23 in our core estimates.

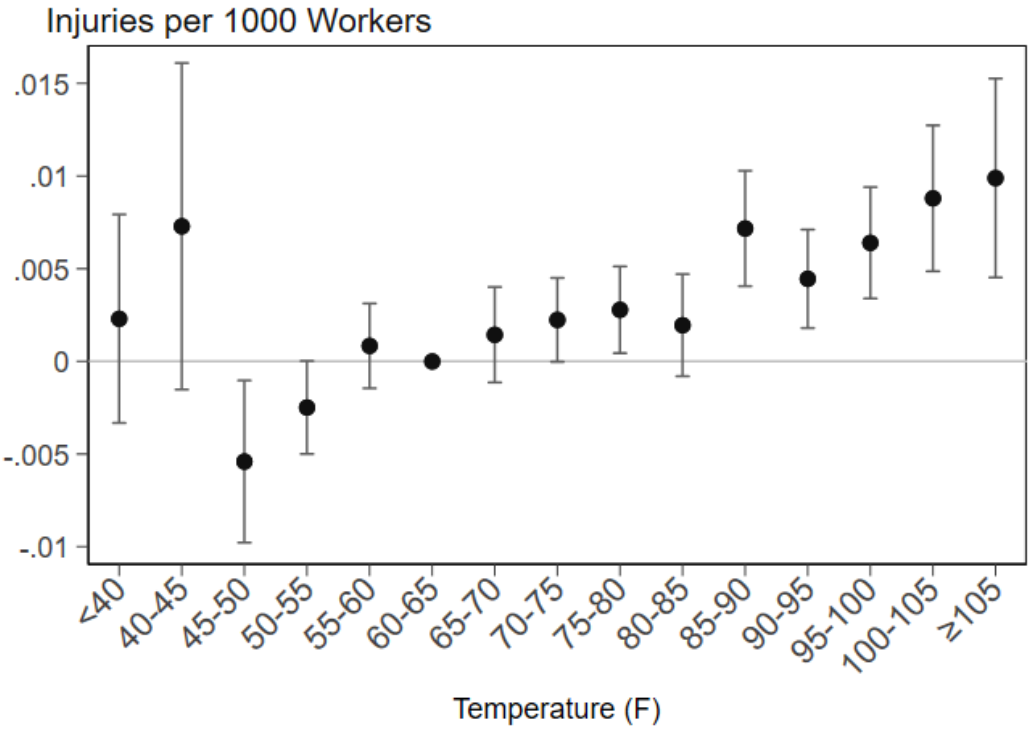


Figure A5: Temperature and Injury Rates

This figure plots the full set of temperature coefficients obtained from regressions specified in Equation 5 (point estimates from Table A7) on the dependent variable injury rates per 1000 workers. Injury rates are calculated as the number of injuries in an MSA-occupation-day divided by yearly employment (1000 workers) at the MSA-occupation level. All coefficients are obtained from Poisson regressions of injury rates per MSA, occupation, and day as the dependent variable. They reflect residual variation in injury rates after regressing on MSA-month, year-month, and occupation fixed effects, as well as controls for precipitation. Daily maximum temperatures are assigned to a vector of 15 temperature bins from below 40°F to 105°F and greater in 5°F increments. The coefficients should be interpreted as the increase in injuries per 1000 workers for an additional day in that temperature range relative to a day in the omitted category (daily maximum temperatures between 60 and 65°F). Heteroskedasticity robust standard errors are clustered by MSA-year, and error bars denote 95 percent confidence intervals. The data cover 26 metropolitan statistical areas in California from 2000-2020.

Table A7: Temperature and Injury Rates

	(1)		(2)
Max T (°F)		Max T (°F)	
≥105	0.0099***	≥90	0.0035***
	(0.0027)		(0.0007)
100-105	0.0088***	<50	-0.0023*
	(0.0020)		(0.0012)
95-100	0.0064***		
	(0.0015)		
90-95	0.0045***		
	(0.0014)		
85-90	0.0072***		
	(0.0016)		
80-85	0.0020		
	(0.0014)		
75-80	0.0028**		
	(0.0012)		
70-75	0.0022*		
	(0.0012)		
65-70	0.0014		
	(0.0013)		
55-60	0.0008		
	(0.0012)		
50-55	-0.0025*		
	(0.0013)		
45-50	-0.0054**		
	(0.0022)		
40-45	0.0073		
	(0.0045)		
<40	0.0023		
	(0.0029)		
Observations	62,316,075		62,316,075
MSA-Month FEs	X		X
Year-Month FEs	X		X
Soc Code FEs	X		X
Precipitation	X		X
Clustering	MSA-Year		MSA-Year

This table shows the effect of temperatures and on injury rates for California-based work sites over the period 2000 to 2020. Injury rates are calculated as the number of injuries in an MSA-occupation-day divided by yearly employment (1000 workers) at the MSA-occupation level. The coefficients in all columns are obtained from regressions of injury rates on the listed temperature, precipitation controls, and the listed fixed effects. Column 1 includes the full set of 5°F temperature bins, from below 40°F to 105°F and above, with the 60 to 65°F bin omitted. Column 2 only includes the below 50°F and 90°F and above coefficients, and so should be interpreted relative to a day between 50 and 90°F. Heteroskedasticity robust standard errors are clustered by MSA-year. *p<0.1 **p<0.05 ***p<0.01

Table A8: Temperature, Injury Rates, and Outside Occupation Options

	(1)	(2)
		Contemporaneous
	No Interaction,	OOW
Max T $\geq$ 90°F	0.0035***	0.0138***
	(0.0007)	(0.0033)
Max T $<$ 50°F	-0.0023*	-0.0184**
	(0.0012)	(0.0073)
Ppt $>$ 0	-0.0019***	-0.0019***
	(0.0004)	(0.0004)
Log(OOW)*Max T $\geq$ 90°F		-0.0036***
		(0.0011)
Log(OOW)*Max T $<$ 50°F		0.0056**
		(0.0025)
Log(OOW)		0.0167***
		(0.0049)
Observations	62,316,075	62,316,075
MSA-Month FEs	X	X
Year-Month FEs	X	X
Soc FEs	X	
MSA-Year FEs		X
Soc-Year FEs		X
Clustering	MSA-Year	MSA-Soc-Year

This table shows the effect of temperatures and outside occupation options on injury rates for California-based work sites over the period 2000 to 2020. Injury rates are calculated as the number of injuries in an MSA-occupation-day divided by yearly employment (1000 workers) at the MSA-occupation level. The coefficients in all columns are obtained from regressions of injury rates on the listed temperature, precipitation, and outside options quality variables, as well as the listed fixed effects. Column 1 includes no interaction effects. Coefficients should be interpreted as relative to a day between 50 and 90°F. Column 2 includes the log of the outside options wages (log(OOW)), as well as interaction terms between log(OOW) and each of the temperature bins. Heteroskedasticity robust standard errors are clustered by MSA-year in column 1, and MSA-occupation-year in column 2. *p<0.1 **p<0.05 ***p<0.01

D OOW Instrument Validity Assumptions

For the OOW IV to be a valid instrument, the leave-one-out national wage of destination occupation p must be correlated with local wages of destination occupation p in a given metro area k (relevance condition), but must not affect the local wage in the origin occupation o other than by increasing the quality of local outside options (exclusion restriction), conditional on controlling for occupation-year and metro-year fixed effects.

The assumption necessary for these conditions to hold is that national occupation-level wage shocks are quasi-randomly assigned, conditional on the fixed effects, which control for national wage trends in that occupation o and wage trends that are common to all occupations in a given metro area k.

Suppose solar installation worker is a relevant outside option for construction laborers. Suppose that changes in production technology that lead to an increase in the demand for solar installation workers nationwide. Our IV leverages the fact that different MSA's – for instance, San Francisco and Atlanta – have different initial exposures to solar installation, that occupation-year and metro-year fixed effects isolate variation in demand for solar installation workers relative to SF and Atlanta's overall labor market trends, and that we are isolating variation that is orthogonal to any average trends in construction laborer's wages.